Institutional Trading on Information Diffusion across Fundamentally Related Firms*

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Abstract

I document a strong cross-predictability of stock returns driven by institutional investors' private information about firms' fundamental relations. A value-weighted arbitrage portfolio yields a monthly alpha of 1.65%. The magnitude of predicted returns increases with firm size, number of institutional shareholders, and institutional trading intensity while not changing with analyst coverage. Further evidences confirm that institutional investors strategically trade a stock in response to shocks to its peers, which subsequently causes permanent price movements. Overall, my results suggest that institutional trading propagates the diffusion of value-relevant information across firms but only gradually due to information asymmetries among investors.

Keywords: cross-predictability · informed trading · information asymmetry · institutional investors · common ownership

JEL Classification: G12 · G14 · G23

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1 Introduction

Firms are fundamentally related if they are prone to the same economic shocks or if their businesses depend upon each other; for example, industry peers are related by their common technology and supply chain. In an efficient market, information diffusion across related firms should be immediate so the stock prices of related firms should correlate simultaneously only. However, mounting evidence shows that stock returns are correlated with thus predictable by previous returns of their peers. This cross-predictability of stock returns, also known as the lead-lag effect or momentum spillovers, has been well documented in the literature. Researchers often attribute it to the gradual information diffusion in the stock market.

What drives the gradual information diffusion? A common explanation is limited attention[1] – investors are unable to pay attention to all the relevant news such as the news about other firms even though they are fundamentally related to the focal firm. Nevertheless, using institutional ownership as a proxy for investor attention, the existing literature obtains mixed results. Some find that stocks with greater institutional ownership lead or are less predictable than stocks with less institutional ownership[2], while others show institutional ownership has no significant impact on return predictability of related stocks.[3]

To resolve this puzzle, it is worthwhile to explore a more fundamental question "What drives the information diffusion at the first place?" The literature of microstructure and information-based asset pricing suggests that informed trading pushes stock prices to their intrinsic level. Information asymmetry among investors is likely to cause latency of stock prices picking up the fundamental shocks from the industry or other related firms. Yet, this channel has been much less discussed compared to the attention-based channel in the cross-firm information diffusion literature.

This study re-examines the role of institutional investors in information diffusion across firms from the perspective of information asymmetry. I test the hypothesis that institutional investors have private information about firms' fundamental relations and their strategic trading propagates sequential stock price updates across the related firms in a gradual manner. It is distinct from the implication of limited attention which suggests that institutional ownership weakens stocks' cross-predictability.

[1]Seminal work by Hirshleifer and Teoh (2003) models the relation between learning and stock price under investor limited attention.

[2]Examples include Badrinath, Kale, and Noe (1995), Hou and Moskowitz (2005), Hou (2007), Cohen and Frazzini (2008), Menzly and Ozbas (2010), Hameed, Morck, Shen, and Yeung (2015), and Parsons, Sabbatucci, and Titman (2019).

[3]Cohen and Lou (2012) find institutional ownership does not affect the return predictability caused by the complicated information processing. Gao, Moulton, and Ng (2017) show institutional ownership only matters for the cross-predictability between economically unrelated firms on a weekly basis.

From a theoretical perspective, compared with retail investors, institutional investors are more likely to own private information or at least comparative advantage of acquiring the information about firms' fundamental relations. If so, such private information and comparative advantage could motivate institutional investors to own fundamentally related firms despite the conventional wisdom about portfolio diversification. Recent work by van Nieuwerburgh and Veldkamp (2009, 2010) models the optimum where investors concentrate on assets of which they have information advantage. Compared with news watching, holding shares of related firms could earn investors extra benefits from trade coordination as implicated in Edmans, Levit, and Reilly (2018).

Motivated by the theories, I reverse engineer firms' fundamental relations from their institutional common ownership. I infer a stronger relationship between two firms if they are commonly held by more institutional investors and if the common investors own fewer other firms. This approach creates an innovative many-to-many relation network. To lump together the fundamental shocks transmitted from all the other firms in the relation network, for each firm, I construct a syndicated peer which is a portfolio of firms weighted by their relationships to the focal firm. The composition of the syndicated peer changes over time as institutional investors adding new firms into the portfolio or selling out old firms.

Firms and their syndicated peers show strong positive correlation in fundamentals such as size, investments, profitability, etc. Moreover, one firm's future growth of Research and Development (R&D) expenditure and growth of total assets are shown to be predictable by those of its syndicated peer respectively. The correlation and predictability are economically and statistically more significant than most of the ones estimated with the Fama-French 48 industry peers and peers followed by the same analysts (Ali and Hirshleifer, 2019). This indicates that institutional investors have more accurate information about firms' fundamental relations in comparison with conventional industry classifications and sell-side analysts.

How efficiently does the stock market price in the fundamental spillovers from the peer firms inferred from institutional common ownership? To answer this question, I investigate firms' stock market performance after their syndicated peers experience unanticipated shocks. Sorting and grouping stocks by past abnormal returns of their syndicated peers, the portfolio analysis predicts that stocks in the top quintile (whose syndicated peers had highest abnormal returns) significantly outperform stocks in the bottom. Specifically, a value-weighted long-short equity portfolio yields a monthly alpha of 1.65% (t = 8.47) after controlling the market risk, size, and value factors as well as the momentum and the short-term reversal effects. This finding agrees on a gradual information diffusion between firms and their syndicated peers. Comparative analyses confirm that the syndicated peer effect is distinct from other peer momentums, and reinforces the private information argument about institutional investors.

Results from a close examination of stock prices' ex-ante informativeness question the mechanism of information diffusing across firms. The magnitude of a firm's returns predicted by its syndicated peer shocks increases with its market capitalization and the number of its institutional shareholders while not changing with the number of analysts following the firm. Obviously, limited attention theory alone cannot explain these findings. These observations hint that institutional investors play an active role in cross-firm information diffusion.

To better understand the mechanism, I further scrutinize the dynamics between institutional trading and stock returns of fundamentally related firms. I first test whether institutional trades convey information about the peer shocks. If so, institutional trades should at least positively correlate with the peer shocks. My analysis shows that institutional investors are indeed more likely to buy (sell) a stock when its related peers gain higher (lower) abnormal returns in the same quarter. At security level, institutional excess demand for a stock is even more sensitive to the abnormal return of the peer stocks than the return of the traded stock itself. The trade-return correlation is stronger if the institutional investors already own both the firm and its peers, compared with the case of initial purchases and the case where firms' relations are derived from sources other than institutional common ownership. Similar patterns are confirmed at institution-security level after accounting for exogenous fund flow shocks and other time-varying stock characteristics. Interestingly, the intra-quarter correlations become less clear when measuring institutional trading based on the number of shares traded instead of the number of traders or buy/sell indicators. This appears to be in line with the strategic "stealth" trading by privately informed investors (e.g., Kyle, 1985; Barclay and Warner, 1993).

Next, if the market subsequently updates its valuation based on the pricing signals carried by institutional trading, we should observe a larger adjustment of stock prices to their peer shocks when institutional investors trade more intensely. Both ex-ante and ex-post trading intensities are studied. Forecasting an institution's future trading frequency by its past churn rates, I find a stronger stock peer shock effect from institutional portfolios with higher ex-ante churn rates than institutional portfolios with lower ex-ante churn rates. In addition, I estimate the extent of ex-post trading intensity by the number of institutional investors that actually trade the stock in a quarter and find that the predicted returns in the same quarter become greater in magnitude when more institutional investors trade.

Finally, I check whether the return predictability documented in this study results from some transitory price impacts via testing two alternative hypothesis. On the one hand, it is possible for institutional investors to overreact to the news of other firms that are fundamentally related to firms they own. When it happens, stock prices would be pushed to follow their related peers but soon bounce back once institutions' overreaction diminishes. I find no significant stock price reversals in either short- or long-run after a series of robustness tests. On the other hand, portfolio rebalancing or exogenous fund flows may force institutional investors to simultaneously trade stocks regardless of their fundamental relations, which could lead to a temporary cross-serial correlation in stock returns. My results show little support for such mechanism either.

The reminder of the paper is organized as follows. Section 2 reviews the related literature and highlights my contributions. Section 3 describes the data and methodology. Section 4 presents the main results regarding firms' fundamental relations and the implications for their stock market performances. Section 5 examines the mechanism. Section 6 provides the robustness tests. Section 7 concludes.

2 Literature Review

First and foremost, this paper is built upon the theoretical foundation about information-based trading and asset pricing pioneered by Grossman and Stiglitz (1976, 1980) and advanced by an extensive literature. Numerous interesting features of asset price dynamics have been derived from the asymmetric and imperfect information of investors. Kyle (1985) model is one of the first showing how information is gradually traded into asset price by informed investors. Taking gradual information diffusion as given, Hong and Stein (1999) demonstrate that limited information can give rise to return predictability. Pasquariello (2006) finds that financial contagion can be an equilibrium outcome when investors possess heterogeneous information.

Recent developments of focused learning and concentrated investing help develop my intuition regarding institutions' intended ownership of fundamentally related firms. For example, Peng and Xiong (2006) propose a model showing that limited capacity causes investor to focus too much on aggregated information. From a non-behavioral view, van Nieuwerburgh and Veldkamp (2009, 2010) rationalizes portfolio concentration with comparative information advantage. Empirically, researchers also find extensive evidences revealing investors' preference and pecuniary incentive for holding stocks related by industry (e.g., Kacperczyk, Sialm, and Zheng, 2005, 2007; Fedenia, Shafer, and Skiba, 2013) and location (e.g., Coval and Moskowitz, 1999, 2001; Ivković and Weisbenner, 2005; Seasholes and Zhu, 2010; Choi, Fedenia, Skiba, and Sokolyk, 2017).

This paper adds to a growing body of literature about cross-predictability of stock returns. Since Lo and MacKinlay (1990) first point out that large stocks lead small stocks in return, several papers bring to light such cross-autocorrelation among stocks with different degrees of common characteristics such as the number of analysts following, institutional ownership, and trading volume (e.g., Brennan, Jegadeesh, and Swaminathan, 1993; Badrinath et al., 1995; Chordia and Swaminathan, 2000, respectively). More recent studies focus on return predictability that arises from ways in which stocks are related. Most of the relations are clear and explicit such as industry and technology (e.g., Eleswarapu and Tiwari, 1996; Moskowitz and Grinblatt, 1999; Hou, 2007; Hoberg and Phillips, 2018; Lee, Sun, Wang, and Zhang, 2019), supply chain and market segment (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), competition (e.g., Eisdorfer, Froot, Ozik, and Sadka, 2019), and geographic proximity (e.g., Addoum, Kumar, and Law, 2017; Parsons et al., 2019). A few studies derive firms' relations in a more implicit way like mine; for example, Ali and Hirshleifer (2019) infer firms' fundamental linkage from shared analyst coverage and claim that it unifies all the known momentum spillover effects. My results suggest that institutional common ownership contains information about firms' fundamental relations that is beyond the one indicated by shared analyst coverage.

There are other papers using institutional common ownership to study return dynamics across stocks. My paper is different from them in several aspects including research question, measurement of common ownership, and implication of results. Anton and Polk (2014) show that common ownership by mutual funds which are exposed to exogenous fund flow shocks induce stocks' excessive comovement and overvaluation, which generates a negative cross-serial correlation between stocks. Bartram, Griffin, Lim, and Ng (2015) study the impact of institutional common ownership on stock covariation between foreign stock markets and suggest that their findings are driven by institutions' discretionary trading. Gao et al. (2017) also find stocks that are commonly held by institutional investors positively predict each other's subsequent returns, although, they focus on the non-informative effect of portfolio rebalancing on the economically unrelated stock pairs.

The findings in this paper contribute to the broad literature on institutional trading. There is a long-standing debate in academia on whether institutional investors trade based on private information. While some find evidences supporting informed trading by institutional investors, for example, Nofsinger and Sias (1999), Ke and Petroni (2004), Bushee and Goodman (2007), and Ivashina and Sun (2011), different opinions arise from contradicting results such as the ones in Potter (1992) and Hendershott, Livdan, and Schürhoff (2015). If institutional investors are uninformed, their trading could be alternatively driven by certain mechanical strategies such as momentum trading (e.g., Grinblatt, Titman, and Wermers, 1995; Cai and Zheng, 2004) and contrarian trading (e.g., Rakowski and Wang, 2009). Since momentum traders and contrarian traders coexist in the institutional investor population and trade alongside each other, evidently in Badrinath and Wahal (2002), it is not surprising that regressions of institutional trades on returns of the traded stock lead to mixed or weak results. But that is much less a concern for studying institutions' cross-stock trading. To the best of my knowledge, my paper is the first one that provides direct evidences of institutions' cross-stock trading at both security and institution-security levels.[4] My results support the informed trading hypothesis for institutional investors.

This paper also joins the debate about the price impact of institutional trading. On the one hand, Sias and Starks (1997), Wermers (1999), and Boehmer and Kelley (2009) argue that institutional trading promotes price adjustments according to new information. On the other hand, as modeled by Vayanos and Woolley (2013), end-investor fund flows can push stock price away from its intrinsic value. The fund flow effect has been found among stocks owned by mutual funds in particular (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012[5]). Even though it is possible for institutional trading to induce both transitory and permanent price impacts as shown in Sias, Starks, and Titman (2006) and Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), my findings lean towards the latter.

Last but not the least, results from this study have meaningful implications on corporate decisions with the presence of common ownership. It is getting researchers' attention that institutional common ownership has substantive influences across firms including corporate governance, anti-competition, innovation, and managerial incentives.[6] The similarity and predictability of fundamentals between firms that are commonly held by institutional investors could have resulted from common ownership effect.

3 Data and Methodology

3.1 Data and Sample

Firms' stock market data from the Center for Research in Security Prices (CRSP) is merged with their financial statement data from Compustat. SEC 13F institutional investors holdings data come from Thomson Reuters. Analyst coverage information is extracted from the Institutional Brokers Estimate System (IBES). I download asset-pricing factors and Fama-

[4]Menzly and Ozbas (2010) also examine the correlation between institutional trading and peer stock returns at security level. One issue is that they do not account for the same-quarter return on the focal stock which is likely to affect institutional trading as well. Another issue arises from their use of the percentage changes in institutional ownership as the measure of institutional trading. The percentage of institutional ownership can also be affected by the excess demand from the non-institutional investors.

[5]Coval and Stafford (2007) and Frazzini and Lamont (2008) document a immediate stock price reversal after excessive fund flows in and out, while Lou (2012) finds fund flows first induce a momentum up to 12 months and a reversal afterwards.

[6]See, for example, Edmans et al. (2018), Azar, Schmalz, and Tecu (2018), Kostovetsky and Manconi (2018), Gilje, Gormley, and Levit (2019), and Backus, Conlon, and Sinkinson (2019).

French industry definitions from Kenneth R. French Data Library.

The sample covers the period 1980–2017. Each year, I remove the institutional investors from the sample if they are identified as managers of any mutual funds according to Thomson Reuters' 's12type5' file, for two reasons. First, mutual fund managers' trading decisions are more likely to be affected by end-investor fund flows as already reviewed in section 2. Second, institutional investors sometimes delegate their diversified portfolios to other mutual funds, therefore,the mutual fund managers' portfolio allocation is more likely to be driven by the diversifying incentive instead of their specialized information. Since Thomson Reuters only started creating the mapping from the first quarter of 1994, I use the 1994 mapping table for earlier data. I hereafter refer to the non-mutual fund managers when mentioning institutional investors in the paper unless otherwise specified.

I restrict my analysis to common stocks (share codes 10 and 11) traded on NYSE, NYSE MKT (formerly AMEX), and NASDAQ and held by at least one institutional investor. I further require sample firms to have at least 6 months of stock returns in the past 12 months, and non-missing value of book equity at prior fiscal-year end. These filters help to screen out close-end funds and exchange-traded funds (ETFs) held by institutional investors as well as the stocks that lack sufficient price and accounting data for institutional investors to extract information from.

[Table 1 about here.]

After applying those criteria, my sample on average still covers 95% of the CRSP common stock universe in terms of market capitalization, as shown in Panel A of Table 1. Institutional investors hold more stocks listed on the NYSE than the NASDAQ. Panel B reports a lower percentage in terms of number than market capitalization for institutional coverage of NASDAQ-listd stocks, suggesting the non-covered stocks are more likely to be small-caps. Panel C shows that the median number of stocks held by institutional investors is 78, averaging over the sample period, which is much less than most of non-sector equity ETFs. Table 1 also reports various characteristics of sample firms. As shown in Panel D, my sample covers firms with a wide range of fundamentals.

Figure 1 illustrates the declining trend of the median number of stocks held by institutional investors in spite of the growing population of institutional investors. The number of institutional investors grows almost 9 times from the 80s while the median number of stocks held goes down to 60 from 100 back in the 80s. These two contrasting trends hint at benefits of a concentrated investment strategy. With the increasing convenience of delegating diversifying portfolio to external mutual funds, institutional investors can better focus and strategically bet on fundamentally related firms.

[Figure 1 about here.]

3.2 Institutional Common Ownership

I infer firms' fundamental relations from their institutional common ownership. The basic idea is that two firms are more closely related if they share a larger number of institutional investors and if the common investors have more concentrated portfolios. Therefore, we need a measure of common ownership that accounts for both factors.

At the end of quarter q, there are N_q institutional investors holding M_q firms in total. The overall ownership distribution can be expressed as a matrix,

$$O_q = \begin{bmatrix} o_{1,1,q} & \cdots & o_{1,M_q,q} \\ \vdots & \ddots & \vdots \\ o_{N_q,1,q} & \cdots & o_{N_q,M_q,q} \end{bmatrix} \tag{1}$$

where $o_{n,m,q} = 1$ if investor n holds shares of firm m by the end of quarter q and $o_{n,m,q} = 0$ otherwise. The extent of common ownership between firm i and firm j is thus measured as,

$$c_{i,j,q} = \sum_{n=1}^{N_q} \left(\frac{o_{n,i,q} o_{n,j,q}}{\sum_{m=1}^{M_q} o_{n,m,q} - 1} \right) \tag{2}$$

The numerator inside the bracket equals 1 only if investor n owns both firms. The denominator calculates the number of other firms investor n owns other than either i or j. In the extreme case where investor n owns only firm i and j, the value of the fraction inside the bracket equals 1. As the common investors of firm i and j increases the number of firms in their portfolios, their learning efforts are spread thinner as the value of the fraction declines. Last, I sum up the equally divided learning efforts of all the common investors.

Here is a simplified example to better see the point: three investors own four firms; investor 1 holds shares of firm A, B, and C; investor 2 holds shares of firm A, C, and D; investor 3 holds shares of A and B. The extent of common ownership is 1.5 (= 0.5 + 1) between firm A and B, 1 (= 0.5 + 0.5) between firm A and C, and 0.5 between firm A and D. Ordering the common ownership, I infer that firm B is the most related to A, C is less, and D is the least. Note that the relationship is not necessarily symmetric, for instance, firm A is the most related to firm C but not vice versa.[7]

I use the example above to illustrate the differences between my measure of common ownership and others in the literature. Anton and Polk (2014, p. 6) consider two stocks to have

[7] The extent of common ownership between B and C is 0.5, and so is it between D and C.

greater common ownership if the common investors own a higher percentage of total market value of both stocks. Consider the case in which firm D has the largest market value and is almost held entirely by investor 2 while the other three firms have much smaller market value and are equally held by their shareholders. Firm A thus has the greatest common ownership with firm D. Bartram et al. (2015, Eqn. 10, Eqn. 11) measure the common ownership by calculating the scaled Manhattan distance between both firms' institutional investors and then weighting it by their relative institutional holdings in dollar value. According to them, firm C would be related to firm A the most if investor 2 holds most of A and puts more portfolio weight on C than she does on D. Gao et al. (2017, p. 4) simply counts the number of common institutional investors, which results in the same extent of common ownership of firm B and firm C with firm A.

I argue that my measure of common ownership is better for studying institutional investors' private information and its effects on institutional trading and stock prices for the following reasons. First of all, according to the theories reviewed in Section 2, institutions who invest in less firms are more likely to have a greater advantage of acquiring the common information about those firms. My measure considers such implication. Besides, the inferred relationship does not depend on institutional investors' exact portfolio weights and the market value of commonly owned shares thus is less affected by the noise from portfolio rebalancing and fund flows. Lastly, the asymmetry of the inferred relationship has better resemblance to reality.

For each firm, I construct a syndicated peer (SP) which is a portfolio of other firms weighted by their inferred relationships to the focal firm. More specifically, firm i is said to have a syndicated peer defined by

$$X_{SP,i} = \sum_{j \neq i} \frac{c_{i,j} X_j}{\sum_{j \neq i} c_{i,j}}, \; i, j \in (1, 2, \ldots, M) \tag{3}$$

where X_i and $X_{SP,i}$ are stock returns or various fundamentals of firm i and its syndicated peer. The original subscript q in Equation (2) is omitted for generality because later analyses are based on different time horizons.

The construction of syndicated peers deliberately ignores the exact institutional shares for the same reason aforementioned. In addition, the literature on institutional trading lean towards that the number of institutional traders contains greater pricing signals than the number of shares traded by institutional investors.[8] I modify the construction in robustness tests to take into account any flow-induced price pressures.

[8] See, for example, Chen, Hong, and Stein (2002), Sias et al. (2006), Edelen, Ince, and Kadlec (2016), and Guo and Qiu (2016).

4 Main Results

4.1 Firm's Fundamental Relations

It is not immediately clear how well institutional common ownership reflects firms' fundamental relations. Neither can the literature conclude whether the documented portfolio concentration is driven by institutional investors' advantageous information or some systematic behavioral bias. Korniotis and Kumar (2013) explore the same question with a sample of retail investors and find the existence of both driving forces.

Therefore, I conduct the following tests to examine the resemblance between institutional common ownership and firms' fundamental relations. I first run a contemporaneous regression of several annual gauges of sample firms' fundamentals on those of their syndicated peers. One firm is considered to be a related peer to the other if both firms are once owned by any institutional investor at any time during the year. Using Equation (3), for each firm's each financial statement variable, I calculate a respective variable X_{SP} for its syndicated peer. Specifically, I look into six categories of financial statement variables: size, investment, profitability, market valuation, financing, and firm-specific risk, each of which includes at least one testing variable. Besides, I construct two alternative peers: X_{ana}, a portfolio of peer firms weighted by the number of common analysts following as in Ali and Hirshleifer (2019),[9] and X_{ff48}, a equal-weighted portfolio of industry peers defined by the Fama-French 48 Industry classification, for comparison. They summarize analysts' specialized knowledge and the public information about firms' fundamental relations, respectively.

[Table 2 about here.]

Results are reported in Table 2. The syndicated peer constructed by institutional common ownership significantly correlates with the focal firm in fundamentals. For example, as shown in Panel A, 1% weighted average increase in total assets of all the other commonly owned firms by institutional investors, or simply 1% increase in the syndicated peer's total assets, is associated with 0.13% increase in the focal firm's total asset. Institutional investors also seem to be able to identify the technology links as they own firms that share similar R&D expenditure and R&D growth. I find such peer correlations in institutional portfolios for other variables such as age, asset growth, gross profit, profit growth, dividend yield, book-to-market ratio, and idiosyncratic risk. The only exception is leverage ratio. The results are consistent with the hypothesis that institutional investors decide portfolio composition based on firms' fundamental relations.

[9] Following Ali and Hirshleifer (2019), I define a stock to be followed by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the stock over the past 12 months.

It is questionable whether institutional investors simply follow the firms of which relations are publicly known, such as SIC-based industry membership, or some obvious supplier-customer pairs. Panel B in Table 2 presents evidences suggesting otherwise. If institutional investors have no private information about firms' fundamental relations, the correlation between the syndicated peer and the focal firm should become weaker after adding the common-analysts peer and Fama-French industry peer in the regression. But that is not the case. Moreover, the coefficients of the syndicated peer in regard to most of the variables become more significant either economically or statistically. Comparing the coefficients between all three peers shows that the focal firm is more closely related to the syndicated peer than to the two alternative peers. To address the concern of a possible multicollinearity issue,[10] I report the largest VIF from the multicollinearity test for each set of peer variables. None of the VIFs exceeds the acceptable threshold.

Beyond the contemporaneous correlation, I test whether the syndicated peers can predict the focal firms in fundamentals. The predictive test is motivated by the strong connection between future stock returns and firms' fundamentals documented in the literature. For instance, firms' R&D expenditure and R&D growth predict both their own future stock returns (e.g., Chan, Lakonishok, and Sougiannis, 2001; Eberhart, Maxwell, and Siddique, 2004) and their peers (e.g., Jiang, Qian, and Yao, 2015; Lee et al., 2019). Another example is the well known asset growth effect. Cooper, Gulen, and Schill (2008), Watanabe, Xu, Yao, and Yu (2013), and Titman, Wei, and Xie (2013) find a negative relation between firms' asset growth and future stock returns in both domestic and foreign stock markets. These stock market anomalies may be associated with institutional investors' relation-based prediction.

[Table 3 about here.]

Table 3 reports the results from the predictive regressions of firms' future R&D growth and asset growth on the lagged respective variables of their peers in addition to other lagged financial statement variables. As shown in column (2)–(4), the syndicated peer significantly leads the focal firm in R&D growth. The lead-lag relation of R&D growth implies technology races or spillovers among firms – not all firms but the ones whose technology connections are recognized by institutional investors. The technology spillover effect is much less significant between firms which are classified as industry peers by SIC-based Fama-French definition or firms which are commonly followed by analysts. Column (6)–(8) reveal a similar cross-firm momentum of asset growth which is particularly strong among firms that are commonly held

[10] Indeed, the syndicated peer inferred from institutional common ownership may overlap with the two alternative peers in terms of stocks coverage. For example, institutional investors and sell-side analysts tend to follow each other, as discussed in O'Brien and Bhushan (1990).

by institutional investors. The R&D growth and asset growth momentum do not seem to be originated by the focal firms themselves as their lagged growth in R&D and total assets are not significantly associated with their future changes.

Results from both the contemporaneous and the predictive regressions strengthen the belief that institutional investors tend to commonly hold shares of firms that are fundamentally related, and the relations are private information acquired by institutional investors due to their specialized knowledge. Institutional investors may still follow the public information and the analysts coverage, however, empirical evidence show that they know something beyond.

4.2 Stock Return Predictability

Prior studies show that stock returns of explicitly related firms cross-predict each other. In this section, I test whether firms whose relations are inferred from institutional common ownership have such cross-predictability for their stock returns as well, and whether the cross-predictability is distinct from the ones documented in the existing literature. I will also examine whether the findings are subject to investor attention which is the explanation commonly seen in the existing literature, or caused by investor information asymmetry. Moreover, any stock return cross-predictability anomalies could be arbitraged right away by institutional investors thus becomes weaker, or it could become more pronounced as institutional investors trade in a way that their private information is only gradually incorporated into stock prices as modeled in Kyle (1985). This section explores those competing hypotheses. For all the return predictability tests, I exclude the stocks of which previous month-end price is lower than or equal to $5 from the sample described in section 3.

4.2.1 Baseline Portfolio Tests

Stocks are first sorted at the beginning of each month by the firm-specific shocks that their syndicated peers experienced during the past month. The firm-specific shocks are measured as the industry-adjusted Daniel, Grinblatt, Titman, and Wermers (1997) (DGTW) return. Different from prior studies in which peer stocks' gross returns are used as the predictors, I argue that the abnormal returns can better represent the new information that is gradually disseminated by institutional investors because institutional investors are able to differentiate the firm-specific shocks from the industry- and market-wide shocks.[11] The syndicated peers are defined by institutional common ownership at the end of last quarter. For each stock

[11]Burt and Hrdlicka (2019) make similar arguments and show that sorting on idiosyncratic returns better measures information diffusion. Estimating DGTW returns does not require factor regressions as estimating idiosyncratic returns thus is not subject to the alpha attenuation issue discussed in Burt and Hrdlicka (2019).

i, I calculate its monthly syndicated peer shock ($R_{SP,i,t}$) by averaging all its peers' DGTW returns with the weighting scheme indicated in Equation (3):

$$R_{SP,i,t} = \sum_{j \neq i} \frac{c_{i,j,q-1} R_{DGTW,j,t}}{\sum_{j \neq i} c_{i,j,q-1}} \tag{4}$$

where $c_{i,j,q-1}$ is defined in section 3.2 as the extent of fundamental relation between stock i and j inferred from institutional common ownership at the end of quarter $q-1$. $R_{DGTW,j,t}$ is the DGTW return of stock j in month t of the current quarter q. This definition presumes that the portfolio holdings of an institutional investor at the end of quarter $q-1$ indicate his state of information about firms' relations in quarter q to which he refers when trading in response to peer shocks in month t of quarter q.

Next, at the beginning of month $t+1$, I create a portfolio for each quintile of stocks ranked by their $R_{SP,t}$'s. Portfolios are constructed with both market value weights and equal weights. In addition to the five quintile portfolios, I create a self-financing arbitrage portfolio which long holds the top quintile stocks (highest $R_{SP,t}$) and short sells the bottom quintile stocks (lowest $R_{SP,t}$). Portfolio performance is evaluated by its return in month $t+1$. Stocks are re-sorted and re-assigned every month.

To measure the portfolios' monthly performance, I calculate their average excess returns relative to the U.S. 3-month T-bill rate and estimate alphas from regressing portfolio excess returns on risk factors including the market risk, size, and value factors defined in Fama and French (1993) as well as Carhart (1997)'s momentum factor and the short-term (one month) reversal factor. It is particularly important to account for the short-term reversal because investors' contrarian trading strategy may push stock prices back following the initial changes originated from institutional investors trading new information into stock prices.

[Table 4 about here.]

Table 4 presents the portfolios' monthly abnormal returns. Both excess return and alphas show that stocks with higher syndicated peer shocks significantly outperform stocks with lower syndicated peer shocks. The long-short value-weighted equity portfolio yields a monthly alpha of 1.65%, approximately 21.7% annualized.

A closer examination of the value weighted portfolios in Panel A shows that stocks respond to their syndicated peer shocks in an asymmetric manner: after their peers are hit by negative shocks last month, their stock prices plunge to a greater extent than they surge after their peers are hit by positive shocks. Nonetheless, the asymmetry is almost non-existing in equal weighted portfolios reported in Panel B. The equal weighted portfolios on average respond less intensely to their syndicated peer shocks than the value weighted counterparties. Evidence appear to suggest that stocks with larger market capitalization are more sensitive to their syndicated peer shocks especially after their peers are hit by negative shocks. This finding is in contrast with the existing literature which often find the cross-predictability to decline with stock capitalization size.

[Table 5 about here.]

Portfolio risk loardings and firm characteristics are reported in Table 5. Even though the arbitrage portfolio has a significant loading on the size factor but the sizes of stocks in the portfolios do not follow the same pattern as stocks' syndicated peer shocks and their returns. Same for the momentum factor loadings; in fact, in untabulated results, the momentum factor loading flips the sign for the arbitrage portfolio in the 4-factor regression. The loadings on the short-term reversal factor across five quintile portfolios and the last-month return (mom1) of the included stocks confirm that the results are not driven by investors overreacting and contrarian trading in regard to stocks' own past returns. It also implies a continuation of stock price movements both during and after peer firms get hit by shocks.

Panel C in Table 5 gives more details about which kinds of firms are included in each quintile portfolio. From the top quintile to the bottom, most of firms' fiscal year-end variables follow either a U-shape or a reversed U-shape. Firms whose peers experienced extremely positive or negative shocks are also firms which have had greater R&D growth, asset growth, and profit growth. Those firms are more likely to be in fast expanding industries in which fundamental shocks hit frequently. Meanwhile, those firms have had lower dividend yield, higher equity-to-debt ratio, and higher idiosyncratic risk. Stocks in both the top and bottom quintiles are more likely to be the winning stocks in the past 12 month than stocks in the middle quintiles. Overall, the results suggest that the monotonic pattern of predicted returns is not likely to be driven by those examined risk factors or firm fundamentals.

4.2.2 Predicted Returns and Information Advantage

Section 4.1 provide some evidence that institutional investors have private information about firms' fundamental relations as revealed in their common ownership. I further examine whether the return predictability induced by the gradual diffusion of institutional private information is different from the ones documented in the existing literature, namely, the common analysts momentum (Ali and Hirshleifer, 2019) and industry momentum (Hou, 2007). Following the literature, a stock's common analysts momentum $R_{ana,t-1}$ is calculated as the average last-month return of other stocks weighted by the number of common analysts following; its industry momentum $R_{ff48,t-1}$ is calculated as the last-month return of the respective value-weighted Fama-French 48 industry portfolio excluding the focal firm itself.

[Table 6 about here.]

To isolate the impacts of institutional investors' private information, I orthogonalize the syndicated peer shock $R_{SP,t}$ onto $R_{ana,t}$ and $R_{ff48,t}$ cross-sectionally each month, and repeat the portfolio tests in section 4.2.1 using the orthogonalized shock $\tilde{R}_{SP,t}$. Test results reported in Table 6 show that the arbitrage portfolios still yield significant abnormal returns after excluding the common analyst momentum effect and the industry momentum effect. For example, after being orthogonalized onto both aforementioned momentum, the syndicated peer shock still predicts a monthly 5-factor alpha of 0.94% (t = 4.83) for the long-short portfolio. Comparing to the baseline results, orthogonalization indeed weakens the impact of syndicated peer shocks. It is very likely due to the existence of overlapped information about firms' relations from institutional common ownership, common analyst following, and Fama-French industry classification. The difference between Panel A and B is consistent with the belief that analysts know more about firms' relations than their industry classifications.

[Table 7 about here.]

I also compare the extent of return-relevant information contained in the syndicated peer shocks, common analyst momentum, and industry momentum by performing portfolio tests with double sorting. Both independent and dependent sorts are implemented because three sorting variables are possibly correlated, in which case independent sorting may end up with some portfolios with too few stocks to make meaningful estimations. Results are presented in Table 7.

For both independent and dependent double sorting, stocks with higher syndicated peer shocks significantly outperform stocks with lower syndicated peer shocks regardless of their common analysts momentum. But the return gaps between high common analysts momentum stocks and low common analysts momentum stocks are only significant when they both have either the lowest or the highest syndicated peer shocks according to the independent sorting results in Panel A. If stocks are first sorted into quintile portfolios by their syndicated peer shocks and then sorted by their common analysts momentum within each previously assigned portfolio, the portfolios' 4-factor alphas in Panel B suggest that the common analysts momentum is unable to differentiate the future returns of stocks with higher syndicated peer shocks. For instance, in the top quintile portfolios (highest R_{SP}), the gap of predicted returns between high and low common analysts momentum is only 0.45% with t-statistic of 1.52. Results in Panel A and B of Table 7 together indicate the cross-predictability is more prominent between stocks whose relations are identified by institutional investors than sell-side analysts.

I find similar pattern when sorting stocks by their syndicated peer shocks and industry momentum. Even though the syndicated peer effect slightly declines with the industry momentum, it is still significant economically (0.68%) and statistically (t = 2.16) when the industry momentum is at its highest.

Can the return predictability be driven by limited attention instead of information asymmetry? It is possible that retail investors pay more attention to firms' industry membership and analysts' earning forecasts than their institutional ownership. Most of the related studies find the return predictability to be weaker when stocks gain more attention. They usually use the number of institutional shareholders and the number of analysts following as the gauges of attention. Exceptions include Cohen and Lou (2012) which find institutional ownership does not affect the return predictability that is powered by the information complexity. Investor information asymmetry interacts with stock information complexity: complex stocks require sufficient informed trading to be fairly priced.

I reconcile the mixed evidence using stock double sorting technique. Stocks are independently sorted into 5×5 quintile portfolios by their syndicated peer shocks and one of the following measures of attention: the number of analysts following *nana* and the number of institutional shareholders *ninv*. As shown in Panel A of Table 8, the number of analysts following does not affect the return predicting power of the syndicated peer shocks. For example, the return spread between high R_{SP} stocks and low R_{SP} stocks is 1.44% if they are both followed by the most analysts while the return spread is 1.56% if they are both followed by the least analysts. The difference is -0.07% (t= -0.21)[12], small and insignificant. For stocks in each R_{SP} quintile, varying the number of analysts following makes no significant changes to their returns. These results suggest that the syndicated peer shock effect is not under the influence of investor attention.

[Table 8 about here.]

The number of institutional shareholders, on the other hand, appears to matter more significantly but in a way that disagrees on the attention-based explanation. Panel B in Table 8 shows that stocks with more institutional shareholders have larger responses to their syndicated peer shocks. This finding has two implications: (1) greater attention from institutional investors does not weaken the return predictability induced by information asymmetry; (2) institutional trading may enhance the spillovers of the syndicated peer shocks in the stock market.

[12]The difference is slightly off from $1.44\% - 1.56\%$ or $0.07\% - 0.17\%$ due to lack of sufficient number of stocks in one or two of the 5×5 portfolios for certain months. There are only a few months like that during the sample period but when it occurs, it is more commonly seen in the top or bottom quintiles because of the slight correlation between R_{SP} and nana. Double sorting R_{SP} and ninv has the same issue.

4.2.3 Fama-MacBeth Regressions

Now I examine the syndicated peer shock effect using Fama and MacBeth (1973) regressions. Raw returns of the sample stocks are first cross-sectioanlly regressed on their syndicated peer shock R_{SP} and other control variables for each month, and then the coefficients are averaged over the sample period. Results reported in Table 9 confirm the findings from the portfolio tests. The syndicated peer shock shows an economically and statistically significant influence on the focal stock's future return across all the differently specified regressions. When no interaction term is included, 1% DGTW return of the syndicated peer leads about 0.5% future raw return of the focal stock.

[Table 9 about here.]

Results in section 4.1 suggest that firms' fundamentals are strongly correlated with their syndicated peers. Hence, it is worth inspecting whether the lagged stock returns stem from investors' delayed response to firms' own changes in fundamentals or to their peers'. Column (2) shows that the return predictability of the syndicated peer shock is different from the previously found stock market anomalies with respect to the focal firm's investment, profitability, and investor sentiment for short-term and long-term prior returns. Column (3) provides further evidence that institutional investors have advantageous information which induces a return predictability that is distinguishable from common analysts momentum and industry momentum. Column (4) and (5) examine the interaction effects with investor attention. Stock returns have greater responses to their syndicated peer shocks when the stocks are followed by more analysts and held by more institutional investors. These results are consistent with the double sorting tests in section 4.2.2 suggesting the return predictability does not reply on investor limited attention.

Subsample results are presented in column (6) and (7). I split the sample stocks into two groups by their size which is measured as the market value of equity by the end of the most recent June. Some pricing factors are more significant for smaller stocks such as the value premium, the Carhart (1997) momentum, and the industry momentum while size and asset growth effect are only significant for larger stocks. The coefficient of the key variable of interest $R_{SP,t-1}$ is statistically significant for both large and small stocks but $R_{SP,t-1}$ leads higher next-month returns for large stocks than small stocks.

The results from portfolio tests and Fama-MacBeth regressions together tell a consistent story: investors' asymmetry information about firms' fundamental relations prevents stock price from sufficiently integrating shocks from other related firms. The delayed stock price responses are stronger if the firm has larger market value, higher analysts coverage, and more institutional shareholders, which signals a better informed investor base. This finding seemingly contradicts with the conventional wisdom which supposes that stocks with better informed investor base should be more efficiently priced. One probable explanation is that institutional trading strategically disseminates value-relevant signals such that the market can only updates its valuations gradually.

5 Mechanism

Results in section 4 establish the association between the cross-predictability of stock returns and institutional common ownership. To close the circle, in this section, I emphasize on institutional trading, namely, examining whether institutional investors strategically trade in a way that their privately informed trading propagates information diffusion across firms gradually. To accomplish this goal, I proceed with the following two steps. First, I check whether institutional investors trade a stock in response to the contemporaneous shocks from its peer stocks. Second, I inspect the price impact of institutional trading by comparing the return predictability between stocks with different extents of ex-ante and ex-post institutional trading activities.

5.1 Cross-firm Trading

5.1.1 Evidence at Security Level

If all institutional investors consider cross-firm shocks when making trading decisions, the aggregated excess demand from institutional investors for a stock would be positively correlated with the abnormal returns of the stock's peers in the same quarter. To study the contemporaneous correlation, I run a panel regression specified as follows:

$$ED_{i,q} = \alpha_i + \gamma_q + \beta R_{SP,i,q} + controls + \epsilon_{i,q} \tag{5}$$

where $ED_{i,q}$ is the institutional excess demand for stock i in quarter q; $R_{SP,i,q}$ is the DGTW return of stock i's syndicated peer in quarter q and the syndicated peer is constructed based on the institutional common ownership by the end of quarter $q-1$; α_i and γ_q are firm and time fixed effects, respectively. Controls include the excess demand in last quarter $ED_{i,q-1}$ to account for the institutional investors' sequential herding tendency, and stock i's return in quarter q and $q-1$ ($R_{i,q}$ and $R_{i,q-1}$) to account for the feedback and momentum trading. I also include the contemporaneous returns of the peer stocks defined by common analysts coverage $R_{ana,i,q}$ and Fama-French 48 industry peers $R_{ff48,i,q}$. $R_{ana,i,q}$ is peer stock returns weighted by the number of common analyst as in Ali and Hirshleifer (2019) and $R_{ff48,i,q}$ is the return of value-weighted industry portfolio excluding the focal stock.

Following Lakonishok, Shleifer, and Vishny (1992), I measure the institutional excess demand for a stock by its Nratio and Dratio. $Nratio_{i,q}$ is calculated as the number of institutional investors who increase their holdings of stock i divided by the number of institutional investors who change – either increase or reduce – their holdings of stock i in quarter q. $Dratio_{i,q}$ is the net change of stock i's institutional shares dividend by the sum of shares bought and sold by institutional investors in quarter q. These two measures could greatly diverge from each other, for example, when there is only one institutional buyer but he buys a large number of shares while the other institutional traders sell a much smaller number of shares. More importantly, privately informed institutional investors have incentive to spread their trades over time to disguise the information, which creates more noises to the share-based measure of trades.

Since the cross-predictability of stock returns documented in the previous sections is based on the end-of-quarter holdings of institutional investors, I account only the trades made by the institutional investors who have positive number of shares by the end of last quarter. All the initial buys are excluded from calculating the excess demand. Even though the initial buys may also be triggered by peer news and impound the news into stock prices, they are not responsible for the cross-predictability inferred from institutional common ownership at the end of last quarter.

[Table 10 about here.]

Results are presented in Table 10. By examining the coefficients of $R_{SP,i,q}$, it is clear that more institutional investors increase than reduce their holdings of a stock when the stock's peers are hit by greater positive shocks. The trading is more sensitive to the peer shocks than the focal stock's own return in the same quarter. The peer shocks, however, do not necessarily determine the number of shares institutional investors buy or sell. Evidently, the coefficients of $R_{SP,i,q}$ are more significant in Panel A for $Nratio$ than the ones in Panel B for $Dratio$. This appears to be consistent with the strategic "stealth" trading hypothesis posited by Barclay and Warner (1993) and Chakravarty (2001). Meanwhile, the coefficients of $R_{ff48,i,1}$ stay significant in the regressions of $Dratio$, most likely because industry membership are public information thus institutional investors have no need to camouflage their trades.

It is worth noting that the coefficients of $R_{ana,i,q}$ switch the signs between the regressions of $Nratio$ and $Dratio$, which suggests that common analyst momentum drives dispersed and asymmetric trades among institutional investors, i.e., there are more buyers than sellers but the shares bought is less than the shares sold, or vice versa.

The different impacts of peer shocks on the number of institutional traders versus the number of traded shares also support the findings in prior studies such as Chen et al. (2002) and Guo and Qiu (2016) which find institutional trading estimated by counting the traders is more informative than counting the shares. Positive coefficients of the stock's last-quarter return $R_{i,q-1}$ suggest that institutions momentum trade; negative coefficients of the stock's same-quarter return $R_{i,q}$ suggest either institutional investors contrarian trade in higher frequency or excessive returns cause portfolio rebalancing. The positive coefficients of $Nratio_{i,q-1}$ and $Dratio_{i,q-1}$ are consistent with the positive correlation of institutional demands between adjacent quarters documented in Sias (2004).

For comparison, I also check the initial buys which are excluded from the main sample. Similarly, the initial buys are quantified by two methods: they are first estimated as the number of institutional investors who initiate their purchases of stock i in quarter q, $IBN_{i,q}$, and they are also estimated as the percentage of shares of stock i in quarter q that is initially bought by institutional investors, $IBS_{i,q}$. Panel regression results are reported in Table 11.

[Table 11 about here.]

Panel A shows that shocks from common analysts peers and industry peers increase the odds of institutions initiating their buying while shocks from already owned peers by institutions reduce the odds. This finding suggests that institutional investors rely more on cross-referring to common analysts coverage and industry membership than their existing ownership when deciding investments in a new firm. The negative coefficient of $R_{SP,i,q}$ could be explained as institutions prefer to allocate constrained capital to the existing positions over initiating a new position after learning about good news of already owned firms. Results in Table 10 and Table 11 together reinforce the intuition about investors' learning process: investors are better informed about a firm and its fundamental relations with other firms when they become shareholders of the firm. Till investors have skin in the game, they resort to other information sources such as analysts' reports for individual firms and reports of industry research.

Similar to the results for trading the existing holdings, Panel B shows that the impact of peer shocks on the number for shares initially purchased either becomes weaker or changes the sign. On a side note, the significantly positive coefficients of $R_{i,q}$ appear to evince that the positive contemporaneous correlation between institutional trading and stock returns, documented in the existing literature, is primarily driven by initial buys other than the adjustments of existing holdings.

5.1.2 Evidence at Institution–Security Level

One concern about the results in section 5.1.1 arises from the impacts of portfolio rebalancing and fund flows on institutions' trading decisions. Indeed, institutional investors have incentives to change the holdings of a stock to maintain the initial weights if they realize gains or losses from the other stocks. Besides, the performance of other stocks in the portfolio may trigger funds inflow or outflow which will in turn force institutional investors to buy or sell a stock away from its information-based optimum. If institutional investors are independent with each other in regard to their portfolio rebalancing need and fund flow shocks, aggregating institutional trades at the security level will not cause any bias in regression analysis. Otherwise, it is likely that results in section 5.1.1 capture institutions' mechanical and noninformed trading other than informed trading.

To address the potential issue, I run a three-dimensional panel regression of institutional investors' trading propensity on peer shocks and other control variables with the following specification:

$$trade_{n,i,q} = \lambda_{n,q} + \theta_{i,y} + \beta R_{SP,i,q} + controls + \epsilon_{n,i,q} \tag{6}$$

where $trade_{n,i,q}$ is either a dummy variable indicating that institutional investor n buys or sells stock i in quarter q or a continuous variable as the number of shares bought or sold by this investor scaled by the stock's total shares outstanding. $\lambda_{n,q}$ is the institution-quarter fixed effect and $\theta_{i,y}$ is the firm-year fixed effect. $R_{SP,i,q}$ is the syndicated peer shock for stock i in quarter q as defined in previous sections. *controls* include institutions' previous trade $trade_{n,i,q-1}$, stock i's same-quarter return $R_{i,1}$ and prior-quarter return $R_{i,q-1}$, realized value-weighted return of institution n's stock portfolio in quarter q excluding the focal stock i denoted as $I_{n,-i,q}$, as well as common-analyst peer return $R_{ana,i,q}$ and industry peer return $R_{ff48,i,q}$ which are already defined in previous sections. Including the institution-quarter fixed effect $\lambda_{n,q}$ helps account for the fund flow shocks. $I_{n,-i,q}$ is used to capture the portfolio rebalancing effect induced by excessive gains or losses realized in the rest of the portfolio. For the same reason discussed in the security-level analysis, I exclude the initial buys from the sample trades.

[Table 12 about here.]

As shown in Table 12, 1% increase (decrease) of the syndicated peer DGTW return is associated with about an additional 0.2% likelihood for an institutional investor to buy (sell) the stock. The peer shock effect is stronger when the peers are commonly held by institutional investors than when the peers are followed by common analysts or they are classified into the same Fama-French 48 industry group. More importantly, the peer shock effect found at the institution-security level is robust to the portfolio rebalancing demand and any fund flow shocks.

Institutions' selling propensity is less significantly correlated with the syndicated peer shock when terminating sells are included. Instead, it seems that institutions refer to analyst coverage more in that case, as shown in column (5). This finding suggests that when institutional investors decide to liquidate the entire holdings of a stock, they no longer consider it to be related to the other stocks in the portfolio. Such behavior is consistent with the sequential learning and trading modeled in van Nieuwerburgh and Veldkamp (2010).

In keeping with the regression results at the security level, the continuous share-based measure of institutional trading in column (7) – (9) shows unclear association with the syndicated peer shocks but positively correlates with the industry peer shocks at 1% significance level. It further strengthens the argument about the strategic trading by privately informed institutional investors.

5.2 Institutional Trading and Price Impact

Results in section 4.2 show that more institutional shareholders is associated with stronger stock return predictability. Nonetheless, it does not speak directly to how institutional trading effectuates the information diffusion; institutional investors may passively hold the stocks instead of trading actively. In this section, I directly test the price impact of institutional trading by comparing the return predictability between stocks with different extents of institutional trading intensities. If institutional investors strategically disseminates the information about cross-firm shocks, stocks traded by more institutional investors should respond more intensely to their peer shocks.

I first examine how ex-ante institutional trading affects the cross-predictability of stock returns. To be more specific, I differentiate the peer shock effect inferred by the more active institutional traders' common ownership from the peer shock effect inferred by the less active institutional common ownership. Institutional investors' activeness of trading is estimated by their trading frequency which I forecast by their past churn rate. Following Gaspar, Massa, and Matos (2005) and Yan and Zhang (2007), institutional investor n's churn rate for quarter q is defined as the less of his buy churn rate and sell churn rate:

$$CR_{buy,n,q} = \frac{\sum_{i=1}^{M_q} o_{n,i,q-1} |S_{n,i,q} P_{i,q} - S_{n,i,q-1} P_{i,q-1} - S_{n,i,q-1} \Delta P_{i,q}| \mathbb{1}_{S_{n,i,q} > S_{n,i,q-1}}}{\frac{1}{2} \sum_{i=1}^{M} o_{n,i,q-1} \left(S_{n,i,q} P_{i,q} + S_{n,i,q-1} P_{i,q-1} \right)} \tag{7}$$

$$CR_{sell,n,q} = \frac{\sum_{i=1}^{M_q} o_{n,i,q-1} |S_{n,i,q} P_{i,q} - S_{n,i,q-1} P_{i,q-1} - S_{n,i,q-1} \Delta P_{i,q}| \mathbb{1}_{S_{n,i,q} \leq S_{n,i,q-1}}}{\frac{1}{2} \sum_{i=1}^{M} o_{n,i,q-1} \left(S_{n,i,q} P_{i,q} + S_{n,i,q-1} P_{i,q-1} \right)} \tag{8}$$

where M_q and $o_{n,i,q}$ are defined in section 3.2. $S_{n,i,q}$ is the number of shares of stock i held by institutional investor n by the end of quarter q. $P_{i,q}$ is the quarter-end stock price. The numerators in Equation (7) and (8) are investor n's total buys and total sells in dollar value within quarter q, respectively. They are then scaled by the investor's portfolio value averaged over two adjacent quarters. Hence, investor n's churn rate for quarter q is determined as $CR_{n,q} = min(CR_{buy,n,q}, CR_{sell,n,q})$. His ex ante churn rate for quarter $q+1$ is the simple average of his churn rate from quarter q to $q-3$:

$$\overline{CR}_{n,q+1} = \frac{1}{4} \left(CR_{n,q} + CR_{n,q-1} + CR_{n,q-2} + CR_{n,q-3} \right) \tag{9}$$

For each quarter q, I sort institutional investors into terciles: high, middle, and low, by $\overline{CR}_{n,q}$. Then, following the same procedure described in section 4.2.1, I separately calculate the syndicated peer shock based on the high churning institutional common ownership R^H_{SP} and the syndicated peer shock based on the low churning institutional common ownership R^L_{SP}, and sort sample stocks into quintile portfolios based on their $R^H_{SP,t-1}$ and $R^L_{SP,t-1}$. If more frequent institutional trading sequentially integrates more cross-firm shocks into stock prices, the long-short equity portfolio based on $R^H_{SP,t-1}$ should outperform the one based on $R^L_{SP,t-1}$.

[Table 13 about here.]

As shown in Panel A of Table 13, stocks respond more strongly to the syndicated peer shocks inferred from the high churning institutional investors than to the peer shocks inferred from the low churning investors. Is it possible that high churning investors tend to hold stocks that are more sensitive to their peer shocks? Indeed, high churning investors are more likely to actively search for those neglected thus undervalued stocks. To alleviate this endogeneity concern, I orthogonalize the churning-based syndicated peer shocks with respect to common analyst momentum and industry momentum, and repeat the portfolio tests with $\tilde{R}^H_{SP}$ and $\tilde{R}^L_{SP}$. Results are presented in Panel B of Table 13. All the results consistently point towards institutional trading's amplifying effect to stocks' cross-predictability.

The association of institutional churning and the cross-firm information diffusion may also be related to the observations in Yan and Zhang (2007) which find institutional investors with higher churn rate are better informed. Better informed institutions are more likely to recognize any changes to the focal firm's fundamental relations with other firms and update their cross-firm trading strategy accordingly. Such strategic updating also promotes the sequential stock price movements across firms.

Next, I take an ex-post approach which measures the trading intensity by the realized institutional trades. Namely, I count the number of institutional investors who buy or sell the stock i in quarter q, $NT_{i,q}$, and run portfolio tests sorting stocks independently by their $R_{SP,t-1}$ and NT_q. Since the portfolios are formed monthly but NT_q is counted on a quarterly basis, I associate stock returns $R_{i,t}$ in the first month of quarter $q+1$ and second and third months of quarter q with $NT_{i,q}$. In this way of matching, $\frac{1}{3}NT_{i,q}$ approximates the monthly ex-post trading activities in quarter q which are hypothesized to affect the stock returns in the following month.

[Table 14 about here.]

The 4-factor alphas of the 25 double sorted quintile portfolios are reported in Table 14. The long-short portfolio based on $R_{SP,t-1}$ is less profitable if the stocks in the portfolio are traded by less institutional investors. For example, the long-short portfolio made of the least traded stocks yields a 4-factor alpha of 0.95% while the long-short portfolio made of the most traded stocks yields an alpha of 1.77%. Within each quintile of stocks sorted by their syndicated peer shocks, greater trading intensity exaggerates stocks' lagged response to the peer shocks, especially when the peer shocks are either extremely low or extremely high.

Overall, my results provide evidence that institutional trading magnifies the cross-predictability of stock returns and further support the hypothesis that institutions' cross-firm trading signals their private information about firms' fundamental relations which aids the market in updating stock valuations subsequently.

6 Robustness and Alternative Explanations

In this section, I perform a series of robustness tests to check whether the results presented above are driven by some transitory price impacts. Two alternative explanations are emphasized. First, news about peer firms may cause institutional investors to overreact, and this irrational investor sentiment may push stock prices to follow their peers but away from their intrinsic values. Second, institutional trading is subject to portfolio rebalancing or exogenous fund flows, which could lead to a temporary cross-serial correlation in stock returns of firms that are not fundamentally related.

6.1 Institutional Investor Overreaction

Brown, Wei, and Wermers (2014) find certain mutual funds overreact and herd in response to analyst revisions, which in turn causes subsequent stock price reversals. It is possible for institutional investors to overreact to the peer firm news and overtrade the focal firm. In such case, the long-short arbitrage portfolio based on the syndicated peer shock should have reversed returns afterwards.

Figure 2 illustrates the cumulative returns of the arbitrage portfolio from one month to 12 months since the portfolio formation. Both value and equal weighted portfolios continue to grow in value after the first month. No significant return reversal is observed. There is a small up-and-down for the value-weighted portfolio between the fourth and fifth months which is possibly related to some market sentiments and adjustments after SEC publishes the 13F filings for the past quarter.

[Figure 2 about here.]

I continue to examine the return pattern after 12 months by two different tests. The first one is to evaluate a cross-firm momentum strategy inspired by Jegadeesh and Titman (1993). Stocks are sorted at the beginning of month t by their syndicated peer shocks in month $t-13$ and assigned into equal weighted quintile portfolios. Each portfolio will be held for 6, 12, or 24 months and rebalanced monthly to maintain equal weights. For each month, I average the returns of the newly formed portfolio and the existing ones by equal weights. If stock returns reverse after the syndicated peer shocks in long run, the portfolio which includes stocks hit by high peer shocks one year ago should underperform the portfolio that consists of stocks hit by low peer shocks during the same time. Panel A of Table 15 presents the 4-factor alphas of the top and bottom quintile portfolios as well as the long-short portfolio. Obviously, there is no sign of return reversals as the long-short portfolio yields an insignificant yet positive abnormal return.

[Table 15 about here.]

The second test is to perform Fama-MacBeth regressions of stocks' 6-, 12-, and 24-month returns compounded from month t on their past syndicated peer shocks $R_{SP,t-13}$. To account for the price impacts from the more recent peer shocks and firms' current fundamentals, I include $R_{SP,t-1}$ in the regressions together with other control variables dated as if predicting returns in month t. If stock prices bounce back after the initial movements led by the syndicated peers, the holding period return in the next 6, 12, or 24 month should be negatively correlated with the $R_{SP,t-13}$. Regression coefficients are reported in Panel B of Table 15. Again, I find no evidence of return reveals after the earlier syndicated peer shocks in long run.

The figure of the cumulative returns and results from both tests unanimously show that the predicted returns do not reverse in either short run or long run, which suggests that institutional investors' correlated trading indeed causes permanent changes of stock prices thus is not likely to be driven by overreaction or other irrational sentiments.

6.2 Portfolio Rebalancing and Fund Flows

Gao et al. (2017) points out that portfolio rebalancing by institutional investors can cause economically unrelated stocks to move in a lead-lag way. Even though results in section 4.1 show that firms with greater institutional common ownership indeed correlate with each other in fundamentals, it is still worth testing how likely my findings are driven by institutional investors' portfolio rebalancing practice.

Investors need to rebalance their portfolios when some stocks outgrow their initial weights. The need becomes greater when the stocks have larger weights already from the beginning. In other words, investors are more likely to adjust their holdings of a stock if another stock in which they allocate more capital had greater price fluctuation during the last period. An investor's portfolio rebalancing trades will have greater price impact if the investor has more shares of the stock. Therefore, returns of a stock should be more likely to follow the past return of stocks that are owned in more dollar value by their common shareholders.

To test this hypothesis, I modify the original measure of firms' relatedness in such a way that firms are more likely to be artificially correlated in stock returns via institutions' portfolio rebalancing. At the end of quarter q, with N_q institutions and M_q firms, I define a new ownership matrix D_q,

$$D_q = \begin{bmatrix} d_{1,1,q} & \dots & d_{1,M_q,q} \\ \vdots & \ddots & \vdots \\ d_{N_q,1,q} & \dots & d_{N_q,M_q,q} \end{bmatrix} \tag{10}$$

where $d_{n,i,q}$ equals the dollar value of capital investor i allocate to stock i at the end of quarter q. A value-based common ownership is then defined as $c'_{i,j,q}$, and correspondingly, I estimate a peer-induced portfolio rebalancing shock $R_{PR,i,t}$ for stock i during month t,

$$c'_{i,j,q} = \sum_{n=1}^{N_q} d_{n,i,q} d_{n,j,q} \tag{11}$$

$$R_{PR,i,t} = \sum_{j \neq i} \frac{c'_{i,j,q-1} R_{DGTW,j,t}}{\sum_{j \neq i} c'_{i,j,q-1}} \tag{12}$$

Similar to the method in Bartram et al. (2015), $R_{PR,i,t}$ assigns heavier weights on abnormal returns of peer stocks that are held more in dollar value than the other peers by the common institutional shareholders who also own more shares of stock i.

I then repeat the portfolio tests with $R_{PR,i,t-1}$. If my previous findings are mainly driven by institutions' portfolio rebalancing, this value-based measure of peer shocks should exaggerate the pattern found in the baseline tests – stocks in the top quintile (highest $R_{PR,i,t-1}$) and the bottom quintile (lowest $R_{PR,i,t-1}$) should have higher and lower returns than the respective stocks sorted by $R_{SP,i,t-1}$. However, the portfolio abnormal returns presented in Table 16 provide evidence against this hypothesis. Compared to the portfolio abnormal returns reported in Table 4, it is very clear that stocks response more strongly to the syndicated peer shocks R_{SP} than the portfolio rebalancing shocks R_{PR}. This result indicates my previous findings are not driven by portfolio rebalancing of institutions.

[Table 16 about here.]

Prior studies also find end-investor fund flows to have a transitory impact on stock prices. They either document an immediate bounceing back of stock prices after the flow events (e.g., Coval and Stafford, 2007), or show that it could take months or even years till the stock returns completely reverse (e.g., Lou, 2012). Unlike them, the returns predicted by the syndicated peer shocks appear to not reverse in either short or long run. Also their results are obtained using mutual funds holdings which are excluded in my sample. Nevertheless, it would be helpful to examine whether flow-induced price pressure exaggerates or weakens the cross-predictability.

The price pressure of fund flows comes from institutions' aggregate disproportional demand of stock shares with respective to the stock's fair value. Since institutional investors' external fund in- and out-flows are not observable, I instead directly examine the price impact of institutions' abnormal demand in stock shares. Namely, for quarter q, I estimate the institutional investors' net buy (NB) of stock i as a percentage of the stock's total shares outstanding:

$$NB_{i,q} = \frac{\text{\# of shares bought}_{i,q} - \text{\# of shares sold}_{i,q}}{\text{\# of shares outstanding}_{i,q}} \tag{13}$$

The institutional net buy measure is related the trading intensity measure NT which is the number of institutions that trade. Both are ex-post measures of institutional trading activities. However, they have very different implications and price impacts. If institutional investors trade in the same direction, both NT and NB could be high for the quarter and stock price would be pushed to move. But if institutions trade against each other, NT may be high but NB may not be and the stock price is likely to not change. Besides, high NB could be driven by bulk buys from a few institutions while high NT could be associated with numbers of small trades. The former puts upward pressure on stock price but the latter does not necessarily have the same effect.

If the cross-firm momentum documented earlier is driven by institutional fund flows, the return predictability tests should yield more significant results conditional on high ex-post institutional net buy. Hence I double sort stocks by their syndicated peer shocks $R_{SP,t-1}$ and their institutional net buy in the current quarter NB_q, and compare the performances of the 5×5 quintile portfolios. As shown in Table 17, institutional net buy basically has no impact on the syndicated peer shock effect. Evidently, even if institutions are subject to flow-induced trading, the price pressure caused by such trading neither reinforces nor weakens the cross-firm information diffusion. This finding also agrees with Chen et al. (2002), Edelen et al. (2016), and other studies which argue that the number of institutional traders is more informative than the number of shares traded by institutions.

[Table 17 about here.]

7 Conclusion

Firms are fundamentally related in a very complex way. Cash flow shocks can be transmitted via industry cooperation and technology spillovers. When determining the value of a firm, investors should take into account its entire business relation network. However, not all the investors are equipped with sufficient knowledge and skills to identify and trade upon the relations between firms. The information asymmetry slows down the collective assessment of the worth of a firm from approaching its intrinsic value.

This paper provides new insights into how information diffuses across firms. Emphasis has been put on the role of institutional investors. I infer firms' fundamental relations from an innovative measure of institutional common ownership which accounts for institutions' heterogeneous information advantages. A syndicated peer is defined as a portfolio of firms weighted by their institutional common ownership to the focal firm. Firms are shown to be significantly correlated with and even predicted by their syndicated peers in annual fundamentals.

Moreover, the syndicated peer shocks defined as the syndicated peers' last-month DGTW return are shown to significantly lead the focal firms' future returns. A value-weighted long-short equity portfolio yields a monthly alpha of 1.65%, approximately 21.7% annualized. This strong syndicated peer shock effect goes beyond the industry momentum and the common analyst momentum. Further results suggest that the syndicated peer shock effect is driven by institutions' information advantage instead of investor limited attention.

By examining the mechanism, I find that institutional investors strategically trade a stock in response to news about its syndicated peers. Institutional investors are more likely to buy (sell) a stock if its syndicated peer gains higher (lower) DGTW return in the same quarter. Their trading propensity is more correlated with the syndicated peer shock than the focal stock's own return. Evidences are found at both security level and institution-security level. This correlated trading behavior is more pronounced for existing holdings than initial purchases. Closing the circle, I show that institutional trading indeed enhances the syndicated peer shock effect.

At the end, a series of robustness tests alleviate the concerns with the alternative explanations such as institutional overreaction and other transitory price impacts from portfolio rebalancing and fund flows. Results confirm that the syndicated peer shock causes permanent price impact on the focal stock.

Overall, my findings suggest the following: as the better informed players in financial markets, institutional investors have superior knowledge about firms' fundamental relations. Such information advantage motivates institutions to strategically trade a stock in response to news about its related peers. This privately informed cross-firm trading behavior of institutional investors in turn leads the market to sequentially integrate the news into stock prices across firms.

Appendix

A1 Variable Definitions

mv	Log of market value of equity in million dollars by the end of December.
size	Log of market value of equity in million dollars by the end of June.
at	Log of total assets in million dollars.
age	Firm age is counted from the firm's first record on Compustat.
rd	R&D expenditure is scaled by total assets.
rdg	R&D growth is the percentage change of assets-scalded R&D from previous year.
ag	Asset growth is the percentage change of total assets from previous year.
grp	Gross profit is scaled by total assets.
pftg	Profit growth is the change of gross profit scaled by total assets.
div	Dividend yield is annual cash dividend payment divided by market value of equity.
bm	Book-to-market ratio is the fraction of book value to market value of equity.
lev	Leverage ratio is the fraction of market value of equity to long-term liability.
yvol	Annual idiosyncratic risk is calculated based on daily returns and Fama-French 3 factors.
mvol	Monthly idiosyncratic risk is calculated based on daily returns and Fama-French 3 factors.
mom1	last month stock return.
mom11	Last 12 month stock return excluding the last month return.

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Figure 1: Time Trend of Institutional Investments from 1980 to 2017

This figure shows the time trend of the number of U.S. institutional investors (dotted line) and the median number of domestic common stocks held by institutional investors (solid line) for each quarter from Q1 1980 to Q4 2017. The institutional investors in the sample are defined as the SEC 13F investment companies which are not mapped to any mutual funds by Thomson Reuters.

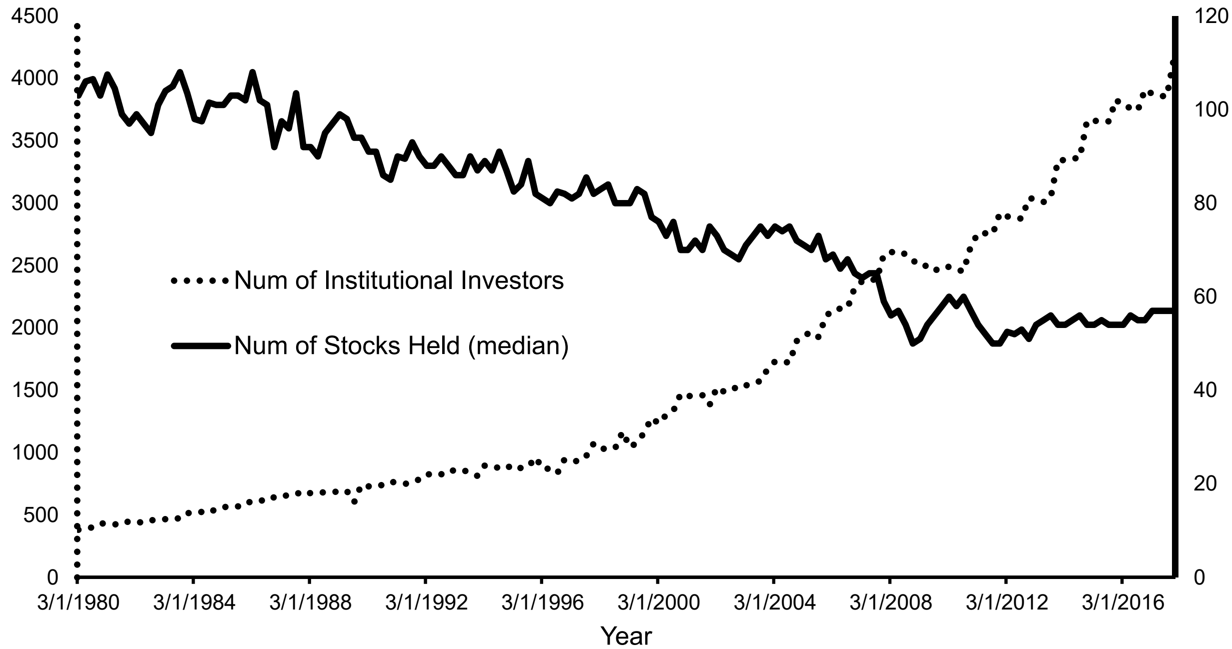

Figure 2: Cumulative Returns of Long-short Equity Portfolios

This figure shows the cumulative returns of the value-weighted and equal-weighted long-short equity portfolios based on the syndicated peer shocks. The portfolio long holds 20% of the sample stocks with the highest syndicated peer shocks $R_{SP,t-1}$ defined by Equation (4) and short sells 20% of the sample stocks with the lowest $R_{SP,t-1}$. The sample period is from May 1980 to December 2017. Stocks with prior month-end price lower than or equal to \$ 5 are excluded from the sample.

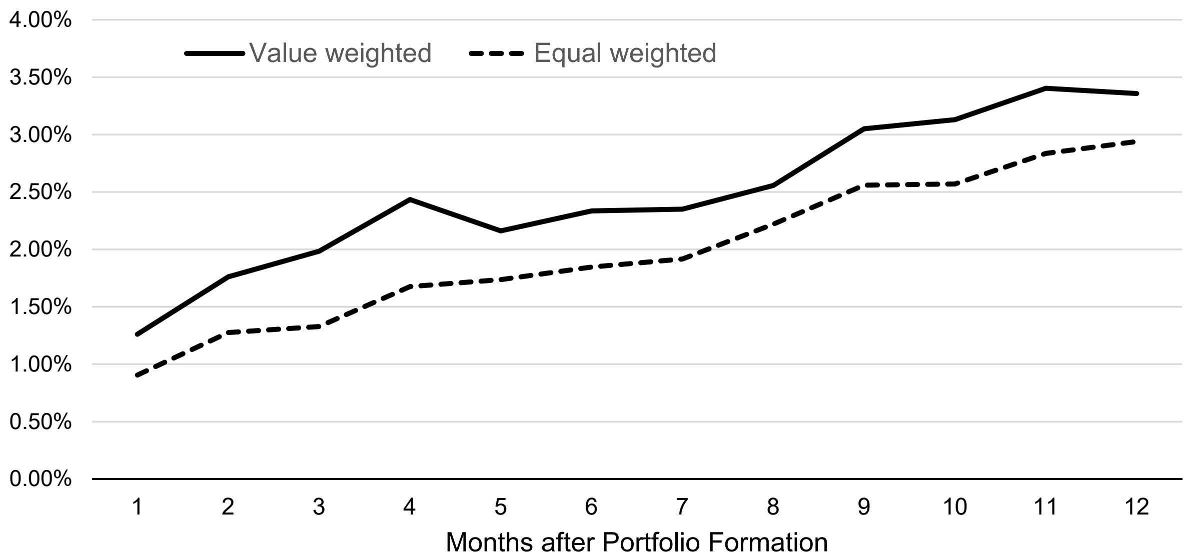

Table 1: Summary Statistics

This table presents summary statistics of sample firms from April 1980 to December 2017. Numbers in Panel D are calculated from pooled firm-year observations while the rest in the table are time-series statistics. Panel A and B report the percentage of stock universe covered in terms of market capitalization and number of stocks, which are calculated monthly. A stock is covered in the sample if it is held by at least one institutional investor by the prior quarter-end. Panel C describes the number of institutional investors and the median number of stocks held by institutional investors each quarter. Firm characteristics variables in Panel D are winsorized at 1% and 99% levels. Number of institutional shareholders (ninv) and number of analysts (nana) following is counted by the end of the year. A stock is considered to be followed by an analyst if the analyst issues at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. See Appendix A1 for more variable definitions.

	Mean	Median	Max	Min	SD
Panel A: Stocks Coverage (market capitalzation)					
All Common Stocks	0.95	0.96	0.98	0.89	0.02
NYSE	0.97	0.97	0.99	0.94	0.01
NASDAQ	0.86	0.90	0.98	0.50	0.13
Panel B: Stocks Coverage (number)					
All Common Stocks	0.75	0.77	0.94	0.48	0.13
NYSE	0.92	0.92	0.96	0.86	0.02
NASDAQ	0.69	0.72	0.94	0.27	0.19
Panel C: Institutional Holdings					
Number of Investors	1582	1077	4167	382	1075
Number of Stocks	78	80	108	50	18
Panel D: Firm Characteristics					
mv	5.29	5.15	11.88	-0.02	2.07
at	5.64	5.54	12.23	0.44	2.19
age	17	13	67	1	14
rd	0.04	0.00	0.88	0.00	0.09
rdg	0.00	0.00	0.25	-0.22	0.03
ag	0.16	0.07	5.65	-0.63	0.42
grp	0.31	0.27	1.27	-0.87	0.28
pftg	0.03	0.02	0.59	-0.49	0.11
div	0.01	0.00	0.29	0.00	0.02
bm	0.77	0.60	9.16	0.02	0.70
lev	5.77	1.58	222.40	0.02	13.60
yvol	0.03	0.03	0.14	0.01	0.02
ninv	58	17	1485	1	114
nana	7	4	49	0	9

Table 2: Contemporaneous Fundamental Relations

This table presents the results of contemporaneous regressions of firms' annual financial statement variables on the respective variables of their peers. The sample period spans 1980-2017. Column (1)–(6) include variables that represent six aspects of firms' fundamentals: size, investment, profitability, market valuation, financing, and firm-specific risk, respectively. X_{SP} is the respective variable of the syndicated peer defined by institutional common ownership. X_{ana} and X_{ff48} represent the respective variables of two alternative peers constructed based on shared analysts followings and Fama-French 48 industry membership. Panel A reports the results of the regressions on the syndicated peer only. Panel B reports the results of the regressions on the syndicated peer and two alternative peers. Constant terms in regressions are estimated but not reported for concision. See Appendix A1 for variables definition. Max VIF reports the largest VIFs of three peer variables from multicollinearity tests. All regressions include firm and year fixed effects, and size (mv) and book-to-market (bm) ratio as control variables except when bm is the dependent variable. t-statistics (reported in parentheses) are based on the standard errors clustered by both firm and year. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)		(2)			(3)			(4)	(5)	(6)
	at	age	rd	rdg	ag	grp	pftg	div	bm	lev	yvol
Panel A: The syndicated peer only											
X_{SP}	0.133***	0.019***	0.238**	2.060***	0.979***	0.491***	2.657***	0.623***	1.053***	-0.036	0.857***
	(10.28)	(3.21)	(2.13)	(4.41)	(2.84)	(8.32)	(13.82)	(5.84)	(6.96)	(-0.07)	(7.78)
N	157,493	157,493	157,493	145,266	145,265	156,784	144,528	157,493	157,493	157,023	148,686
Adjusted R^2	0.969	0.993	0.660	0.107	0.401	0.774	0.201	0.223	0.539	0.615	0.684
Panel B: The syndicated peer and alternative peers											
X_{SP}	0.298***	0.017*	0.266	2.416***	1.789***	0.810***	3.579***	0.698***	1.307***	0.332	0.923***
	(12.20)	(1.88)	(1.65)	(6.07)	(4.84)	(8.75)	(13.34)	(4.62)	(6.18)	(0.55)	(8.04)
X_{ana}	0.120***	0.009**	0.169***	0.172***	0.237***	0.221***	0.404***	0.285***	0.519***	0.002	0.312***
	(19.35)	(2.33)	(6.46)	(2.94)	(3.99)	(12.97)	(14.28)	(2.99)	(6.90)	(0.48)	(11.53)
X_{ff48}	0.051***	0.023**	0.284***	0.414***	0.067***	0.195***	0.272***	0.182***	0.168***	0.003	0.266***
	(4.77)	(2.17)	(6.92)	(6.92)	(3.43)	(7.56)	(5.58)	(5.67)	(5.62)	(0.23)	(11.11)
N	111,309	111,309	111,309	104,539	104,519	110,941	104,120	111,309	111,309	110,950	106,610
Adjusted R^2	0.970	0.995	0.747	0.155	0.249	0.815	0.275	0.317	0.554	0.781	0.757
Max VIF	2.08	2.25	3.01	1.51	1.37	2.73	1.66	2.03	2.06	1.05	2.86

Table 3: Predictive Fundamental Relations

This table presents the results from predictive regressions of firms' R&D growth and asset growth on the lagged respective variables of their peers and the lagged variables of other fundamentals. The sample period spans 1980-2017. X_{SP} is the respective variable of the syndicated peer defined by institutional common ownership. X_{ana} and X_{ff48} represent the respective variables of two alternative peers constructed based on common analysts followings and Fama-French 48 industry membership. See Appendix A1 for more variable definitions. Max VIF reports the largest VIFs of all independent variables from multicollinearity tests. All regressions include firm and year fixed effects. t-statistics (reported in parentheses) are based on the standard errors clustered by both firm and year. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Dep. Var.	rdg_{t+1}				ag_{t+1}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
X_{SP}		1.037***	1.024***	1.234***		0.500**	0.422*	0.749**
		(3.34)	(3.27)	(4.41)		(2.12)	(2.02)	(2.40)
X_{ana}				0.075				0.062
				(1.31)				(1.69)
X_{ff48}				0.076				0.020
				(1.09)				(1.53)
at	-0.009***		-0.009***	-0.010***	-0.264***		-0.264***	-0.218***
	(-8.45)		(-8.56)	(-8.25)	(-11.78)		(-11.78)	(-13.11)
age	0.000		0.000	0.000	0.007***		0.007***	0.007**
	(0.25)		(0.34)	(0.66)	(3.03)		(3.00)	(2.62)
rd	-0.412***		-0.412***	-0.452***	0.418***		0.433***	0.519***
	(-10.44)		(-10.46)	(-9.14)	(3.15)		(3.22)	(4.22)
rdg	-0.048		-0.051	-0.048***	-0.028		-0.053	-0.010
	(-1.60)		(-1.69)	(-2.78)	(-0.23)		(-0.42)	(-0.07)
ag	-0.000		-0.000	-0.001	-0.034		-0.035	-0.057
	(-0.18)		(-0.44)	(-1.13)	(-1.54)		(-1.56)	(-1.19)
grp	-0.000		0.000	0.004	-0.035		-0.030	0.093*
	(-0.05)		(0.02)	(0.56)	(-0.57)		(-0.49)	(1.93)
pftg	0.010***		0.009**	0.007**	0.353***		0.340***	0.325***
	(3.01)		(2.70)	(2.09)	(5.34)		(5.19)	(4.75)
div	-0.003*		-0.003	-0.001	-0.004		-0.003	0.056
	(-1.69)		(-1.61)	(-0.41)	(-0.13)		(-0.12)	(1.15)
bm	-0.001***		-0.001***	-0.001*	-0.072***		-0.069***	-0.070***
	(-3.05)		(-2.82)	(-1.82)	(-4.81)		(-4.84)	(-4.18)
lev	0.000		0.000	0.000	0.000		0.000	0.000
	(1.02)		(1.03)	(1.06)	(1.14)		(1.14)	(1.29)
yvol	-0.099***		-0.101***	-0.149***	-1.352***		-1.469***	-2.320***
	(-5.84)		(-5.74)	(-3.77)	(-5.31)		(-6.30)	(-6.46)
Cons.	0.072***	-0.002	0.068***	0.081***	1.643***	0.056	1.559***	1.310***
	(10.37)	(-1.46)	(10.08)	(9.48)	(12.00)	(1.25)	(11.40)	(10.66)
N	127,371	128,537	127,369	92,574	127,371	128,536	127,369	92,557
Adjusted R^2	0.338	0.111	0.339	0.379	0.218	0.174	0.219	0.262
Max VIF	1.73	n/a	1.73	1.90	1.73	n/a	1.73	1.89

Table 4: Portfolio Abnormal Returns by Syndicated Peer Shocks

This table reports the monthly abnormal returns of stock portfolios ranked by their syndicated peer shocks (R_{SP}). The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are ranked into quintile portfolios based on their $R_{SP,t-1}$ defined by Equation (4). Performances of value weighted and equal weighted portfolios are presented separately in Panel A and B. Excess return is relative to U.S. 3-month T-bill rate. CAPM alpha and 3-factor alpha are estimated by regressing the portfolio excess return on the market risk, size, and value factors defined in Fama and French (1993). 4-factor is Fama-French 3 factors plus Carhart (1997)'s momentum factor. 5-factor is the 4-factor plus the short-term (one month) reversal factor. t-statistics from time-series regressions are reported in parenthesis.

Quintile	Excess return	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A: Value weighted					
1 (low)	0.05%	-0.82%	-0.80%	-0.73%	-0.90%
	(0.15)	(-5.15)	(-5.09)	(-4.63)	(-7.42)
2	0.43%	-0.31%	-0.34%	-0.30%	-0.39%
	(1.81)	(-3.31)	(-3.67)	(-3.16)	(-5.30)
3	0.81%	0.14%	0.08%	0.10%	0.10%
	(3.87)	(2.20)	(1.39)	(1.68)	(1.58)
4	0.98%	0.33%	0.29%	0.30%	0.38%
	(4.52)	(3.44)	(3.05)	(3.12)	(4.59)
5 (high)	1.29%	0.58%	0.62%	0.58%	0.76%
	(4.81)	(3.48)	(4.04)	(3.73)	(6.84)
5-1	1.24%	1.41%	1.42%	1.32%	1.65%
	(4.39)	(4.97)	(4.97)	(4.55)	(8.47)
Panel B: Equal weighted					
1 (low)	0.33%	-0.45%	-0.51%	-0.46%	-0.60%
	(1.19)	(-3.03)	(-4.52)	(-4.03)	(-7.72)
2	0.67%	-0.06%	-0.20%	-0.12%	-0.19%
	(2.78)	(-0.59)	(-2.65)	(-1.70)	(-3.20)
3	0.87%	0.17%	0.03%	0.10%	0.08%
	(3.85)	(1.94)	(0.45)	(1.67)	(1.46)
4	1.01%	0.33%	0.20%	0.25%	0.29%
	(4.49)	(3.32)	(3.15)	(3.91)	(5.04)
5 (high)	1.24%	0.59%	0.53%	0.54%	0.64%
	(5.00)	(3.77)	(5.10)	(5.09)	(8.11)
5-1	0.91%	1.04%	1.04%	1.00%	1.24%
	(4.58)	(5.29)	(5.24)	(4.94)	(9.52)

Table 5: Portfolio Risk Factor Loadings and Characteristics

This table reports the risk factor loadings of stock portfolios ranked by their syndicated peer shocks (R_{SP}). The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than $5 are ranked into quintile portfolios based on their $R_{SP,t-1}$ defined by Equation (4). Risk factor loadings of value weighted and equal weighted portfolios are presented separately in Panel A and B. MKT, SMB, and HML are the market risk, size, and value factors defined in Fama and French (1993). UMD is Carhart (1997)'s momentum factor. ST Revs is the short-term (one month) reversal factor. Fiscal year-end variables are associated with stock returns from July next year to June of the year after. See Appendix A1 for more variable definitions. t-statistics from time-series regressions are reported in parenthesis.

Quintile	MKT	SMB	HML	UMD	ST Revs	MKT	SMB	HML	UMD	ST Revs
	Panel A: Value weighted portfolio risk loadings					Panel B: Equal weighted portfolio risk loadings				
1	1.065	0.214	-0.144	0.042	0.688	0.939	0.683	0.054	0.035	0.567
	(36.09)	(5.29)	(-3.32)	(1.52)	(18.18)	(49.88)	(26.40)	(1.96)	(1.96)	(23.47)
2	1.004	-0.059	0.041	0.013	0.392	0.975	0.490	0.249	-0.037	0.282
	(56.17)	(-2.38)	(1.57)	(0.77)	(17.09)	(67.09)	(24.51)	(11.67)	(-2.72)	(15.16)
3	0.995	-0.083	0.132	-0.018	0.025	0.981	0.439	0.297	-0.073	0.053
	(66.37)	(-4.04)	(5.98)	(-1.27)	(1.29)	(70.78)	(23.02)	(14.54)	(-5.55)	(3.00)
4	1.031	0.044	0.096	-0.070	-0.337	0.979	0.568	0.282	-0.088	-0.181
	(50.79)	(1.57)	(3.22)	(-3.66)	(-12.92)	(69.18)	(29.16)	(13.53)	(-6.54)	(-9.98)
5	1.085	0.540	-0.053	-0.079	-0.740	0.929	0.896	0.126	-0.088	-0.461
	(40.08)	(14.53)	(-1.32)	(-3.08)	(-21.32)	(47.84)	(33.57)	(4.40)	(-4.78)	(-18.52)
5-1	0.020	0.326	0.092	-0.121	-1.427	-0.010	0.213	0.071	-0.123	-1.028
	(0.42)	(4.97)	(1.30)	(-2.69)	(-23.34)	(-0.32)	(4.86)	(1.53)	(-4.08)	(-25.18)
Panel C: Portfolio Characteristics										
	size	bm	rdg (%)	ag	pftg	div	lev	yvol	mom1	mom11
1	5.355	0.754	0.582	0.230	0.041	0.016	10.892	0.027	-0.005	0.247
2	6.360	0.711	0.330	0.175	0.038	0.020	5.563	0.023	0.005	0.181
3	6.505	0.715	0.282	0.161	0.036	0.021	4.790	0.022	0.016	0.170
4	6.157	0.732	0.331	0.178	0.038	0.020	5.499	0.023	0.028	0.190
5	5.093	0.791	0.579	0.209	0.042	0.016	8.213	0.028	0.050	0.273

Table 6: Portfolio Abnormal Returns by Orthogonalized Syndicated Peer Shocks

This table reports the monthly abnormal returns of top and bottom quintile portfolios ranked by their orthogonalized syndicated peer shocks ($\tilde{R}_{SP}$) with respect to common analyst momentum (R_{ana}) and industry momentum (R_{ff48}). The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are ranked into quintile portfolios based on their $\tilde{R}_{SP,t-1}$ which is $R_{SP,t-1}$ defined by Equation (4) orthogonalized with respect to $R_{ana,t-1}$ and $R_{ff48,t-1}$. Portfolios are all value weighted. Excess return is relative to U.S. 3-month T-bill rate. CAPM alpha and 3-factor alpha are estimated by regressing the portfolio excess return on the market risk, size, and value factors defined in Fama and French (1993). 4-factor is Fama-French 3 factors plus Carhart (1997)'s momentum factor. 5-factor is the 4-factor plus the short-term (one month) reversal factor. t-statistics from time-series regressions are reported in parenthesis.

Quintile	Excess return	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A: Orthogonalized on common analysts momentum					
1	0.37%	-0.52%	-0.45%	-0.50%	-0.53%
	(1.30)	(-4.13)	(-3.76)	(-4.19)	(-4.40)
5	1.15%	0.36%	0.39%	0.47%	0.50%
	(4.45)	(2.89)	(3.28)	(3.92)	(4.20)
5-1	0.78%	0.88%	0.84%	0.98%	1.03%
	(3.97)	(4.44)	(4.21)	(4.87)	(5.19)
Panel B: Orthogonalized on industry momentum					
1	0.16%	-0.70%	-0.65%	-0.63%	-0.73%
	(0.56)	(-5.17)	(-4.94)	(-4.68)	(-6.05)
5	1.19%	0.49%	0.53%	0.55%	0.65%
	(4.73)	(3.45)	(4.00)	(4.05)	(5.41)
5-1	1.03%	1.19%	1.19%	1.18%	1.38%
	(4.45)	(5.20)	(5.13)	(5.00)	(6.88)
Panel C: Orthogonalized on both common analysts and industry momentum					
1	0.41%	-0.47%	-0.39%	-0.44%	-0.45%
	(1.44)	(-3.76)	(-3.31)	(-3.65)	(-3.77)
5	1.15%	0.38%	0.40%	0.49%	0.49%
	(4.52)	(3.02)	(3.32)	(4.02)	(3.98)
5-1	0.75%	0.85%	0.80%	0.93%	0.94%
	(3.90)	(4.43)	(4.12)	(4.79)	(4.83)

Table 7: Portfolio Abnormal Returns from Heterogeneous Information

This table reports the monthly 4-factor portfolio alphas from double sorting the sample stocks. The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are sorted and assigned into double quintile (5×5) based on their $R_{SP,t-1}$ defined by Equation (4) and one of the two previously documented cross-firm momentum: common analysts momentum $R_{ana,t-1}$ and industry momentum $R_{ff48,t-1}$. Portfolios are all value weighted. 4-factor alpha is estimated by regressing portfolio excess returns on the Fama-French 3 factors plus Carhart (1997)'s momentum factor. t-statistics from time-series regressions are reported in parenthesis.

Second sort	First sort					
	1(low)	2	3	4	5(high)	5-1
Panel A: Independent Sorting: R_{SP} and R_{ana}						
R_{SP} 5-1	0.83%	1.21%	0.86%	1.00%	0.75%	-0.09%
	(2.77)	(4.44)	(3.28)	(3.76)	(2.64)	(-0.26)
R_{ana} 5-1	0.96%	0.52%	0.44%	0.37%	0.88%	-0.09%
	(3.30)	(1.92)	(1.78)	(1.48)	(3.01)	(-0.26)
Panel B: Dependent Sorting: R_{SP} and R_{ana}						
R_{SP} 5-1	1.07%	1.28%	0.51%	1.03%	0.96%	-0.11%
	(3.67)	(4.91)	(2.14)	(4.43)	(3.14)	(-0.30)
R_{ana} 5-1	1.09%	0.50%	0.44%	0.15%	0.45%	-0.63%
	(3.89)	(2.14)	(1.97)	(0.63)	(1.52)	(-1.80)
Panel C: Independent Sorting: R_{SP} and R_{ff48}						
R_{SP} 5-1	1.29%	1.42%	1.04%	1.33%	0.51%	-0.78%
	(4.18)	(4.80)	(3.78)	(4.16)	(1.74)	(-2.41)
R_{ff48} 5-1	1.07%	0.70%	0.44%	0.10%	0.29%	-0.78%
	(4.27)	(3.38)	(2.15)	(0.48)	(1.14)	(-2.41)
Panel D: Dependent Sorting: R_{SP} and R_{ana}						
R_{SP} 5-1	1.35%	1.01%	0.94%	0.93%	0.68%	-0.68%
	(4.22)	(3.61)	(3.48)	(3.02)	(2.16)	(-1.93)
R_{ff48} 5-1	1.01%	0.62%	0.36%	0.03%	0.07%	-0.93%
	(4.35)	(3.23)	(1.83)	(0.17)	(0.31)	(-2.98)

Table 8: Portfolio Abnormal Returns from Attention versus Information

This table reports the monthly 4-factor portfolio alphas from double sorting the sample stocks. The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are sorted independently and assigned into double quintile (5×5) based on their $R_{SP,t-1}$ defined by Equation (4) and one of the following: nana and ninv. nana is defined as the number of analysts who issue at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. ninv is defined as the number of institutional shareholders at the end of last quarter. Portfolios are all value weighted. 4-factor alpha is estimated by regressing portfolio excess returns on the Fama-French 3 factors plus Carhart (1997)'s momentum factor. t-statistics from time-series regressions are reported in parenthesis.

Panel A: Syndicated peer shock and number of analysts following

	R_{SP}					
nana	1(low)	2	3	4	5(high)	5-1
1 (least)	-0.86%	-0.11%	0.03%	0.14%	0.69%	1.56%
	(-5.44)	(-0.85)	(0.28)	(1.12)	(4.79)	(6.06)
2	-0.67%	-0.16%	0.14%	0.03%	0.41%	1.08%
	(-3.76)	(-1.26)	(1.33)	(0.25)	(2.48)	(3.56)
3	-0.53%	-0.26%	0.15%	0.18%	0.43%	0.96%
	(-3.18)	(-2.39)	(1.53)	(1.78)	(2.33)	(3.03)
4	-0.73%	-0.26%	0.03%	0.15%	0.64%	1.37%
	(-4.04)	(-2.31)	(0.34)	(1.46)	(3.54)	(4.31)
5 (most)	-0.66%	-0.22%	0.09%	0.40%	0.77%	1.44%
	(-3.00)	(-2.05)	(1.19)	(3.26)	(3.46)	(3.77)
5-1	0.17%	-0.11%	0.06%	0.21%	0.07%	-0.07%
	(0.77)	(-0.76)	(0.43)	(1.29)	(0.33)	(-0.21)

Panel B: Syndicated peer shock and number of institutional investors

	R_{SP}					
ninv	1(low)	2	3	4	5(high)	5-1
1 (least)	-0.33%	-0.21%	-0.23%	0.03%	0.55%	0.88%
	(-2.47)	(-1.52)	(-1.55)	(0.25)	(3.46)	(4.25)
2	-0.61%	-0.25%	-0.12%	0.16%	0.65%	1.26%
	(-4.18)	(-2.42)	(-1.23)	(1.77)	(4.58)	(5.16)
3	-0.69%	-0.29%	-0.05%	0.18%	0.46%	1.14%
	(-4.31)	(-3.06)	(-0.57)	(2.21)	(2.83)	(3.97)
4	-0.79%	-0.22%	0.04%	0.16%	0.57%	1.36%
	(-4.42)	(-2.30)	(0.52)	(1.66)	(2.90)	(4.10)
5 (most)	-0.94%	-0.32%	0.11%	0.31%	0.71%	1.70%
	(-4.22)	(-2.98)	(1.65)	(2.70)	(2.87)	(4.18)
5-1	-0.58%	-0.11%	0.34%	0.27%	0.15%	0.83%
	(-2.42)	(-0.65)	(2.09)	(1.51)	(0.60)	(2.22)

Table 9: Fama-MacBeth Regressions

This table reports the Fama-MacBeth regression coefficients for the sample stocks. The sample period is from May 1980 to December 2017. Month t returns of stocks with prior month-end price higher than \$5 are regressed on their syndicated peer shocks $R_{SP,t-1}$ defined by Equation (4) and other control variables. $R_{ana,t-1}$ is the common analysts momentum as in Ali and Hirshleifer (2019). $R_{ff48,t-1}$ is the industry momentum calculated as the last-month return of the value-weighted Fama-French 48 industry portfolio excluding the focal stock. nana is defined as the number of analysts who issue at least one FY1 or FY2 earnings forecast for the stock over the past 12 months. ninv is defined as the number of institutional shareholders at the end of last quarter. See Appendix A1 for more variable definitions. Column (1)–(6) are based on the full sample; column (7) is based on large-cap stocks of which size are above the periodical median and column (8) is based on small-cap stocks of which size are below the periodical median. t-statistics from Newey-West adjusted (12 lags) standard errors are reported in parenthesis. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
			Full sample			Large	Small
$R_{SP,t-1}$	0.587***	0.471***	0.450***	0.536***	0.382***	0.823***	0.479***
	(5.83)	(6.85)	(5.79)	(5.45)	(5.52)	(4.46)	(5.23)
$R_{ana,t-1}$			0.096***			0.120***	0.118***
			(3.86)			(6.16)	(11.11)
$R_{ff48,t-1}$			0.030**			0.011	0.045***
			(2.48)			(0.96)	(3.44)
nana$\times R_{SP,t-1}$				0.036*			
				(1.91)			
nana				0.000			
				(0.54)			
ninv$\times R_{SP,t-1}$					0.011***		
					(3.69)		
ninv					-0.000*		
					(-1.92)		
beta		0.000	-0.001	-0.000	0.000	0.000	0.001
		(0.33)	(-0.39)	(-0.08)	(0.31)	(0.18)	(0.84)
size		-0.001**	-0.001	-0.001	-0.000	-0.001*	-0.000
		(-2.06)	(-1.49)	(-1.32)	(-1.47)	(-1.85)	(-0.23)
bm		0.002**	-0.001	0.002**	0.002***	0.001	0.002***
		(2.37)	(-0.47)	(2.53)	(2.59)	(1.24)	(2.62)
rd		0.009	0.009	0.021*	0.009	0.019**	0.002
		(1.15)	(1.18)	(1.66)	(1.15)	(2.10)	(0.21)
ag		-0.002***	-0.003***	-0.002***	-0.002***	-0.002***	-0.001
		(-3.05)	(-3.42)	(-2.86)	(-3.14)	(-2.89)	(-0.30)
grp		0.006***	0.005***	0.006***	0.005***	0.004***	0.008***
		(4.55)	(4.25)	(3.98)	(4.52)	(2.59)	(3.81)
mvol		-0.184***	-0.152***	-0.156***	-0.184***	-0.167***	-0.168***
		(-7.02)	(-4.75)	(-4.27)	(-7.06)	(-4.60)	(-4.70)
mom1		-0.030***	-0.029***	-0.028***	-0.030***	-0.041***	-0.037***
		(-8.26)	(-3.13)	(-6.03)	(-8.32)	(-7.53)	(-6.13)
mom11		0.005***	0.004**	0.005***	0.005***	0.002	0.004**
		(3.47)	(2.18)	(2.95)	(3.55)	(0.95)	(2.08)
Average R^2	0.008	0.067	0.086	0.082	0.070	0.117	0.079

Table 10: Institutional Excess Demand and Peer Firm Shocks

This table reports the coefficient estimates from the panel regression of institutional excess demand for the sample stocks on returns of their peer stocks and other control variables. The sample period is from Q2 1980 to Q4 2017. $Nratio_{i,q}$ is the number of institutional buyers divided by the number of institutional investors who trade stock i in quarter q. $Dratio_{i,q}$ is the net change of institutional shares of stock i divided by the total number of shares traded in quarter q. Initial buys are excluded from calculating $Nratio_{i,q}$ and $Dratio_{i,q}$. $R_{SP,i,q}$ is the quarterly DGTW return of the syndicated peer defined by institutional common ownership at the end of quarter $q-1$ as in Equation 3. $R_{ana,i,q}$ is the averaged quarterly return of peer firms weighted by the number of common analysts following Ali and Hirshleifer (2019). $R_{ff48,i,q}$ is the quarterly Fama-French 48 industry value-weighted portfolio return excluding the stock i. $R_{i,q}$ and $R_{i,q-1}$ are the returns of stock i in quarter q and $q-1$. All regressions include firm and year fixed effects. t-statistics (reported in parentheses) are based on the standard errors clustered by both firm and quarter. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	# of traders $\geq$ 5		# of traders $\geq$ 10		# of traders $\geq$ 10	
Panel A: Excess demand (dependent variable) measured as $Nratio_{i,q}$						
$R_{SP,i,q}$	0.243***	0.181**	0.307***	0.228***	0.336***	0.233***
	(3.25)	(2.38)	(3.71)	(2.76)	(4.06)	(2.90)
$R_{ana,i,q}$		0.011**		0.015***		0.017***
		(2.16)		(2.81)		(3.53)
$R_{ff48,i,q}$		0.010*		0.006		0.009**
		(1.96)		(1.19)		(2.02)
$Nratio_{i,q-1}$	0.125***	0.122***	0.127***	0.123***	0.133***	0.130***
	(22.34)	(21.73)	(20.31)	(19.50)	(17.99)	(17.19)
$R_{i,q}$	-0.004*	-0.006**	-0.003	-0.005**	-0.005**	-0.008***
	(-1.71)	(-2.59)	(-1.26)	(-2.11)	(-2.11)	(-3.12)
$R_{i,q-1}$	0.014***	0.014***	0.013***	0.013***	0.013***	0.013***
	(5.57)	(5.51)	(5.36)	(5.33)	(5.36)	(5.53)
N	372,843	335,735	300,713	282,559	259,992	247,738
Adjusted R^2	0.171	0.175	0.186	0.188	0.195	0.197
Panel B: Excess demand (dependent variable) measured as $Dratio_{i,q}$						
$R_{SP,i,q}$	0.415**	0.408**	0.119	0.216	0.042	0.136
	(2.26)	(2.38)	(0.59)	(1.14)	(0.21)	(0.63)
$R_{ana,i,q}$		-0.036***		-0.032**		-0.024
		(-2.78)		(-2.14)		(-1.46)
$R_{ff48,i,q}$		0.034***		0.031**		0.032**
		(2.67)		(2.29)		(2.40)
$Dratio_{i,q-1}$	0.123***	0.116***	0.112***	0.107***	0.101***	0.099***
	(36.67)	(32.87)	(30.67)	(28.37)	(23.85)	(22.83)
$R_{i,q}$	-0.045***	-0.050***	-0.058***	-0.061***	-0.070***	-0.074***
	(-8.38)	(-8.37)	(-9.26)	(-9.23)	(-10.11)	(-10.25)
$R_{i,q-1}$	0.040***	0.036***	0.026***	0.024***	0.017***	0.017***
	(6.56)	(6.18)	(4.93)	(4.39)	(3.13)	(2.90)
N	372,843	335,735	300,713	282,559	259,992	247,738
Adjusted R^2	0.100	0.100	0.099	0.100	0.102	0.102

Table 11: Initial Buys and Peer Firm Shocks

This table reports the coefficient estimates from the panel regression of institutions' initial buys for the sample stocks on returns of their peer stocks and other control variables. The sample period is from Q2 1980 to Q4 2017. $IBN_{i,q}$ is the number of institutional investors initiate purchases of stock i in quarter q. $IBS_{i,q}$ is the percentage of shares of stock i traded by the new buyers in quarter q. $R_{SP,i,q}$ is the quarterly DGTW return of the syndicated peer defined by institutional common ownership at the end of quarter $q-1$ as in Equation 3. $R_{ana,i,q}$ is the averaged quarterly return of peer firms weighted by the number of common analysts following Ali and Hirshleifer (2019). $R_{ff48,i,q}$ is the quarterly Fama-French 48 industry value-weighted portfolio return excluding the stock i. $R_{i,q}$ and $R_{i,q-1}$ are the returns of stock i in quarter q and $q-1$. All regressions include firm and year fixed effects. t-statistics (reported in parentheses) are based on the standard errors clustered by both firm and quarter. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Dep. Variable	$IBN_{i,q}$		$IBS_{i,q}$	
	(1)	(2)	(3)	(4)
$R_{SP,i,q}$	-3.395	-18.643***	-0.014*	-0.015
	(-0.76)	(-3.37)	(-1.96)	(-1.60)
$R_{ana,i,q}$		2.849***		-0.003***
		(5.56)		(-3.43)
$R_{ff48,i,q}$		1.988***		-0.001
		(3.47)		(-0.88)
$R_{i,q}$	2.931***	3.583***	0.011***	0.014***
	(14.00)	(13.23)	(17.40)	(16.84)
$R_{i,q-1}$	2.115***	2.744***	0.004***	0.005***
	(12.53)	(11.74)	(12.27)	(10.74)
N	419,382	351,443	419,382	351,443
Adjusted R^2	0.641	0.645	0.185	0.198

Table 12: Institutional Trading Propensity and Peer Firm Shocks

This table reports the coefficient estimates from the panel regression of institutional trading propensity for the sample stocks on returns of their peer stocks and other control variables. The sample period is from Q2 1980 to Q4 2017. $buy_{n,i,q}$ is a dummy variable which equals to 1 if institutional investor n increases his holdings of stock i in quarter q and equals to 0 otherwise. $sell_{n,i,q}$ is a dummy variable which equals to 1 if institutional investor n reduces his holdings of stock i in quarter q and equals to 0 otherwise. $trd_{n,i,q}$ is a continuous variable as the number of stock i's shares traded by institutional investor n in quarter q scaled by the stock's total shares outstanding. Initial buys are excluded from sample trades for the regressions. Terminating sells are excluded for column (3),(6), and (9). $R_{SP,i,q}$ is the quarterly DGTW return of the syndicated peer defined by institutional common ownership at the end of quarter $q-1$ as in Equation 3. $R_{ana,i,q}$ is the averaged quarterly return of peer firms weighted by the number of common analysts following Ali and Hirshleifer (2019). $R_{ff48,i,q}$ is the quarterly Fama-French 48 industry value-weighted portfolio return excluding the stock i. $R_{i,q}$ and $R_{i,q-1}$ are the returns of stock i in quarter q and $q-1$. $I_{n,-i,q}$ is the realized value-weighted portfolio return of institution n in quarter q excluding the focal stock i. Coefficients in column (7) – (9) are scaled up by $\times 100$. All regressions include institution-quarter fixed effect and firm-year fixed effect. t-statistics (reported in parentheses) are based on the standard errors clustered by quarter. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

Dep. Variable	$buy_{n,i,q}$			$sell_{n,i,q}$			$trd_{n,i,q}$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$R_{SP,i,q}$	0.194***	0.193***	0.262***	-0.204***	-0.111*	-0.184***	-0.006	-0.073	-0.039
	(4.43)	(3.98)	(4.76)	(-4.01)	(-1.93)	(-3.19)	(-0.12)	(-1.60)	(-0.87)
$R_{ana,i,q}$		0.007	-0.001		-0.017***	-0.006		-0.003	0.000
		(1.59)	(-0.34)		(-3.39)	(-1.36)		(-1.61)	(0.04)
$R_{ff48,i,1}$		0.010***	0.007***		-0.014***	-0.011***		0.006***	0.007***
		(4.27)	(2.59)		(-5.23)	(-4.05)		(4.10)	(5.28)
$buy/sell/trd_{n,i,q-1}$	0.123***	0.121***	0.135***	0.122***	0.120***	0.134***	14.06*	-15.11	-12.00
	(70.50)	(71.03)	(70.72)	(82.21)	(70.59)	(84.72)	(-1.67)	(-1.53)	(-1.01)
$R_{i,q}$	-0.016***	-0.019***	-0.048***	0.009***	0.012***	0.051***	-0.009***	-0.007***	-0.016***
	(-7.72)	(-7.65)	(-15.44)	(3.76)	(4.35)	(15.77)	(-7.36)	(-4.92)	(-9.90)
$R_{i,q-1}$	0.011***	0.011***	-0.002	-0.008***	-0.009***	0.013***	0.004***	0.004***	-0.006***
	(7.18)	(6.65)	(-1.25)	(-5.31)	(-5.58)	(7.52)	(3.59)	(3.88)	(-5.94)
$I_{n,-i,q}$	0.860***	0.943***	1.226***	-0.957***	-1.054***	-1.269***	0.926***	0.967***	1.309***
	(12.19)	(11.73)	(12.60)	(-13.10)	(-12.71)	(-12.73)	(6.62)	(6.55)	(9.56)
Terminating Sells	Included	Included	Excluded	Included	Included	Excluded	Included	Included	Excluded
N	32,203,743	30,816,139	28,954,786	32,203,743	30,816,139	26,927,808	34,590,683	33,136,583	28,954,786
Adjusted R^2	0.188	0.187	0.197	0.200	0.198	0.190	0.110	0.106	0.090

Table 13: Portfolio Abnormal Returns and Ex-ante Institutional Trading Intensity

This table reports the monthly abnormal returns of the long-short equity portfolios constructed based on different ex-ante trading intensities of institutional investors. The sample period is from May 1980 to December 2017. $R^H_{SP,t-1}$ ($R^L_{SP,t-1}$) is the syndicated peer shock defined by Equation (4) but based on common ownership of institutional investors who have high (low) churn rate over the past 4 quarters. At the beginning of month t, stocks with prior month-end price higher than \$5 are ranked into quintile portfolios based on their $R^H_{SP,t-1}$, $R^L_{SP,t-1}$, and $R^H_{SP,t-1} - R^L_{SP,t-1}$, separately. Panel A presents the baseline results. Panel B presents the results with the orthogonalized syndicated peer shocks $\tilde{R}^H_{SP,t-1}$ and $\tilde{R}^L_{SP,t-1}$ with respect to common analyst momentum ($R_{ana,t-1}$) and industry momentum ($R_{ff48,t-1}$). Portfolios are all value weighted. Excess return is relative to U.S. 3-month T-bill rate. CAPM alpha and 3-factor alpha are estimated by regressing the portfolio excess return on the market risk, size, and value factors defined in Fama and French (1993). 4-factor is Fama-French 3 factors plus Carhart (1997)'s momentum factor. 5-factor is the 4-factor plus the short-term (one month) reversal factor. t-statistics from time-series regressions are reported in parenthesis.

Sort by	Excess return	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A: L-S portfolios based on the syndicated peer shocks					
$R^H_{SP,t-1}$	0.93%	1.03%	1.04%	0.95%	1.26%
	(3.62)	(3.99)	(4.00)	(3.63)	(6.98)
$R^L_{SP,t-1}$	0.56%	0.68%	0.63%	0.62%	0.82%
	(2.93)	(3.53)	(3.26)	(3.11)	(5.47)
$R^H_{SP,t-1} - R^L_{SP,t-1}$	0.36%	0.39%	0.44%	0.40%	0.60%
	(1.78)	(1.91)	(2.15)	(1.93)	(3.59)
Panel B: L-S portfolios based on the orthogonalized syndicated peer shocks					
$\tilde{R}^H_{SP,t-1}$	0.53%	0.56%	0.53%	0.66%	0.68%
	(3.41)	(3.60)	(3.38)	(4.18)	(4.35)
$\tilde{R}^L_{SP,t-1}$	0.31%	0.38%	0.31%	0.40%	0.38%
	(2.10)	(2.57)	(2.11)	(2.63)	(2.54)
$\tilde{R}^H_{SP,t-1} - \tilde{R}^L_{SP,t-1}$	0.29%	0.31%	0.32%	0.35%	0.40%
	(1.96)	(2.06)	(2.14)	(2.30)	(2.66)

Table 14: Portfolio Abnormal Returns and Ex-post Institutional Trading Intensity

This table reports the monthly 4-factor portfolio alphas from double sorting the sample stocks. The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are independently sorted and assigned into double quintile (5×5) portfolios by their syndicated peer shocks $R_{SP,t-1}$ defined by Equation (4) and NT_q which is the number of institutional investors buy or sell the stock in the current quarter q. Portfolios are all value weighted. 4-factor alpha is estimated by regressing portfolio excess returns on the Fama-French 3 factors plus Carhart (1997)'s momentum factor. t-statistics from time-series regressions are reported in parenthesis.

	$R_{SP,t-1}$					
NT_q	1(low)	2	3	4	5(high)	5-1
1 (least)	-0.48%	-0.27%	-0.20%	-0.05%	0.48%	0.95%
	(-3.54)	(-2.00)	(-1.42)	(-0.37)	(3.15)	(4.76)
2	-0.56%	-0.26%	-0.12%	0.15%	0.62%	1.18%
	(-3.94)	(-2.36)	(-1.28)	(1.67)	(4.37)	(4.93)
3	-0.71%	-0.24%	-0.04%	0.19%	0.46%	1.17%
	(-4.53)	(-2.52)	(-0.46)	(2.41)	(2.87)	(4.14)
4	-0.72%	-0.25%	0.08%	0.18%	0.58%	1.29%
	(-4.10)	(-2.65)	(1.05)	(2.02)	(2.97)	(3.94)
5 (most)	-0.94%	-0.32%	0.11%	0.32%	0.80%	1.77%
	(-4.35)	(-2.98)	(1.56)	(2.76)	(3.13)	(4.37)
5-1	-0.43%	-0.05%	0.31%	0.36%	0.31%	0.84%
	(-1.87)	(-0.29)	(1.93)	(2.03)	(1.20)	(2.26)

Table 15: Stock Long-run Returns and Syndicated Peer Shocks

This table presents the results from examining the predictability of stock long-run returns with the syndicated peer shocks. The sample period is from May 1980 to December 2017. Stocks with prior month-end price lower than or equal to $5 are excluded. Panel A presents the 4-factor alphas of Jegadeesh and Titman (1993) momentum portfolios formed at the beginning of month t with holding period of 6, 12, and 24 months. Stocks are sorted by $R_{SP,t-13}$ defined by Equation (4). Portfolios are all equal weighted. 4-factor alpha is estimated by regressing portfolio excess returns on the Fama-French 3 factors plus Carhart (1997)'s momentum factor. t-statistics from time-series regressions are reported in parenthesis. Panel B presents the Fama-MacBeth regressions of stock long-run returns on $R_{SP,t-13}$ and other control variables including $R_{SP,t-1}$, beta, size, bm, rd, ag, grp, mvol, mom1, mom11. Control variables are dated as if predicting returns in month t. See Appendix A1 for more variable definitions. t-statistics from Newey-West adjusted standard errors are reported in parenthesis. ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, or 10% level, respectively.

	$R_{t,t+6}$	$R_{t,t+12}$	$R_{t,t+24}$
Panel A: 4-factor alpha of stock portfolios sorted by $R_{SP,t-13}$			
1 (low)	0.10%*	0.09%*	0.10%**
	(1.72)	(1.90)	(2.18)
5 (high)	0.11%**	0.12%**	0.12%***
	(2.01)	(2.35)	(2.62)
5-1	0.01%	0.02%	0.02%
	(0.13)	(0.46)	(0.61)
Panel B: Fama-MacBeth regression			
$R_{SP,t-13}$	0.011	0.090	0.010
	(0.04)	(0.22)	(0.01)
$R_{SP,t-1}$	1.182***	2.037***	2.224***
	(5.85)	(6.80)	(4.44)
Controls	Yes	Yes	Yes
NW lags	24	48	96
Average R^2	0.078	0.079	0.073

Table 16: Portfolio Abnormal Returns by Portfolio Rebalancing Shocks

This table reports the monthly abnormal returns of stock portfolios ranked by their portfolio rebalancing shocks (R_{PR}). The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than $5 are ranked into quintile portfolios based on their $R_{PR,t-1}$ defined by Equation (12). Performances of value weighted and equal weighted portfolios are presented separately in Panel A and B. Excess return is relative to U.S. 3-month T-bill rate. CAPM alpha and 3-factor alpha are estimated by regressing the portfolio excess return on the market risk, size, and value factors defined in Fama and French (1993). 4-factor is Fama-French 3 factors plus Carhart (1997)'s momentum factor. 5-factor is the 4-factor plus the short-term (one month) reversal factor. t-statistics from time-series regressions are reported in parenthesis.

Quintile	Excess return	CAPM Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
Panel A: Value weighted					
1 (low)	0.42%	-0.34%	-0.33%	-0.36%	-0.41%
	(1.71)	(-3.41)	(-3.41)	(-3.75)	(-4.37)
2	0.55%	-0.17%	-0.17%	-0.15%	-0.18%
	(2.46)	(-2.79)	(-2.73)	(-2.36)	(-3.05)
3	0.79%	0.13%	0.11%	0.12%	0.12%
	(3.91)	(3.04)	(2.70)	(2.73)	(2.84)
4	0.85%	0.19%	0.19%	0.19%	0.22%
	(4.16)	(3.34)	(3.20)	(3.17)	(3.87)
5 (high)	0.98%	0.31%	0.33%	0.30%	0.34%
	(4.40)	(3.08)	(3.41)	(3.01)	(3.60)
5-1	0.56%	0.65%	0.66%	0.66%	0.75%
	(3.47)	(4.07)	(4.07)	(4.01)	(4.82)
Panel B: Equal weighted					
1 (low)	0.58%	-0.15%	-0.23%	-0.20%	-0.27%
	(2.33)	(-1.26)	(-3.13)	(-2.58)	(-4.30)
2	0.74%	-0.01%	-0.13%	-0.06%	-0.10%
	(3.02)	(-0.12)	(-2.25)	(-1.09)	(-1.97)
3	0.87%	0.16%	0.02%	0.09%	0.08%
	(3.74)	(1.66)	(0.31)	(1.58)	(1.40)
4	0.88%	0.19%	0.09%	0.14%	0.16%
	(3.92)	(2.08)	(1.64)	(2.61)	(2.97)
5 (high)	1.05%	0.39%	0.31%	0.32%	0.36%
	(4.54)	(3.16)	(4.55)	(4.69)	(5.73)
5-1	0.47%	0.54%	0.54%	0.52%	0.63%
	(4.15)	(4.81)	(4.76)	(4.47)	(6.86)

Table 17: Portfolio Abnormal Returns and Ex-post Price Pressure

This table reports the monthly 4-factor portfolio alphas from double sorting the sample stocks. The sample period is from May 1980 to December 2017. At the beginning of month t, stocks with prior month-end price higher than \$5 are independently sorted and assigned into double quintile (5×5) portfolios by their syndicated peer shocks $R_{SP,t-1}$ defined by Equation (4) and NB_q which is institutions' net buy of a stock as a percentage of the stock's total shares outstanding in the current quarter q. Portfolios are all value weighted. 4-factor alpha is estimated by regressing portfolio excess returns on the Fama-French 3 factors plus Carhart (1997)'s momentum factor. t-statistics from time-series regressions are reported in parenthesis.

	$R_{SP,t-1}$					
NB_q	1(low)	2	3	4	5(high)	5-1
1 (least)	-0.79%	-0.11%	0.14%	0.43%	0.51%	1.31%
	(-4.20)	(-0.83)	(1.30)	(3.54)	(2.58)	(4.01)
2	-0.65%	-0.44%	-0.01%	0.11%	0.51%	1.17%
	(-3.27)	(-3.55)	(-0.17)	(0.93)	(2.65)	(3.50)
3	-0.76%	-0.41%	0.05%	0.25%	0.70%	1.47%
	(-4.03)	(-3.54)	(0.58)	(2.05)	(4.18)	(4.70)
4	-0.57%	-0.08%	0.21%	0.36%	0.55%	1.12%
	(-3.29)	(-0.58)	(1.90)	(2.78)	(2.86)	(3.64)
5 (most)	-0.74%	-0.18%	0.03%	0.27%	0.41%	1.15%
	(-4.18)	(-1.50)	(0.31)	(2.07)	(2.24)	(3.68)
5-1	0.05%	-0.08%	-0.11%	-0.16%	-0.10%	-0.16%
	(0.31)	(-0.58)	(-0.83)	(-1.23)	(-0.52)	(-0.60)