Essays in Empirical Finance: Common Ownership Linkage

by

Haesung Kim
B.S., Iowa State University, 2010
M.S., University of Chicago, 2012

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Business Administration
in the Graduate College of the
University of Illinois at Chicago, 2020

Chicago, Illinois

Defense Committee:
Re-Jin Guo, Chair and Advisor
Gilbert Bassett
Hsiu-Lang Chen
Chang Joo Lee, Korea Advanced Institute of Science and Technology
Yuheng Hu, Information and Decision Sciences

This thesis is dedicated to my father Bongcheon Kim, my mother Kyungja Park, my wife Sohyun Min, and my daughter Celine Kim, without whom it would never have been accomplished.

ACKNOWLEDGMENT

I would like to thank my thesis committee, Re-Jin Guo, Gilbert Bassett, Hsiu-Lang Chen, Chang Joo Lee, and Yuheng Hu, for their continuous encouragement and extensive discussions. I am especially grateful to my thesis advisor, Re-Jin Guo, who patiently spent time helping me to complete my thesis. I would also like to thank professor Stanley Sclove and professor Ali Tafti for their unconditional support and encouragement. In addition, I would like to extend my sincere appreciation to all the professors in the Finance department and the Information and Decision Science department.

HK

TABLE OF CONTENTS

CHAPTER		PAGE
1	**LITERATURE REVIEW**	1
1.1	Related Asset Pricing Studies	1
1.1.1	Effect of Institutional Trading on Stock Returns	1
1.1.2	Price Momentum	3
1.1.2.1	Time-series Momentum	3
1.1.2.2	Cross-sectional Momentum	3
1.2	Related Corporate Finance Studies	5
1.2.1	Corporate Financial Policy	5
1.2.1.1	Dividend Policy	5
1.2.1.2	Investment Policy	8
1.2.1.3	Cash Holdings	9
1.2.1.4	Capital Structure Choice	10
1.2.2	Peer Effects	11
1.2.3	Effect of Common Ownership in Corporate Finance	13
2	**COMMON OWNERSHIP LINKAGE AND RETURN PREDICTABILITY**	16
2.1	Introduction	16
2.2	Hypotheses	21
2.3	Methodology	23
2.4	Data	25
2.4.1	Institution Holding	25
2.4.2	Firm Characteristics and Stock Return	26
2.4.3	Descriptive Statistics	27
2.5	Return Predictability Analysis	28
2.5.1	Portfolio Tests	28
2.5.2	Cross-sectional Regression Tests	30
2.6	Mechanisms of Return Predictability	33
2.6.1	Flow-based Explanation	33
2.6.2	Limited Attention and Limits to Arbitrage	35
2.7	Robustness	36
2.7.1	Return Predictability across Time	36
2.7.2	Mutual Funds vs. Other Type of Institutional Investors	37
2.7.3	Alternative Common Ownership Closeness Measure	38
2.7.4	L/S Strategies with Different Look-back and Holding Periods	39
2.8	Conclusion	40

TABLE OF CONTENTS (Continued)

CHAPTER		PAGE
3	**COMMON OWNERSHIP LINKAGE AND PEER EFFECTS IN CORPORATE POLICIES**	58
3.1	Introduction	58
3.2	Hypotheses	62
3.3	Identification of Common Ownership Linkage	63
3.3.1	Measuring Common Ownership Closeness	63
3.3.2	Network Centrality	65
3.4	Econometric Framework	66
3.4.1	The Empirical Model	67
3.4.2	Identification Problem	68
3.4.3	Identification Strategy	69
3.5	Variable Construction and Summary Statistics	71
3.5.1	Firm-specific Factors	71
3.5.2	Peer Firm Average Variables	72
3.5.3	Data Sources and Summary Statistics	73
3.6	Empirical Results	74
3.6.1	Peer Effects in Corporate Financial Policies	74
3.6.2	Heterogeneity in the Peer Effects on Corporate Financial Policies	77
3.6.3	The Role of Financial Constraints	79
3.6.4	Information Environment	80
3.7	Robustness	81
3.8	Conclusion	83
	CITED LITERATURE	97
	APPENDICES	106
	Appendix A	107
	Appendix B	112
	VITA	115

LIST OF TABLES

TABLE		PAGE
I	COMOVEMENT ANALYSIS BOTH FOR THE CHEMISTRY INDUSTRY AND SUB-GROUPS OF APPAREL COMPANIES, JANUARY 2012 TO DECEMBER 2016.	44
II	SUMMARY STATISTICS.	45
III	COMMON OWNERSHIP MOMENTUM STRATEGY, JULY 1982 TO JUNE 2017.	46
IV	CROSS-SECTIONAL REGRESSIONS, JULY 1982 TO JUNE 2017.	47
V	CROSS-SECTIONAL REGRESSIONS WITH DIFFERENT LAGS, JULY 1982 TO JUNE 2017.	48
VI	CONTROLLING FOR OTHER ECONOMIC LINKS, JULY 1982 TO JUNE 2017.	49
VII	FLOW-BASED EXPLANATION OF RETURN PREDICTABILITY, 1982 Q3 TO 2017 Q2.	50
VIII	LIMITED ATTENTION AND LIMITS TO ARBITRAGE.	51
IX	ROBUSTNESS TEST, CROSS-SECTIONAL REGRESSIONS, IN SUB-PERIODS.	52
X	ROBUSTNESS TEST, MUTUAL FUND & IIA VS. OTHER INSTITUTIONS.	54
XI	ROBUSTNESS TEST, MOMENTUM STRATEGY, BASED ON COWN UNDER DIFFERENT LEVELS OF CONDITIONS.	55
XII	ALPHAS OF STRATEGIES WITH DIFFERENT LOOK-BACK AND HOLDING PERIODS.	56
XIII	STOCK RETURN FACTOR REGRESSION RESULTS.	85
XIV	SUMMARY STATISTICS BASED ON DIVIDEND POLICIES. . .	86

TABLE **PAGE**

XV SUMMARY STATISTICS BASED ON INVESTMENT POLICIES. 87

XVI PEER EFFECTS IN CORPORATE FINANCIAL POLICIES: REDUCED-FORM ESTIMATES. 88

XVII PEER EFFECTS IN CORPORATE FINANCIAL POLICIES: IV-2SLS ESTIMATES. 89

XVIII EIGENVECTOR CENTRALITY AND FIRM-SPECIFIC FACTORS: UNIVARIATE EVIDENCE. 90

XIX HETEROGENEITY IN THE PEER EFFECTS ON CORPORATE FINANCIAL POLICIES. 91

XX ROLE OF FINANCIAL CONSTRAINTS. 92

XXI INFORMATION ENVIRONMENT. 94

XXII DIFFERENT SETS OF PEER FIRMS. 95

XXIII EFFECT OF PEER FIRMS ON OTHER PAYOUT POLICIES AND INVESTMENT DECISIONS. 96

LIST OF FIGURES

FIGURE **PAGE**

1 Common Ownership Distribution of Biogen Inc. and TJX Inc. 42

2 The Cumulative Hedge Portfolio Returns 43

3 Hypothetical Common-Owners Network 84

SUMMARY

This dissertation consists of two empirical essays that study issues related to common ownership.

The first essay provides empirical evidence of return predictability across common ownership linked firms. A common ownership momentum-based long-short strategy earns a significant average monthly abnormal returns of 78 basis points from July 1982 to June 2017. This return predictability is distinct from the previously known industry, customer-supplier, standalone-conglomerate momentum, or technology lead-lag effects. A flow-based explanation can account for the observed return predictability with the common ownership-linked returns affecting capital flows to institutional portfolios and such expected flow-induced trading influencing stock returns. In addition, the return predictability is more pronounced for focal firms with less attention from investors and more limits to arbitrage.

The second essay investigates the peer effect of common ownership-linked firms on corporate dividend and investment decisions. We first show that common ownership peer firms are influential in determining U.S. firms' dividend yield and investment capital ratio. Such an effect is distinct from the previously known industry peer effects, more pronounced among more connected firms and firms facing higher uncertainty. Overall, these findings indicate that firms imitate their peers to maintain interest from institutional investors, and/or firms mimic their peers to deal with uncertainty in their decision making.

CHAPTER 1

LITERATURE REVIEW

Share ownership of firms held by common institutional investors, often referred to as "common ownership," is becoming increasingly prevalent. The growing importance of institutional investors in U.S. stock markets not only intensifies the degree of common ownership but also can causes more correlation among stocks held in portfolios of common owners. Common ownership can also affect the competition and coordination among firms. We briefly review the literature on effects of common ownership on asset pricing and corporate finance, which inspires the research and analysis in this dissertation.

1.1 Related Asset Pricing Studies

I investigate the existence of price momentum related to the common ownership in Chapter 2 "Common Ownership Linkage and Return Predictability". My analysis hinges on the idea of flow-induced trading, which can generate significant price pressure on individual stocks, in explaining return predictability across stocks linked by common ownership. In this chapter, I first describe the prior studies on how flow-induced trading can give rise to stock price momentum. We then review the literature of price momentum.

1.1.1 Effect of Institutional Trading on Stock Returns

The relationship between institutional trading and stock returns has been well documented. The price pressure hypothesis, where the demand shocks pressure investors to buy or sell stocks immediately, argues that institutional trading affects contemporaneous stock prices (Harris and Gurel, 1986). Sias et al. (2006) state that price pressure can occur for information revealed or liquidity reasons through institutional trades. Institutional investors who are better informed than others can reveal private information about an individual stock through trading, and then the trading affects stock prices (Easley and O'hara, 1987; Kyle, 1992). An alternative explanation of why institutional trading may affect stock prices is that institutional investors who need immediacy must offer price concessions to other investors as liquidity providers (Stoll, 1978; Grossman and Miller, 1988).

Coval and Stafford (2007) show that fire sales induced by extreme mutual fund flow cause a negative price pressure on the stocks they hold. They also emphasize that future flow-driven transactions are predictable. Lou (2012) provides empirical evidence that expected mutual fund flow-induced trading help predict stock returns, and mutual funds facing past inflows outperform those suffering past outflows in the short-run. Frazzini and Lamont (2008) find that mutual fund flows, as a proxy of investor sentiment, are negatively correlated with the future long-term returns.

Other papers investigate how common ownership affects stock return variation or correlation. Antón and Polk (2014) show that stocks sharing common owners tend to comove. They find that the exogenous variation in common ownership triggered by the 2003 mutual fund trading scandal caused abnormal return correlation among the stocks held by the implicated funds in the following month. Gao et al. (2017) report the weekly lead-lag return predictability among stocks that are economically unrelated but are linked by common institutional ownership. Their results indicate that, when institutional investors adjust their portfolios, i.e., they move capital from certain stocks to others, there are temporary price pressures that can cause the lead-lag effects.

1.1.2 Price Momentum

Existing studies document the momentum effects in both time-series and cross-sectional analysis. While the cross-sectional momentum strategy selects stocks based on their relative performance over certain prior periods, a time-series momentum strategy consists of choosing stocks based on their absolute prior return performance.

1.1.2.1 Time-series Momentum

Several studies document the existence and strength of time-series momentum. Moskowitz et al. (2012) propose the framework of the time-series momentum, by demonstrating that the past 12-month returns of instruments, such as equity index, currency, commodity, and bond futures, predict subsequent monthly return. This time-series momentum also exists in the alternative asset classes such as Commodity Trading Advisors Index, (Baltas and Kosowski, 2013), international equity/commodity (Georgopoulou and Wang, 1990), and China's commodity futures market (Ham et al., 2019).

1.1.2.2 Cross-sectional Momentum

Jegadeesh and Titman (1993) propose a portfolio strategy constructed by buying past winning stocks and selling past losing stocks, known as a cross-sectional momentum strategy. They found that stock returns of such a strategy exhibit persistent medium-term (i.e., 3-12 months) price momentum. Subsequent studies by Jegadeesh (1990) and Lehmann (1990) identified the short-term reversal as driven by temporary liquidity imbalances.

Various momentum strategies have been identified among firms in the same industry (Moskowitz and Grinblatt, 1999), among customer-supplier industries (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), among standalone and conglomerate firms (Cohen and Lou, 2012), among firms sharing similar technology (Lee et al., 2019), and firms covered by the same analysts (Ali and Hirshleifer, 2020). Moskowitz and Grinblatt (1999) provide evidence that industry momentum strategies appear highly profitable and are more profitable than individual stock momentum strategies. Cohen and Frazzini (2008) and Menzly and Ozbas (2010) study the return predictability across industries linked by supplier and customer linkage. Cohen and Frazzini (2008) show that due to customer information delay, the customers' monthly stock returns can help predict the future returns of their suppliers. Menzly and Ozbas (2010) provide evidence of cross-industry momentum with both the returns of customer and supplier industry cross-predict each other. Cohen and Lou (2012) find that investors were slower to incorporate relevant information more gradually about multi-industry conglomerates than single-industry firms, which result in the return predictability in conglomerate firms based on a portfolio of standalone firms' returns. Lee et al. (2019) explain that technological closeness between firms can create technological momentum.

Prior literature of cross-sectional price momentum has mostly concentrated on the economical linkages among competitors, suppliers, or customers. However, cross-sectional price momentum can exist beyond economically connected firms. For example, Ali and Hirshleifer

(2020) report lead-lag stock return relations among stocks sharing the same analyst coverage. Chapter 2 in this thesis documents a common ownership momentum effect resulting from institutional portfolios' trading and fund flows, which is unrelated to the fundamental relationships among firms.

1.2 Related Corporate Finance Studies

Chapter 3 in this thesis, Common Ownership Linkage and Peer Effects in Corporate Policies, identifies peer effects in corporate financial policies among firms with common ownership. We first review literature on the important corporate financial policies such as dividend, investment, cash holding, and capital structure decision. We then discuss prior studies on how peer effects affect the corporate financial policies. Lastly, we evaluate the role of common ownership in the corporate finance literature.

1.2.1 Corporate Financial Policy

1.2.1.1 Dividend Policy

Various arguments, such as the catering theory (Baker and Wurgler, 2004; Li and Lie, 2006; Jiang et al., 2013; Hoberg and Prabhala, 2009; Chahyadi and Salas, 2012), signaling theory (Akerlof, 1970; Bhattacharya, 1979; Miller and Rock, 1985; Ho, 2003), life cycle hypothesis (Mueller, 1972; Fama and French, 2001; DeAngelo et al., 2006; Grullon et al., 2002), the clientele theory (Black and Scholes, 1974; Allen et al., 2000; Grinstein and Michaely, 2005; Graham and Kumar, 2006; Rantapuska, 2008) and the dividend smoothing hypothesis (Lintner, 1956; Brav et al., 2005; Leary and Michaely, 2011), are proposed to describe the decision making on corporate payout policy.

The catering theory hypothesizes that managers accommodate investors' preferences through paying dividends when investors add price premiums to dividend-paying stocks, and not distributing dividends when investor sentiment indicates a preference for non-payers (Baker and Wurgler, 2004). Baker and Wurgler (2004) only examine the binary decision of whether to pay dividend. Li and Lie (2006) extend their model to include a continuous dividend payment amount, and show that the capital market rewards managers who take the investor dividend demand into account when making decisions dividend payments. Jiang et al. (2013) examine the catering theory of dividends in share repurchase decision. However, other studies report different results. Hoberg and Prabhala (2009) and Chahyadi and Salas (2012) indicate that, after controlling for risk and tax, investor sentiment does not significantly influence dividend policy. In other words, they conclude that dividend payment is not a major determinant for investors to choose shares.

The signaling theory, first introduced by Akerlof (1970) and later developed by Bhattacharya (1979) and Miller and Rock (1985), stipulates that the dividend payment allows managers to provide a signal to the market on the firm's value and prospect. While the cost of signaling is the transaction cost for additional external financing in Bhattacharya (1979), the cost of the signal is the opportunity cost of future investment in Miller and Rock (1985). The evidence for the prediction of dividend change on future earnings is mixed. Ho (2003) empirically shows that paying cash dividends is positively related with liquidity in Japan firms, supporting the signaling theory of dividend policy. On the contrary, Grullon et al. (2002) show that dividend changes are negatively correlated with future return on assets, with no signaling effect for future change in profitability and earnings.

The life cycle theory suggests that the dividend policy systematically changes over a firm's life cycle (Mueller, 1972). While young firms reinvest their earnings for future investments rather than paying dividends, mature firms often pay dividends to their shareholders. Empirical research supports the life cycle effect on dividend policy. Fama and French (2001) show that dividend payers in U.S market are larger, more profitable, and have fewer growth opportunities. DeAngelo et al. (2006) find that firms tend to pay more dividends when growth opportunities decline. Grullon et al. (2002) state that firm maturity is negatively related with the growth opportunities. Thus, dividend change can relate to a firm's maturity.

Clientele effect of dividends describe how investor target firms with dividend policies fitting their preferences for investments (Black and Scholes, 1974). Allen et al. (2000) show that investors with less sensitivity to tax prefer dividends because dividend payment increases the opportunity to detect a firm's quality. Grinstein and Michaely (2005), Graham and Kumar (2006), and Rantapuska (2008) demonstrate a clientele effect of dividends, with institutional investors, investors with low income, and investors with low dividend tax rates attracted to high dividend stocks. Grinstein and Michaely (2005) find that institutional investors prefer dividend paying firms, yet favor payers with fewer dividends. Graham and Kumar (2006) analyze the data for over 60,000 individual investors' trading behaviors and show that individual low-income investors prefer to hold high-dividend payout stock portfolios. As a result, firm managers, aware of clienteles' preferences, would at least consider investor preferences in formulating their firm's dividend policy.

Dividend policy is well known to be sticky (Lintner, 1956). Managers are reluctant to change dividends. In particular, firms often do not reduce dividends when earnings decline. Brav et al. (2005) document survey evidence that managers in dividend payers are obliged to continue paying cash dividends due to inertia. Leary and Michaely (2011) report that dividend smoothing is more prevalent among mature firms holding a high level of cash and paying high dividend levels. In the U.S. market, they find evidence that firms tend to smooth dividends as they increase their cash holdings.

1.2.1.2 Investment Policy

In the empirical studies, the main determinants of corporate investment include cash flow (Harford, 1999; Kaplan and Zingales, 1997; Hennessy et al., 2007; Almeida et al., 2010; Erickson and Whited, 2012; Chen and Chen, 2012; Lewellen and Lewellen, 2016), growth opportunities (Dixit et al., 1994; Tobin, 1969), and financial leverage (Lang et al., 1996; Aivazian et al., 2005).

According to the free cash flow theory (Jensen, 1986), managers are likely to misuse excess cash. For example, Harford (1999) shows that acquisitions by cash-rich firms are generally paid by large cash reserves and tend to destroy value. However, the impact of cash flow on investment can be ambiguous. While some studies suggest that cash flow has a small effect on investment at most (Hennessy et al., 2007; Almeida et al., 2010; Erickson and Whited, 2012; Chen and Chen, 2012), Kaplan and Zingales (1997) argue that investment is more sensitive to firms' cash flow among constrained firms. Lewellen and Lewellen (2016) test whether investments are sensitive to cash flows in the U.S. market. They report that for an increase of one dollar of cash flow in the year, fixed investment for constrained firms increases by \$0.32 to \$0.63. Despite the inconclusive strength of the impact, most research agrees that cash flow is a crucial determinant of corporate investment decisions.

Tobin (1969) argues that managers have incentive to invest more when a firm has high growth opportunities, implying that a firm's market value will be higher than the value of its replacement costs of assets (Dixit et al., 1994). Also, Lang et al. (1996) and Aivazian et al. (2005) suggest that the investment policy is negatively related to leverage and the negative effects are pronounced for firms with low growth opportunities.

1.2.1.3 Cash Holdings

Bates et al. (2009) state that, from the 1980s to 2006, U.S. firms have more than doubled their average cash-to-assets ratio. Four motives are provided to explain why firms hold cash; the transaction purpose (Baumol, 1952; Miller and Orr, 1966; Mulligan, 1997), the tax incentives (Foley et al., 2007; Col et al., 2020), the agency motive (Jensen, 1986; Harford et al., 2008; Dittmar and Mahrt-Smith, 2007), and the precautionary motive (Opler et al., 1999; Han and Qiu, 2007; Qiu and Wan, 2015).

Since cash on hand is highly liquid, providing a safety margin against some unforeseen events and future uncertainties, a firm is more likely to hold more cash when the firm faces higher transactions costs in converting non-cash assets to cash (Baumol, 1952; Miller and Orr, 1966). Mulligan (1997) finds that large firms, driven by economies of scale, tend to hold less cash than small firms, consistent with the transaction motive.

Foley et al. (2007) found the tax motive evidence that US multinational firms facing higher tax for repatriating foreign earnings tend to hold more cash. Col et al. (2020) review the 691 corporate inversions from 11 home countries to 45 host destinations, and find that firms conducting inversions from countries with higher tax rates are likely to hold more cash.

Jensen (1986) utilizes the agency model to explain that entrenched managers prefer holding a large amount of cash rather than distributing dividends to shareholders. Harford et al. (2008) find that firms with weaker governance spend cash quickly on acquisitions and capital expenditures, rather than hold the cash. Dittmar and Mahrt-Smith (2007) provide evidence that firms with poor governance waste excess cash resources and destroy firm value.

The precautionary motive provides that managers are likely to hold cash reserve as a contingency to protect against unexpected expenditures. Opler et al. (1999) find that a firm's cash holdings are higher among firms with a higher level of investment opportunities and more uncertainty in future cash flows. Qiu and Wan (2015) show that firms facing greater technology spillovers and a higher level of investment opportunities, hold more cash. Han and Qiu (2007) find that cash flow volatility is positively associated with cash holdings.

1.2.1.4 Capital Structure Choice

The literature on capital structure is vast. We focus on studies related to other financial policies.

Managers have incentive to invest more to increase the firm size at the expense of shareholder wealth (Jensen, 1986). Manager are able to raise the investment size with leverage. Also, debt can reduce free cash flow due to the obligation to pay interest and principal, and decrease overinvestment. In this case, the increase in leverage for overinvestment could be negatively related to the investment level. In debt-overhang theory (Myers, 1977), the levered firms are likely to reduce their investment to avoid the cost of external capital and the possibility of default. However, when firms have higher growth opportunities and fewer agency problems, the leverage could be positively related to the investment level.

Leverage is an important determinant of dividend policy. Firms with higher leverage are likely to pay lower dividends due to the cost of raising external capital (Rozeff, 1982). Also, prior literature shows that the dividend payout ratio is negatively associated with the firm's debt financing (Higgins, 1972) and long-term debt (McCabe, 1979).

1.2.2 Peer Effects

Peer effects refer to the externalities that arise when the average action or strategy within a peer group influences individual agent behavior in the group (Manski, 1993). Manski (1993) proposed a model to identify endogenous effects, which captures the impact of peers' action on an individual's own action, separately from correlated and contextual influences. Peer effects are widely reported in various fields of study: economics in education (Angrist and Lang, 2004; Card and Rothstein, 2007), in health (Fowler and Christakis, 2008), in the labor market (Mas and Moretti, 2009) and in social programs (Bertrand et al., 2000).

There is a growing literature on peer effects in finance. Leary and Roberts (2014) show that peer firms within the same industry play a significant role in affecting corporate capital structures and financial policies. They employ an instrumental variable (IV) technique by using the average of idiosyncratic shocks to the equity of peer firms for solving the endogeneity problems. The instrumental variable (IV) approach proposed by Leary and Roberts (2014) is employed in many other studies on the peer effects in finance afterward: in cash holdings (Chen et al., 2019; Joo et al., 2016), dividend policies (Grennan, 2019; Adhikari and Agrawal, 2018), and investment decisions (Ozoguz et al., 2018; Foucault and Fresard, 2014; Park et al., 2017; Chen and Ma, 2017).

Chen et al. (2019) examine how peer firms' cash ratios influence the corporate cash holdings in U.S. manufacturing firms. They emphasize that firms with higher R&D expenditures are more inclined to imitate the cash holdings of their rivals. Joo et al. (2016) use a sample of Korean manufacturing firms to test the peer effects on corporate cash holdings.

Grennan (2019) reports that a one standard deviation increase in peer firm dividend leads to a reduced duration between a firm's dividend changes by 1.5 quarters and an increase of dividend payout ratio by 16%. The results demonstrate that dividend decisions of peer firms significantly determine corporate dividend policy. While Grennan (2019) concludes that there are no peer effects in repurchases policy, Adhikari and Agrawal (2018) found peer effects in both dividend policy and repurchase transactions.

Peer firm decision is also known to affect a firm's investment policies. Ozoguz et al. (2018) and Foucault and Fresard (2014) show that stock prices in peer firms can be used as a proxy of the peers' information and influence a corporate investment decision. Park et al. (2017) and Chen and Ma (2017) document the peer effect on investment decisions among U.S. firms and Chinese firms, respectively.

Most prior literature on peer effects in firm policies exploits industry classification. However, firms can be connected through multidimensional linkages such as educational social interaction (Shue, 2013) and common financial analysts (Gomes et al., 2017). Chapter 3 revisits the peer effects in dividend policies and investment decision by using the common ownership linkage, instead of the industry classification. In addition, I test why firms mimic peer firms through rival-based and information-based theories provided by Lieberman and Asaba (2006). While the rival-based motive indicates that firms imitate to avoid falling behind their competitors, the information-based motivation points out that managers have an incentive to value information disclosed by their peer firms when they cannot predict the outcome of their decision.

1.2.3 Effect of Common Ownership in Corporate Finance

Common owners may have an incentive to dampen product market competition and maximize the common owners' portfolio value. Thus, recent literature in corporate finance focuses on the interactions between common ownership and product market competition. Azar et al. (2018) argue that common ownership concentration creates anticompetitive effects with higher airline ticket prices. The effect also exists in the banking industry that common ownership concentration increases bank deposit prices (Azar et al., 2019).

Managerial incentive studies examine the anticompetitive effects of common ownership on executive compensation. Liang (2016) shows that common institutional ownership affects CEO compensation contracts in order to alleviate competition. Antón et al. (2018) find that within industries with high concentrations of common ownership, managers are get paid less for their own-firm performance and more for rival-firm performance. In their model, common owners, as diversified asset managers, seek to maximize their existing stock portfolio value, rather than the value of individual firms within their portfolio. As a result, executive pay may be designed for managers to reduce the incentives to compete aggressively against their peer firms. However, such an executive pay design can be subject to the critique of whether institutional investors cause managers to dampen competition (Rock and Rubinfeld, 2018). Kwon (2016) empirically shows that the relative performance evaluation (RPE) is positively associated with common ownership, while executive pay is not a channel of the anticompetitive behavior suggested by Azar et al. (2018).

Other studies focus on the role of common ownership in facilitating collaboration (He and Huang, 2017; Kostovetsky and Manconi, 2020), formulating voluntary disclosure practice (Jung, 2013), internalizing corporate governance (He et al., 2019) and determining corporate financial decisions (Semov, 2017). He and Huang (2017) show that an increase in common institutional ownership leads to more explicit product market collaborations among rival firms in the same industry in the form of joint ventures, strategic alliances, or acquisitions, and improves innovation productivity and operating profitability. Kostovetsky and Manconi (2020) find a diffusion of innovation among commonly held firms via the same board directors or equity analysts. Jung (2013) shows that increases in institutional investor overlap lead to increases in disclosure. He et al. (2019) find that enhancing a firm's governance drive an improvement in governance among common ownership-linked peer firms in the same industry.

While previous studies mostly concentrate on common ownership among industry competitors and the anti-competition effects of the product market among the firms, Chapter 3 in this thesis has a different focus. We start with a sample of common ownership-linked firms in the U.S market and analyze the effect on firms for competing for limited funds from the same set of institutional investors. In addition, the measure of common ownership based on the Modified Herfindahl–Hirschman Index used in many existing studies cannot identify the common ownership among the firms across the different industries. I propose a novel measure based on the institutional ownership distribution to provide a better peer selection among common ownership connected firms.

CHAPTER 2

COMMON OWNERSHIP LINKAGE AND RETURN PREDICTABILITY

This paper provides empirical evidence of return predictability across common ownership linked firms. A common ownership momentum-based long-short strategy earns a significant average monthly abnormal returns of 78 basis points from July 1982 to June 2017. This return predictability is distinct from the previously known industry, customer-supplier, standalone-conglomerate momentum, or technology lead-lag effects. A flow-based explanation can account for the observed return predictability with the common ownership-linked returns affecting capital flows to institutional portfolios and such expected flow-induced trading influencing stock returns. In addition, the return predictability is more pronounced for focal firms with less attention from investors and more limits to arbitrage.

2.1 Introduction

Over the last four decades, the growth of institutional investors in the U.S. stock market has been remarkable. For example, the share of the average S&P 500 firm held by all 13(f) managers has risen greatly in the last 40 years, from under 40% in 1980 to approximately 80% in 2017 (Backus et al., 2019). As a result, shocks to institutional investor demand and capital flows to the institutional portfolios likely affect stock trading and valuation. However, how fast the information of these expected institutional fund flows is incorporated into the stock prices remains an open question.

This paper investigates the gradual information incorporation of institutional fund flows into stock prices and documents the return predictability between the stocks held by common institutional investors. The key idea is that institutional stock portfolio performance, measured by the closeness-weighted returns for a portfolio of common ownership-linked firms, predicts whether fund managers will re-allocate more or less capital to the focal stocks in the current institutional portfolios. However, as investors' information on the common ownership stock connection is limited at best, the gradual diffusion of such information can cause delayed reactions to those focal stocks and result in return predictability among stocks with common ownership links.

This study utilizes both portfolio tests and Fama-MacBeth regressions approaches to examine the return predictability among common ownership-linked stock returns. First, a hedge-portfolio trading strategy which consists of purchasing stocks of firms with the best returns of corresponding common ownership-linked firms and shorting on the stocks of firms with the worst returns of common ownership-linked firms earns a significant average abnormal return. In our sample of 1982-2017, an equal-weighted portfolio with the trading strategy yields an abnormal monthly return of 78 basis points (t=4.85), while a value-weighted portfolio generates an abnormal return of 55 basis points (t=2.18). Both results remained significant and robust when controlling for risk factors (such as market, size, book-to-equity ratio, momentum, profit, and capital investment).

Next, the common ownership-linked return is a significant predictor of stock return in cross-sectional tests. The significance of common ownership-linked return is robust to the inclusion of controls for firm characteristics, such as firm size, book-to-market, gross margin profitability, asset growth, monthly turnover, short-term reversal, medium term price momentum, and industry momentum, in Fama-MacBeth regressions. This return predictability is also distinct from the previously known lead-lag effects such as customer-supplier momentum (Menzly and Ozbas, 2010), standalone-conglomerate momentum (Cohen and Lou, 2012), and technology momentum (Lee et al., 2019). The explanatory power of lead-lag effect is decreasing in the lag length, while the common ownership-linked return in the prior month generates the highest coefficient of 61.3 basis points per month (t=3.18), and the coefficient estimates for the two and three- month lags decrease to 25.2 basis points (t=1.78) and 12.5 basis points per month (t=0.88), respectively.

The paper adds to the following four strands of literature. This paper is related to the literature on price momentum, first documented by Jegadeesh and Titman (1993) as the tendency of stocks with higher past returns to continue to earn higher returns in the following period. Subsequent studies report a lead-lag relationship between stocks in the same industry (Moskowitz and Grinblatt, 1999), among firms along industry-level supply chains (Cohen and Frazzini, 2008; Menzly and Ozbas, 2010), between standalone and conglomerate firms (Cohen and Lou, 2012), and technologically approximate firms (Lee et al., 2019). To date, the literature has mostly focused on economical linkages such as competitors, suppliers, and customers[1]. In contrast, we document a common ownership momentum effect resulting from trading and fund flows of institutional portfolios, above and beyond the fundamental relationships among firms.

Second, this study extends the literature on the price impact of institutional investors (Coval and Stafford, 2007; Lou, 2012). Coval and Stafford (2007) find that price pressure in overlapping holdings leads to a decrease in existing positions by large-outflow funds, and an increase in existing positions by large-inflows funds. While prior studies focus exclusively on extreme mutual fund flows by fire sales, we pay more attention to the flow-induced trading by the returns of common ownership. The closest work is Lou (2012), who provides a fund-flow based explanation with regards to return predictability. While Lou (2012) focuses on mutual funds, this paper estimates flow-induced trading for all institutional investors, including mutual funds.

Third, this paper uncovers new and significant effects of common ownership connection on stock returns[2]. Earlier studies report effects of common institutional ownership in firms in the same industry on anti-competition practices (e.g., Azar et al., 2018; He et al., 2019). This study broadens the scope by identifying inter-firm connection as common ownership by the same institutional shareholders across industries. In addition, this paper utilizes a novel measure of

---

[1] Gao et al. (2017) defined the term "economically unrelated" links of information diffusion between stocks rather than common fundamentals.

[2] While Gao et al. (2017) find weekly lead-lag return predictability in stocks with common ownership, and attribute the lead-lag effect to portfolio reallocations of institutional investors. We document the flow- and behavior-based effects on the return predictability instead.

common ownership distance between firms, measured as the uncentered correlations between firms based on institutional ownership distribution[3]. Earlier studies (Antón and Polk, 2014; Gao et al., 2017) use the number of significant common owners or the total dollars ownership by all common funds to identify common ownership links, which totally disregards information of a focal firm's ownership distributions by institutional investors. In this paper, we explicitly measure the inter-firm similarity between the distribution of institutional investor ownership and more readily capture the time-varying institutional ownership distribution in the stock market.

Fourth, this work adds to the growing body of literature on investors' limited capacity to process information in the stock market. Research papers apply a theoretical framework of the gradual information diffusion model, proposed by Hong and Stein (1999), to examine whether stocks show any predictive ability for each other. For instance, Cohen and Lou (2012), Menzly and Ozbas (2010), Cohen and Frazzini (2008), and Lee et al. (2019) show the empirical evidence that limited investor attention causes the return predictability. In a similar vein to the above-mentioned work, we add new empirical evidence that documents a lead-lag relation between portfolio returns under common ownership.

The rest of the paper is organized as follows. Section 2.2 proposes the flow-based mechanism of the return predictability across the common ownership linked firms and then outlines

[3]The measure, pioneered by Jaffe (1986), has been proved to be an efficiency way of calculating the inter-firm closeness such as technological- (Bloom et al., 2013; Lee et al., 2019), product- (Bloom et al., 2013; Hoberg and Phillips, 2016), and cultural-similarity (Bereskin et al., 2018).

hypotheses from the proposed mechanism. Section 2.3 delineates the methodology to measure common ownership closeness and compute common ownership-linked returns. Section 2.4 describes the data selection procedure. Section 2.5 provides results of empirical analysis on the common ownership return predictability. Section 2.6 presents empirical analysis on the flow-based mechanism. Section 2.7 provides additional robustness analysis, and Section 2.8 concludes.

2.2 Hypotheses

Our paper builds on and contributes to the literature on how common ownership may affect stock return predictability. We then test for the existence of feedback trading, flow-induced price pressure, and limited-attention and limits-to-arbitrage hypotheses, which can explain the potential relation of return predictability based on common ownership.

In the literature on positive-feedback trading, past winning funds attract capital inflows while past losing funds face capital outflows. Ippolito (1992) shows that mutual fund investors react to past mutual fund performance. Chevalier and Ellison (1997) interpret the flow-performance relationship as an incentive scheme implicitly given to fund managers by fund investors. Unlike the previous studies focusing on mutual funds, we extend the analysis to look at the institutional investors' fund flow-performance relationship. This paper identifies past institutional investors' performance with stock portfolio returns, which is estimated based on common ownership-linked returns. The effect of past performance on the institutional investors' fund flows described above will, therefore, be empirically tested as follows:

- H1 (*Feedback-trading hypothesis*): *Institutional shareholders' investment performance as measured by common ownership-linked returns affect subsequent flow-induced trading.*

Given that the flow-induced trading can affect the individual stock returns, it is the next question whether the expected flow-induced trading can forecast stock returns. Lou (2012) finds that the expected flow-induced trading by mutual funds positively predicts stock returns. These results support the price pressure hypothesis, documented by Coval and Stafford (2007), that fund flows lead to stock returns. We test the effect of expected fund flows of institutional investments on stock returns in the following hypothesis:

- H2 (*Flow-induced price pressure hypothesis*): *Expected flow-induced institutional trading affects stock returns.*

We further review the effect of limited attention and arbitrage cost. Since all stock market investors have limited resources to monitor firms, stocks that receive less investor attention and are more costly to arbitrage should be slower to respond to information of these expected institutional fund flows. Levels of investor attention are measured by firm size (Lo and MacKinlay, 1990; Hou, 2007), analyst coverage (Brennan et al., 1993; Hong et al., 2000), and institutional ownership (Badrinath et al., 1995). The level of arbitrage limits is additionally measured as the idiosyncratic stock return volatility (Ang et al., 2006). The behavior-based explanation suggests the following two hypotheses on the cross-sectional variation in common-ownership momentum:

- H3 (*Limited-attention hypothesis*): *Common-ownership momentum is more pronounced for focal firms that receive lower investor attention.*

- H4 (*Limits-of-arbitrage hypothesis*): *Common-ownership momentum is more pronounced for focal firms that are more difficult to arbitrage.*

2.3 Methodology

This paper introduces a new inter-firm linkage measure based on common ownership. We adopt a measure of closeness among firms sharing ownership of common institutional investors. First, for each firm pair, we define $\mathsf{COWN}_{ij,q}$, the degree of common ownership closeness between firm i and j at the end of quarter q, as:

$$\mathsf{COWN}_{ij,q} = \frac{\left(S_{i,q} S'_{j,q}\right)}{\left(S_{i,q} S'_{i,q}\right)^{1/2} \left(S_{j,q} S'_{j,q}\right)^{1/2}} \tag{2.1}$$

where $S_{i,q} = \left(s_{1,q}, s_{2,q}, ..., s_{\tau,q}, ..., s_{6514,q}\right)$ is a vector of institutional ownership structure in firm i at quarter q, and then $s_{\tau,q}$ is a percentage of share outstanding owned by institutional shareholder τ on a rolling average of prior 4 quarters[4]. Second, the closeness-weighted return of common ownership-linked firms for each firm i at month t is calculated as

$$\mathsf{COWNRET}_{i,t} = \frac{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1} \times \mathsf{RET}_{j,t}}{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1}} \tag{2.2}$$

---

[4]We exclude from estimation the observations with $s_{\tau,q}$ less than 1%. In Table XI, we compare the results with and without this exclusion.

where $\mathsf{RET}_{j,t}$ is return of firm j at month t in quarter q, and $\mathsf{COWN}_{ij,q-1}$ is the degree of common ownership closeness between firm i and j as in equation (2.1).

We consider the example of Biogen Inc. and TJX Inc. to better illustrate the common ownership closeness measure. Biogen Inc. (NASDAQ: BIIB) is a leading biotechnology company, while TJX Inc. (NYSE: TJX) is the leading off-price retailer of apparel and home fashions. Biogen and TJX are neither in same industry nor connected by supplier-customer linkage. Furthermore, the two firms have no linkage in the product space based on the text-based product similarity (Hoberg and Phillips, 2016). The technology closeness score (Jaffe, 1986; Bloom et al., 2013; Lee et al., 2019) is zero and there is no correlation in technology space between the two firms.

Figure 1 displays the distribution of firms' ownerships held by each institutional shareholder. In 2016, Biogen Inc. had a total of 1,216 institutional shareholders, while TJX Inc. had a total of 1,255 institutional shareholders[5]. A total of 833 institutional investors who held both stocks, translating to an ownership of approximately 91% and 84% of institutional ownership of Biogen Inc. and TJX Inc., respectively. Our common ownership closeness between two firms, based on the ownership distribution of these two stocks, is high at 0.815 (i.e. $\mathsf{COWN}_{ij,q} = 0.815$). This exemplifies the existence of common ownership linkage, as distinct from other linkages reported in prior studies.

[5]For example, Blackrock Inc. held 8% and 7% of institutional ownership of Biozen Inc. and TJX Inc., respectively.

To explore the stock return comovement among common ownership-linked firms, we conduct correlation analysis between an apparel industry (2-digits SIC = 56) and a chemistry industry (2-digits SIC = 28). First, the apparel industry is divided into three groups (High, Medium, and Low), ranked by common ownership closeness (COWN) to the chemistry industry. For example, from January 2012 to December 2016, with an average common ownership closeness between TJX Inc. and all chemistry firms is 0.437, TJX Inc. is classified as High COWN Group. We then find that the Pearson (Spearman) correlations between value-weighted returns for each of these groups and the chemistry industry return. Panel B in Table I shows that the chemistry industry (SIC 28) comoves more strongly with apparel firms in the High COWN group than with apparel firms in the Low COWN group.

2.4 Data

2.4.1 Institution Holding

We describe the sample selection procedure in this section. We obtain information on quarterly common ownership from Thomson-Reuters Institutional (13f) Holdings database, previously known as CDA/Spectrum S34. All institutional investment managers who exercise over $100 million are required by the U.S Securities and Exchange Commission (SEC) to file their holdings using Form 13F. However, the data can be subject to the deficiency that there is no unique and permanent identifier for each institutional manager. We supplement the CDA/Spectrum S34 records with the institutional investor classification data provided by Brian Bushee[6], who provide a permanent key to identify institutional managers. In subsequent analysis, the 13f institutional investors with less than 20 distinct holdings are excluded. There is a total of 6514 institutional investment managers in our sample in the period of July 1982 to June 2017.

The 13f institutional investors are further classified into two groups (e.g., Brickley and Jr, 1988; Chen et al., 2007). The first group includes institutional investors who tend to have a shorter-term investment horizon such as mutual funds and independent investment advisors (Mutual Fund & IIA). The other group includes those who likely have a longer-term investment horizon such as banks, insurance companies, and the other institutions. In view of coding error[7] of institution types in CDA/Spectrum S34, we use Bushee classification.

2.4.2 Firm Characteristics and Stock Return

Monthly stock return data are obtained from Center for Research in Security Prices (CRSP) database. Our sample consists of all U.S firms listed on the NASDAQ, AMEX and NYSE with nonmissing observations for the variables of interest in the annual CRSP/Compustat Merged (CCM) data, with ordinary common equity (CRSP share code 10 or 11), and at least two years of data on Compustat. Financial firms (SIC 6000-6999), as well as penny stocks with prices of less than $1 are excluded. We further remove firms with fewer than 10 institutional shareholders.

[6]Brian Bushee created a permanent identifier based on the holdings histories of fund managers with changing investment manager numbers. The data is available on website: `http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html`

[7]The type code in the S34 set have classification errors from 1998. Thomson-Reuters has no plans to fix the problem.

The final sample consists of 881,728 firm-month observations in the period of July 1982 to June 2017. The sample firms cover an average of 74% of the CRSP common stock market capitalization. For our return analysis, we obtain risk-factors and risk-free returns are from the Kenneth French's website[8]. The risk-factors include market return (MKT), size (SMB), value (HML), profit (RMW), capital investment (CMA), and momentum (UMD) variables.

2.4.3 Descriptive Statistics

We further restrict the sample to firm-pairs with common ownership closeness of more than 0.2 (i.e. $\mathsf{COWN} > 0.2$)[9] in most of our analysis. Panel A of Table II presents summary statistics of variables used in the analysis. In our sample, the average common ownership closeness per focal firm is 0.340, and the monthly average number of the common ownership linked peer firms is 804. Among an average of 4,451 non-financial firms in our sample period, each focal firm is linked to about 18% of the peer firms in the stock market through common ownership. After ensuring the availability of other firm characteristic variables, the final sample consists of 881,728 firm-month observations with 2,099 firms on average per month. All variable definitions are tabulated in Appendix A.

Panel B of Table II presents results of Spearman (below the diagonal) and Pearson (above the diagonal) correlations analyses. The Pearson (Spearman) correlation coefficient between the $\mathsf{COWNRET}_{t-1}$ and RET_t is 0.013 (0.009) with significance, consistent with a lead-lag return

---

[8] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html`

[9] In Table XI, we compare the results with and without the restriction.

effect. Moreover, $\mathsf{COWNRET_{t-1}}$ has significantly positive Pearson and Spearman correlations with medium-term momentum (MOM), one-month lagged return ($\mathsf{RET_{t-1}}$), and industry return ($\mathsf{INDRET_{t-1}}$). In addition, $\mathsf{COWNRET_{t-1}}$ is significantly correlated with other firm characteristic variables (SIZE, BtoM, AG and $\mathsf{TURNOVER}$).

2.5 Return Predictability Analysis

We hypothesize that the increasing concentration of corporate ownership in the hands of institutional shareholders is likely to generate the return lead-lag effects between stocks owned by same institutional shareholders. In this section, we empirically investigate a predictive relation between common ownership-linked returns and subsequent stock returns.

2.5.1 Portfolio Tests

We construct portfolio tests to examine whether common ownership-linked returns predict focal firm returns. First, at each quarter-end, we compute the common ownership closeness between firms in measuring the degree of overlapping ownership by institutional shareholders. Second, for each focal firm and month in the subsequent quarter, we compute the common ownership-linked returns ($\mathsf{COWNRET}$) as in equation (2.2). To construct portfolios, all sample firms are sorted into deciles based on the common ownership-linked returns in the previous month ($\mathsf{COWNRET_{t-1}}$) at the beginning of each month and are rebalanced on a monthly basis. We implement a long-short trading strategy, taking a long (short) portfolio is in firms with the highest (lowest) common ownership-linked returns in the previous month. That idea is, when the common ownership-linked peer firms the outperform (underperform) in the previous month, institutional shareholders of focal firms in a long (short) position in the current month are more likely to have earned higher (lower) investment returns in the previous month.

Panel A of Table III presents the results of the long-short portfolios. We report significant average excess returns as well as alphas from a variety of factor models. The excess returns are computed by subtracting the risk-free yield from raw returns and the alphas are calculated by using the CAPM, the four-factor model of Carhart (1997), the three- and five-factor models of Fama and French (1993, 2015), and the six-factor extension with a momentum factor. As shown in Panel A of Table III, the equal-weighted long-short strategy yields an average monthly returns of 78 basis points (t = 4.85), while the corresponding value-weighted returns from the long-short portfolio are 55 basis points per month (t = 2.18). After controlling for other confounding factors, the long-short strategy continues to earn significantly positive abnormal returns. The equal-weighted long-short strategy generates monthly alphas from 83 basis points (t = 3.86) to 89 basis points (t = 5.16). The value-weighted long-short strategy generates relatively smaller but still significant alphas, ranging from 54 basis points (t = 2.13) to 67 basis points (t = 1.80). Altogether, our results suggest that there is a lead-lag effect among stocks connected by common ownership by institutional investors.

Table III Panel B presents the portfolio alphas as well as the loadings of the market (MKT), size (SMB), value (HML), and momentum (UMD) factors. The long-short portfolio has a significantly negative loading on the market factors (MKT), which implies that the long-short strategy is affected by market risk, and that the strategy performs well in down markets. In all analysis, alphas are consistently positive and significant.

2.5.2 Cross-sectional Regression Tests

The Fama and MacBeth (1973) monthly cross-sectional regression approach is utilized to test the predictability of stock returns (RET) using the lagged common ownership-linked returns ($\mathsf{COWNRET}_{t-1}$) as the main predictor. We include the value-weighted industry (2-digit SIC code) returns in the prior month (INDRET_{t-1}) to control for the industry momentum effect (Moskowitz and Grinblatt, 1999). Also, a focal firm's lagged return (RET_{t-1}) is added to control the short term reversal effect (Jegadeesh and Titman, 1993). A cumulative return of last 12 months excluding the last month (MOM) is included to control for the medium term momentum effect (Chan et al., 1996). The other control variables include firm size (SIZE), book-to-market ratio (BtoM), gross profitability (GP), asset growth (AG), and monthly turnover (TURNOVER). All explanatory variables are assigned to deciles ranging from zero to one to alleviate the influence of the changes in the intertemporal distribution of these variables and easily interpret the coefficients (Lee et al., 2019).

Table IV presents the cross-sectional regression results. The coefficient on $\mathsf{COWNRET}_{t-1}$ measures the average monthly return spread between the bottom and top decile of focal firm stock return sorted by $\mathsf{COWNRET}_{t-1}$. For example, the coefficient of 0.399 in the Column (1) indicates that firms in the top decile by $\mathsf{COWNRET}_{t-1}$ outperformed those in the bottom decile by a statistically significant 39.9 basis points monthly (t = 3.11), on average. The estimated spread increases to 52.8 basis points per month (t = 2.98) when including the industry fixed effects and control variables. With inclusion of lagged industry return as a control variable in Column (3), the estimated spread goes up to 61.3 basis points per month (t = 3.18). In

Column (1)-(3), all coefficients of $\mathsf{COWNRET}_{t-1}$ are statistically significant, indicating that the common ownership-linked return is a strong predictor of focal firm's stock return in the next month[10].

Next, we use industry-adjusted returns ($\mathsf{RET}_t - \mathsf{INDRET}_t$), by subtracting each stock return over the same period return of the corresponding industry, as a dependent variable in Column (4). Column (4) indicates that coefficient of $\mathsf{COWNRET}_{t-1}$ is nearly identical to those in Column (2) and Column (3). Our results indicate that the common ownership-linked momentum still has strong predictive power of stock returns next month even after controlling for the current industry momentum effect. We also note that the coefficient on lagged industry return (INDRET_{t-1}) is still significant, but decrease by around a half.

We evaluate the speed at which the return information of common institutional ownership-linked firms gets incorporated into the stock return of focal firms. Column (1) of Table V shows that there is a concurrent effect, stocks of focal firms strongly reacting to the common ownership-linked returns within a month. Results in Column (2)-(4) of Table V indicate that the explanatory power of lead-lag effect is decreasing in the lag length. While the coefficient of $\mathsf{COWNRET}_{t-1}$ is the highest with 61.3 basis points per month (t=3.18), the coefficient estimates for $\mathsf{COWNRET}_{t-2}$ and $\mathsf{COWNRET}_{t-3}$ decrease to 25.2 basis points per month (t=1.78) and

---

[10] My results indicate that there are no medium-term momentum effects (MOM) in the cross-sectional regression tests with or without common ownership momentum variable. While the medium-term momentum effect is strongly significant in the first half of the sample period, it is not in the second half, which is similar to what is documented in similar Chordia et al. (2014) on the decline in medium-term momentum trading profits of the U.S. stock market in recent years due to the increased liquidity and trading activity.

12.5 basis points per month (t=0.88), respectively. Column (5) indicates that coefficients of $\mathsf{COWNRET}_{t-1}$ and $\mathsf{COWNRET}_{t-2}$ are nearly identical to those in Column (2) and Column (3). That is, the two different time-lagged signals independently have powers to forecast stock returns.

We further investigate the effect of common ownership-linked return predictability by controlling for those resulting from other economic connections. Menzly and Ozbas (2010) identify return predictability among firms in customer–supplier industries. In Column (2) in Table VI, we show that the effect of $\mathsf{COWNRET}_{t-1}$ in predicting focal firm stock returns persist while controlling for lagged returns in supplier ($\mathsf{SUPPRET}_{t-1}$) as well as customer ($\mathsf{CUSTRET}_{t-1}$) industries. Cohen and Lou (2012) report predictability of the standalone firms returns on those of more complicated firms, i.e., conglomerate firms. The coefficient on $\mathsf{COWNRET}_{t-1}$ in Column (3) continues to be significant after including the lagged pseudo-conglomerate return (PCRET_{t-1}). Moreover, Lee et al. (2019) document return predictability among technologically similar firms. The coefficient on $\mathsf{COWNRET}_{t-1}$ remains significant in Column (4) after adding the lagged technology linked return ($\mathsf{TECHRET}_{t-1}$)[11]. Therefore, stock return predictive power of connection by common ownership is definitely distinct from other return predictability patterns resulting from production network, complex information processing of conglomerate firms, and technological similarity.

---

[11] Kogan et al. (2017) provide data on patents granted through 2010. The data is available on website: `https://iu.app.box.com/v/patents`

2.6 Mechanisms of Return Predictability

In this section, we test hypotheses on the mechanism for the observed return predictability among firms sharing common institutional ownership. As discussed in Section 2.2, the common ownership-linked returns, $\mathsf{COWNRET}_{t-1}$, a performance measure of a focal firm's institutional shareholders, can affect future flow-induced trading. The expected flow-induced trading in turn can affect the individual focal stock return. In addition, we investigate whether investor limited attention and limited arbitrage can account for the slow price adjustment to the information embedded in common institutional ownership.

2.6.1 Flow-based Explanation

In our analysis, the common ownership-linked return serves as a measure for the past investment performance of a focal firm's institutional shareholders. The variable of the flow-induced trading ($\mathsf{FIT}_{i,q}$) is a proxy for institutional fund flows, which is constructed using the following procedure. First, following Griffin et al. (2011) and DeVault et al. (2019), an increase in institutional holdings ($\triangle\mathsf{InstD}_{i,q}$) consists of three components: trades from investor flows ($\mathsf{FIT}_{i,q}$), from managers' decisions ($\mathsf{NActBuy}_{i,q}$), and from reinvested dividends ($\mathsf{Passive}_{i,q}$). Then, the flow-induced trading ($\mathsf{FIT}_{i,q}$) is calculated as institutional demand ($\triangle\mathsf{InstD}_{i,q}$) minus passive holdings ($\mathsf{Passive}_{i,q}$) and net active buying ($\mathsf{NActBuy}_{i,q}$)[12]. With the only availability of quarterly flow induced trading data, the forecasting dates are limited to the first month end in each quarter (i.e., January, April, July, and October). Before testing the feedback-trading

---

[12]The details are shown in Appendix B.

and flow induced price pressure hypotheses, we evaluate and confirm the return predictability among common ownership connected firms in the monthly cross-sectional regressions using the first monthly returns of the respective financial reporting quarter (see Panel B in Table IX). As a result, we show that the common ownership-linked return, $\mathsf{COWNRET}_{t-1}$, is still a strong predictor of future monthly stock returns in January, April, July, and October.

We now use Fama-MacBeth regressions to test the *feedback-trading hypothesis* and *flow-induced price pressure hypothesis*. In the Column (2) of Table VII, the first stage regression decomposes future flow-induced trading into a component caused by common ownership-linked return and a firm-specific component. The results indicate that the monthly lagged common ownership-linked returns ($\mathsf{COWNRET}_{i,t-1}$) predict the flow-induced trading, with a positive and statistically significant coefficient on $\mathsf{FIT}_{i,q}$. In the Column (3) of Table VII, the second stage confirms that stock returns in subsequent months are positively and significantly correlated with the predicted flow-induced trading ($\mathsf{E}_{t-1}[\mathsf{FIT}_{i,q}]$) from the first stage[13].

In summary, we evaluate the flow-based explanation of common ownership return predictability in a two stages analysis. Firstly, common ownership-linked returns - as a proxy for investment performance by institutional shareholders - affect institutions' future fund flows. This is consistent with the feedback-trader hypothesis (DeLong et al., 1990; Warther, 1995; Nofsinger and Sias, 1999; Jank, 2012), which postulates that returns cause subsequent flows. Second, expected flow-induced trading, based on the relationship between past performance

---

[13] $\mathsf{E}_{t-1}[\mathsf{FIT}_{i,q}]$ is quarterly flow-induced trading expected at the begin of the first month of the quarter (i.e., January, April, July, and October).

and future fund flows, affects the stock return. Our results are consistent with the flow-induced price pressure hypothesis (Coval and Stafford, 2007; Lou, 2012), which implies that fund flows affect individual stock return.

2.6.2 Limited Attention and Limits to Arbitrage

We have shown the robust effect of common ownership-linked returns on focal firm's stock return, after controlling for various risk factors and effects of other economical connections. We now investigate whether our findings can be explained by the mechanisms related to the focal firm's characteristics such as firm size, analyst coverage, institutional ownership, and idiosyncratic volatility. The first three variables are measures of investor attention, while idiosyncratic volatility is a proxy for cost of arbitrage.

Lo and MacKinlay (1990) and Hou (2007) show that large firms lead small firms in stock returns, as market investors pay more attention to large firms. As a result, larger firms exhibit a higher speed of price adjustment to information than smaller firms do. As shown in Column (1) of Table VIII, the coefficient on the interaction term between $\mathsf{COWNRET}_{t-1}$ and the large firm dummy is significantly negative, consistent with that the return predictability is stronger for small firms.

Brennan et al. (1993) and Hong et al. (2000) find that stocks with high analyst coverage react faster to common information. Column (2) in Table VIII reports a significantly negative coefficient for the interaction term between $\mathsf{COWNRET}_{t-1}$ and the high analyst coverage dummy, consistent with that stocks with low analyst coverage are slow to react to information of common ownership.

Badrinath et al. (1995) show that the stock returns with a higher degree of institutional ownership drive the stock returns with lower institutional ownership. Similar to the result of analyst coverage, in Column (3) in Table VIII, the negative coefficient of the interaction term between $\mathsf{COWNRET_{t-1}}$ and the high institutional ownership imply that the return predictability is stronger in firms with low institutional ownership.

Further, Ang et al. (2006) report that stocks with high idiosyncratic volatility tend to earn low subsequent returns. Column (4) in Table VIII shows that the common ownership momentum is stronger in high idiosyncratic volatility stocks than in low idiosyncratic volatility ones.

These findings add support to the theory of slow information diffusion model of Hong and Stein (1999) and the literature on stock price momentum (Cohen and Lou, 2012; Cohen and Frazzini, 2008; Hou, 2007; Menzly and Ozbas, 2010; Lee et al., 2019). The return predictability of $\mathsf{COWNRET_{t-1}}$ indicates a delayed price response to information of common ownership-linked firms[14].

2.7 Robustness

2.7.1 Return Predictability across Time

We conduct sub-sample analysis. The full sample is divided into four sub-samples: July 1982 – March 1991, April 1991 – December 1999, January 2000 – September 2008, and October 2008 – June 2017. With the exception of the first sub-period (July 1982– March 1991),

[14] In the flow-based hypothesis, (focal) stocks either with less investor attention or high costs of arbitrage can exhibit common ownership linked returns.

the common ownership-linked return predictability remains positively significant in the other three sub-periods (Panel A, Table IX). Since institutional investors have rapidly increased their percentage holdings of US stock market over the sample period, the estimated $\mathsf{COWNRET}_{t-1}$ effects increase from 42.0 basis points per month (t = 1.75) in the second period (April 1991 – December 1999) to 155.9 basis points per month (t = 2.83) in the third period (January 2000 – September 2008)[15]. While the estimated spread in the fourth period (October 2008 – June 2017) has decreased to 49.7 basis points per month, but its t-statistic is the highest (t = 3.76). Thus, in the stock market with high institutional ownership, the return predictability among firms sharing common ownership is quite robust.

2.7.2 Mutual Funds vs. Other Type of Institutional Investors

Different types of institutional investor may be subject to varying degrees of flow-induced trading pressures. Bushee (2004) documents that investment companies experience much more churn in their funding sources than other types of institutional investors (such as pension and endowments), with trading activities more sensitive to their short-term portfolio performance. We classify mutual funds and independent investment advisors (Mutual Fund & IIA) as ‘independent institutions’, and banks, insurance companies, corporate or private pension funds, and

[15] Antón and Polk (2014) find that the link between share ownership and comovement is stronger for owners facing on the extreme flows. Also Table III Panel B shows that common ownership momentum is stronger in down market. The third period includes dotcom crash (2000-2003), mutual fund scandal (2003) and financial crisis (2007-2008).

university foundations as 'other institutions'[16]. Other institutions are defined as institutional investors with existing or potential business relationships with the firms in which they invest (Brickley and Jr, 1988; Chen et al., 2007), while independent institutions have fewer business relationships with such firms. Therefore, independent institutions with low monitoring costs would generate more flow-induced trading than other institutions with high monitoring costs.

To test the hypothesis of whether independent institutions generate more flow-induced trading than other institutions do, we replicate the regressions in Section 2.6.1. First, Table X demonstrates that the effect of future fund flows is more significant among independent institutions than other institutions. In Column (2), the $\mathsf{COWNRET}_{t-1}$ is estimated using common ownership links by only mutual fund managers and independent investment advisors. The coefficients of $\mathsf{COWNRET}_{t-1}$ on future flow-induced trading ($\mathsf{FIT}_{i,q}$) is significantly positive. In contrast, in Column (5), the $\mathsf{COWNRET}_{t-1}$ is measured by common ownership by other institutions, and the coefficient of $\mathsf{COWNRET}_{t-1}$ is no longer significant. These findings, therefore, support the hypothesis that common ownership by independent institutions (Mutual Fund & IIA) results in stronger return predictability among common ownership-linked firms than by other institutions.

2.7.3 Alternative Common Ownership Closeness Measure

In earlier analysis, we exclude institutional shareholders who own less than 1% institutional shareholding per each stock from the vector of institutional ownership structure in a firm (i.e.,

---

[16]Brickley and Jr (1988) classify mutual funds and investment advisors as "independent institutions" and banks, insurance companies, and others as "grey institutions."

$s_{k,t} > 1\%$) in constructing the variable $\mathsf{COWNRET}_{i,t-1}$. Since investors who hold a smaller fraction of stock are less likely to influence stock price, data trimming removes any potential bias resulting from small institutional ownership. To distinguish effect of common ownership from that of overall market momentum, we exclude firm-pairs with common ownership closeness of less than 0.2 to calculate the common ownership linked return (i.e., $\mathsf{COWN} > 0.2$). Table XI examines the robustness of return predictability under different levels of conditions. Panel A shows the highly positive significant correlations between different versions of $\mathsf{COWNRET}$. Panel B shows that even after using different versions of $\mathsf{COWNRET}$, the long-short strategy still earns significant abnormal returns.

2.7.4 L/S Strategies with Different Look-back and Holding Periods

As an extension of the portfolio tests in Table III, Table XII reports the average monthly excess returns and Carhart 4-factor alphas on the long-short strategies with different look back period of J-months (J = 1, 3, 6, and 12) and different holding period of K months (K = 1, 3, 6, 12, 24, and 36). I construct these (J, K) momentum portfolios using a similar procedure to that in Jegadeesh and Titman (1993). Our results indicate that the (1, 1) strategy, with the shortest-term in both formation period and holding period, is most profitable. The findings provide that the common ownership momentum is strongest in the short-term, while Figure 2 shows the long-term cumulative returns of the hedge-portfolio in twelve months[17]. Neither

---

[17] All firms are arranged into ten decile with ascending order by the previous month's closeness-weighted return of a portfolio of its common ownership-linked peers. Each portfolio returns are equal-weighted as well as value-weighted, and are rebalanced every month to adjust equal or value weights. A long-short portfolio is designed to be short the bottom decile and long the top decile. The figure shows the returns

Table XII nor Figure 2 shows any sign of return reversal. It is an evidence that investors underreact to information from common ownership-linked stocks.

2.8 Conclusion

This paper provides new empirical evidence of return predictability across common ownership-linked firms. We utilize a closeness measure to identify common ownership connection between firms and construct a zero-cost portfolio strategy that buys stocks with the highest common ownership-linked returns in the prior month and sells stocks with the lowest common ownership-linked returns in the prior month. Such a strategy earns significant abnormal returns of 78 basis points per month, and this effect of common ownership momentum is distinct from previously documented momentum as well as other known factors.

The study contributes primarily to the literature on the flow-induced price pressure by identifying a specific channel, namely common ownership links, through which capital inflow and outflow likely occur. By utilizing common ownership-linked returns as a measure of performance by the focal firm's institutional shareholders, we then find that common ownership-linked returns affect subsequent fund flows, and such anticipated flow-induced trading affects individual focal stock returns. These findings are consistent with both the feedback-trader hypothesis and the flow-induced price pressure hypotheses. We also report that common ownership momentum based on independent institutions is associated with stronger return predictability. In addition, return predictability is stronger for stocks with lower investor attention and higher

to value-weighted (dotted line with diamond markers) and equal-weighted (solid line with circle markets) portfolios.

costs of arbitrage. There is also no sign of any return reversal. Therefore, this paper provides firm-level evidence on return predictability due to the delayed price responses to information that originate in related common ownership-connection.

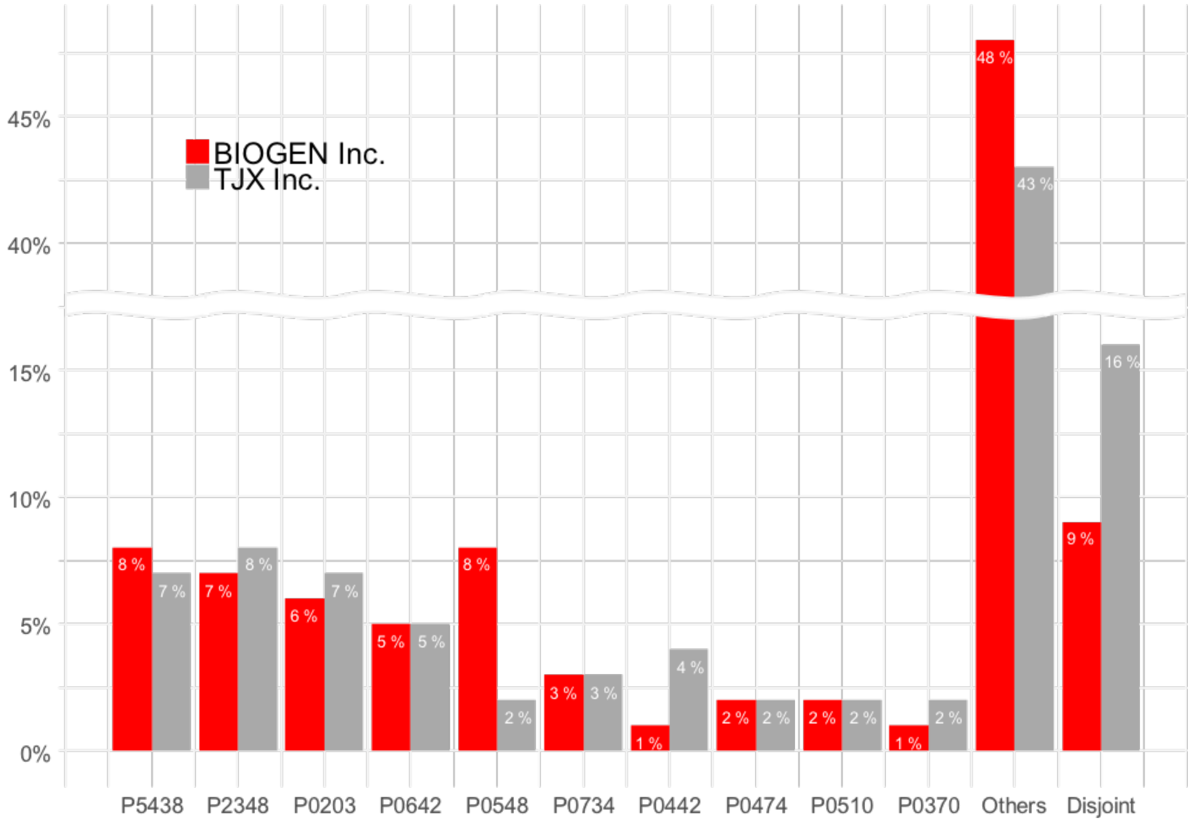

Figure 1: Common Ownership Distribution of Biogen Inc. and TJX Inc.

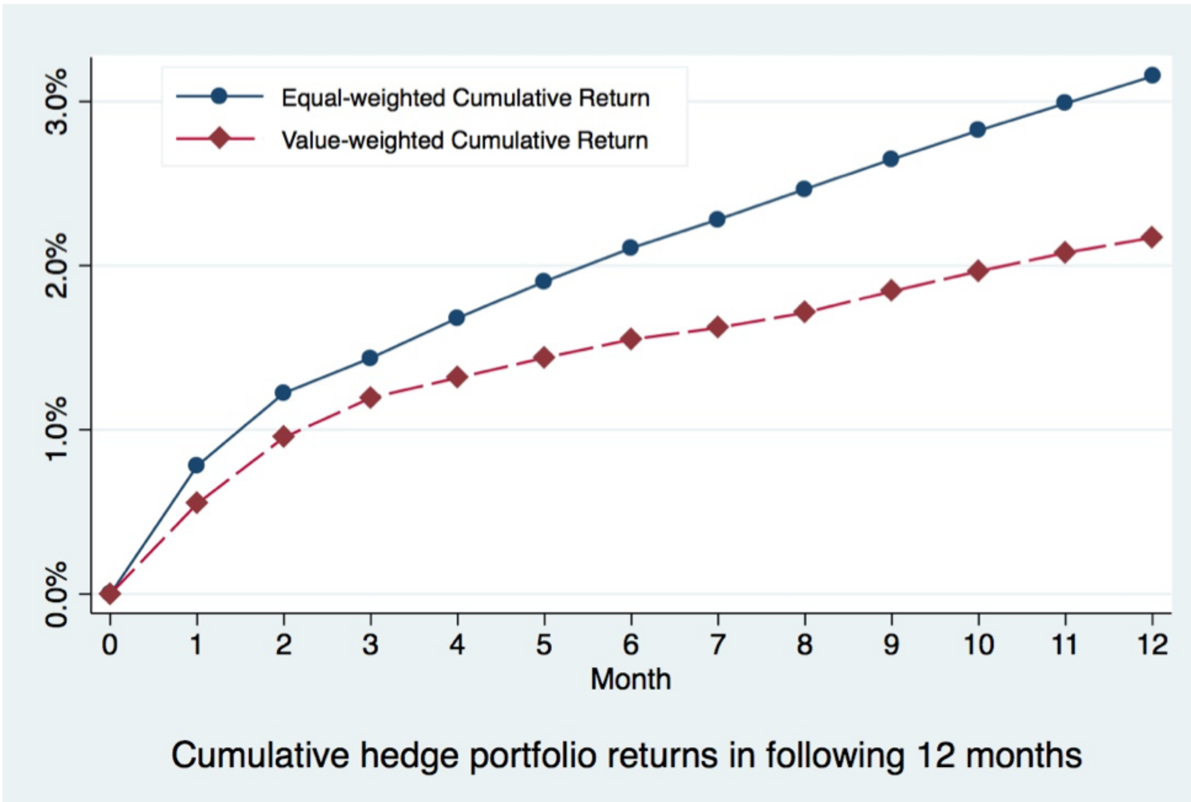

Figure 2: The Cumulative Hedge Portfolio Returns

TABLE I: COMOVEMENT ANALYSIS BOTH FOR THE CHEMISTRY INDUSTRY AND SUB-GROUPS OF APPAREL COMPANIES, JANUARY 2012 TO DECEMBER 2016.

Panel A: Apparel companies list ranked by common ownership closeness (COWN) to Chemical industry

High COWN Group	Medium COWN Group	Low COWN Group
Ross Stores, Inc. (0.472)	Ascena Retail Group, Inc. (0.378)	Zumiez, Inc. (0.306)
TJX Companies, Inc. (0.437)	Hanesbrands Inc. (0.375)	Christopher & Banks Corp. (0.300)
Chico's FAS, Inc. (0.433)	GAP, Inc. (0.367)	Citi Trends, Inc. (0.286)
Foot Locker, Inc. (0.429)	Urban Outfitters, Inc. (0.364)	Destination Maternity Corp. (0.277)
Abercrombie & Fitch Co. (0.420)	J. C. Penney Company, Inc. (0.364)	Lululemon Athletica, Inc. (0.275)
Nordstrom, Inc. (0.419)	Stage Stores, Inc. (0.356)	Buckle, Inc. (0.267)
Express, Inc. (0.417)	Genesco, Inc. (0.353)	ZAGG, Inc. (0.251)
Under Armour, Inc. (0.407)	Children's Place, Inc. (0.342)	New York & Company, Inc. (0.239)
American Eagle, Inc. (0.392)	DSW, Inc. (0.334)	Shoe Carnival, Inc. (0.235)
	Cato Corp. (0.330)	

[a] COWN are reported in parentheses.

Panel B: Pearson (Spearman) correlations above (below) the diagonal

Key variable	1	2	3	4
$\mathsf{INDRET}_{\mathsf{SIC28}}$		**0.427**	**0.383**	**0.284**
$\mathsf{ValueWeighted\ RET}_{\mathsf{High-Group}}$	**0.531**		**0.702**	**0.655**
$\mathsf{ValueWeighted\ RET}_{\mathsf{Medium-Group}}$	**0.430**	**0.681**		**0.635**
$\mathsf{ValueWeighted\ RET}_{\mathsf{Low-Group}}$	**0.352**	**0.639**	**0.615**	

[b] 5% statistical significance indicated in bold.

TABLE II: SUMMARY STATISTICS.

Panel A: Sample statistics

		Mean	Sd	Min	Q1	Med	Q3	Max
Cross-sectional Statistics								
# of firms		4451	941	3038	3613	4627	5031	6230
# of firms w/ all firm characteristic variables		2099	499	696	1748	2178	2448	2877
% market value of CRSP [b]		74.21	11.74	53.23	63.55	71.19	85.2	93.84
Average # of peers per focal firm		804	478	100	473	712	1051	1894
Key variables	[*Description*]							
E[COWN]	[*Average Closeness to Peers*]	0.340	0.061	0.235	0.294	0.329	0.377	0.611
RET	[*Returns of Focal Firm*]	0.012	0.149	-0.941	-0.060	0.006	0.075	9.374
COWNRET	[*Common Ownership Momentum*]	0.013	0.057	-0.341	-0.020	0.016	0.047	0.400
INDRET	[*Industry Momentum*]	0.010	0.061	-0.380	-0.024	0.013	0.046	0.476
SIZE	[*Firm Size*]	6.014	1.827	1.859	4.631	5.839	7.211	12.05
BtoM	[*Book-to-Market*]	0.641	0.548	0.013	0.283	0.499	0.826	5.748
GP	[*Gross Profitability*]	0.372	0.264	-0.545	0.197	0.342	0.516	1.307
AG	[*Asset Growth*]	0.162	0.396	-0.513	-0.002	0.067	0.196	5.402
TURNOVER	[*Turnover*]	0.001	0.001	0.000	0.000	0.001	0.002	0.010
RET_{t-1}	[*Short-term Reversal*]	0.012	0.136	-0.611	-0.060	0.006	0.075	1.406
MOM	[*Medium-term Momentum*]	0.145	0.560	-0.944	-0.175	0.069	0.339	11.596

[a] All variables except for future stock returns are winsorized within each month at the top and bottom 1%.
[b] % market value of CRSP is the market capitalization percentile of the final sample to of the CRSP universe.

Panel B: Pearson (Spearman) correlations above (below) the diagonal

Key variables	1	2	3	4	5	6	7	8	9	10
$COWNRET_{t-1}$		**0.067**	**0.098**	0.007	**-0.031**	**0.033**	0.005	**-0.02**	**-0.034**	**0.013**
$INDRET_{t-1}$	**0.072**		**0.194**	**0.013**	**0.015**	-0.002	**0.015**	-0.005	-0.006	**0.027**
RET_{t-1}	**0.103**	**0.195**		**0.015**	**0.066**	0.000	**0.015**	**-0.022**	-0.012	**-0.027**
MOM	0.005	**0.012**	**0.023**		**0.176**	**-0.174**	**0.056**	**-0.042**	**0.069**	**0.018**
SIZE	**-0.043**	**0.012**	**0.092**	**0.239**		**-0.294**	**-0.014**	**0.042**	**0.147**	**0.064**
BtoM	**0.043**	-0.003	-0.005	**-0.187**	**-0.301**		**-0.197**	**-0.164**	**-0.204**	**0.014**
GP	0.005	**0.017**	**0.019**	**0.057**	**-0.023**	**-0.258**		**-0.059**	**0.035**	**0.013**
AG	**-0.025**	-0.002	**-0.007**	**-0.027**	**0.132**	**-0.232**	**0.049**		**0.208**	**-0.024**
TURNOVER	**-0.044**	-0.005	-0.008	**0.015**	**0.245**	**-0.286**	**0.039**	**0.176**		**-0.022**
RET_t	**0.009**	**0.026**	**-0.029**	**0.037**	**0.095**	0.007	**0.018**	**-0.007**	**-0.016**	

[c] 5% statistical significance indicated in bold.

TABLE III: COMMON OWNERSHIP MOMENTUM STRATEGY, JULY 1982 TO JUNE 2017.

Panel A: Portfolio abnormal returns

Decile	*Excess* *returns* (%)	*CAPM* α (%)	*3Factor* α (%)	*4Factor* α (%)	*5Factor* α (%)	*6Factor* α (%)
1	0.77	-0.31	-0.27	-0.11	-0.18	-0.07
(*Short*)	(2.85)	(-1.98)	(-2.08)	(-0.93)	(-0.98)	(-0.51)
10	1.55	0.58	0.57	0.73	0.65	0.76
(*Long*)	(5.32)	(2.81)	(4.47)	(5.25)	(5.14)	(5.53)
Long - Short	0.78***	0.89***	0.85***	0.84***	0.83***	0.83***
(*Equal-weights*)	(4.85)	(5.16)	(4.55)	(4.40)	(3.86)	(3.86)
Long - Short	0.55**	0.64**	0.66**	0.54**	0.67*	0.59*
(*Value-weights*)	(2.18)	(2.57)	(2.20)	(2.13)	(1.80)	(1.87)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

Panel B: Risk factor loading (Four-factor model)

Decile	*Alpha*	*MKT*	*SMB*	*HML*	*UMD*
1	-0.11	1.07	0.72	-0.07	-0.21
(*Short*)	(-0.93)	(31.95)	(6.94)	(-1.28)	(-4.64)
10	0.73	0.91	0.81	0.06	-0.21
(*Long*)	(5.25)	(24.47)	(15.21)	(0.75)	(-5.14)
Long - Short	0.84***	-0.16***	0.09	0.13	0.01
(*Equal-weights*)	(4.40)	(-3.31)	(0.69)	(1.43)	(0.09)
Long - Short	0.54**	-0.14*	0.15	0.05	0.15
(*Value-weights*)	(2.13)	(-1.94)	(0.67)	(0.44)	(1.64)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE IV: CROSS-SECTIONAL REGRESSIONS, JULY 1982 TO JUNE 2017.

Dependent variable $\times 100$	RET_t (1)	RET_t (2)	RET_t (3)	$RET_t - INDRET_t$ (4)
$COWNRET_{t-1}$	0.399***	0.528***	0.613***	0.541***
	(3.11)	(2.98)	(3.18)	(3.14)
$INDRET_{t-1}$			1.118***	0.686***
			(6.18)	(5.27)
SIZE		5.089***	4.754***	4.585***
		(10.45)	(10.17)	(10.38)
BtoM		2.164***	1.766***	1.710***
		(7.75)	(6.47)	(7.74)
GP		1.078***	1.073***	0.939***
		(6.48)	(6.39)	(6.11)
AG		-0.784***	-0.783***	-0.773***
		(-5.41)	(-4.87)	(-5.16)
TURNOVER		-0.976***	-0.812***	-0.757***
		(-3.59)	(-2.63)	(-3.05)
RET_{t-1}		-2.379***	-2.152***	-2.196***
		(-9.02)	(-8.54)	(-8.84)
MOM		-0.309	-0.203	-0.244
		(-0.91)	(-0.58)	(-0.79)
Intercept	1.022	-1.463*	-1.624***	-2.243***
	(1.45)	(-1.72)	(-2.82)	(-5.70)
IndustryFixed	Yes	Yes	No	No
N	881,728	881,728	881,728	881,728
Months	420	420	420	420
Ave.R^2	0.078	0.118	0.061	0.047

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 12.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE V: CROSS-SECTIONAL REGRESSIONS WITH DIFFERENT LAGS, JULY 1982 TO JUNE 2017.

Dependent variable $\times 100$	RET_t (1)	RET_t (2)	RET_t (3)	RET_t (4)	RET_t (5)
$COWNRET_t$	2.064***				
	(8.31)				
$COWNRET_{t-1}$		0.613***			0.619***
		(3.18)			(3.21)
$COWNRET_{t-2}$			0.252*		0.233*
			(1.78)		(1.72)
$COWNRET_{t-3}$				0.125	
				(0.875)	
$INDRET_{t-1}$	1.121***	1.118***	1.136***	1.135***	1.119***
	(6.21)	(6.18)	(6.16)	(6.14)	(6.18)
SIZE	4.837***	4.754***	4.691***	4.718***	5.198***
	(10.31)	(10.17)	(10.28)	(10.07)	(10.26)
BtoM	1.746***	1.766***	1.791***	1.772***	1.749***
	(6.56)	(6.47)	(6.30)	(6.34)	(6.34)
GP	1.076***	1.073***	1.073***	1.077***	1.068***
	(6.48)	(6.39)	(6.33)	(6.34)	(6.38)
AG	-0.763***	-0.783***	-0.790***	-0.783***	-0.780***
	(-4.87)	(-4.87)	(-4.85)	(-4.81)	(-4.89)
TURNOVER	-0.801***	-0.812***	-0.833***	-0.811**	-0.796***
	(-2.69)	(-2.63)	(-2.66)	(-2.58)	(-2.60)
RET_{t-1}	-2.140***	-2.152***	-2.121***	-2.125***	-2.176***
	(-8.49)	(-8.54)	(-8.49)	(-8.44)	(-8.61)
MOM	-0.218	-0.203	-0.191	-0.192	-0.304
	(-0.62)	(-0.58)	(-0.55)	(-0.55)	(-0.87)
Intercept	-2.474***	-1.624***	-1.422**	-1.371**	-1.923***
	(-4.12)	(-2.82)	(-2.54)	(-2.54)	(-3.17)
IndustryFixed	No	No	No	No	No
N	881,728	881,728	881,728	881,728	881,728
Months	420	420	420	420	420
Ave.R^2	0.063	0.061	0.062	0.061	0.063

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 12.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE VI: CONTROLLING FOR OTHER ECONOMIC LINKS, JULY 1982 TO JUNE 2017.

Dependent variable ×100	RET_t (1)	RET_t (2)	RET_t (3)	RET_t (4)
		add supply-chain	*add conglomerate*	*add tech.link*
$COWNRET_{t-1}$	0.613***	0.617***	0.395**	0.693***
	(3.18)	(3.09)	(2.24)	(2.61)
$INDRET_{t-1}$	1.118***	1.027***	0.444***	0.413**
	(6.18)	(5.53)	(4.15)	(2.43)
$SUPPRET_{t-1}$		0.322***		
		(2.99)		
$CUSTRET_{t-1}$		0.301***		
		(2.59)		
$PCRET_{t-1}$			0.622***	
			(3.85)	
$TECHRET_{t-1}$				0.931***
				(3.58)
SIZE	4.754***	4.598***	3.265***	4.432***
	(10.17)	(9.91)	(8.59)	(8.95)
BtoM	1.766***	1.771***	1.733***	1.896***
	(6.47)	(6.20)	(8.34)	(6.76)
GP	1.073***	1.010***	1.042***	1.230***
	(6.39)	(6.52)	(6.95)	(6.97)
AG	-0.783***	-0.699***	-0.337**	-0.978***
	(-4.87)	(-4.79)	(-2.24)	(-5.14)
TURNOVER	-0.812***	-0.708**	-0.482**	-0.241
	(-2.63)	(-2.35)	(-2.51)	(-0.64)
RET_{t-1}	-2.152***	-2.298***	-2.047***	-2.661***
	(-8.54)	(-8.89)	(-9.35)	(-9.69)
MOM	-0.203	-0.118	0.055	-0.436
	(-0.58)	(-0.33)	-0.17	(-1.18)
Intercept	-1.624***	-1.970***	-1.259**	-1.434**
	(-2.82)	(-3.11)	(-2.44)	(-2.20)
IndustryFixed	No	No	No	No
N	881,728	797,877	208,015	321,720
Months	420	420	420	340
Ave.R^2	0.061	0.071	0.078	0.08

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 12.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE VII: FLOW-BASED EXPLANATION OF RETURN PREDICTABILITY, 1982 Q3 TO 2017 Q2.

Dependent variable ×100	$RET_{i,t}$ (1)	$FIT_{i,q}$ (2)	$RET_{i,t}$ (3)
$COWNRET_{i,t-1}$	0.585***	0.110**	
	(2.39)	(2.32)	
$E_{t-1}[FIT_{i,q}]$			5.058**
			(2.38)
SIZE	5.350***	0.516**	2.307**
	(9.94)	(2.50)	(2.08)
BtoM	2.420***	0.184***	1.252***
	(7.12)	(3.27)	(3.05)
GP	1.093***	0.141***	0.327
	(4.29)	(3.61)	(1.17)
AG	-0.952***	0.026	-0.847***
	(-5.05)	(0.86)	(-4.37)
TURNOVER	-1.135***	0.371***	-2.848***
	(-2.81)	(3.06)	(-2.75)
$RET_{i,t-1}$	-3.340***	0.092***	-3.586***
	(-6.20)	(4.98)	(-6.99)
MOM	-1.039*	0.365***	-2.633***
	(-1.76)	(8.31)	(-2.61)
Intercept	-1.096	-0.469***	1.122
	(-0.98)	(-3.37)	(0.86)
IndustryFixed	Yes	Yes	Yes
N	292,992	292,992	292,992
Quarters	140	140	140
Ave.R^2	0.126	0.158	0.140

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 4.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.
[d] Relevant forecasting date (t) is the end of first month of each quarter (Jan, Apr, Jul, and Oct).

TABLE VIII: LIMITED ATTENTION AND LIMITS TO ARBITRAGE.

Dependent variable $\times 100$	RET_t (1)	RET_t (2)	RET_t (3)	RET_t (4)
	Size	Analyst Coverage	Institutional Ownership	Idiosyncratic Volatility
$COWNRET_{t-1}$	0.860***	1.575***	1.038***	-0.265*
	(4.55)	(7.07)	(5.05)	(-1.82)
$COWNRET_{t-1}$ $Size > Median$	-0.745***			
	(-5.25)			
$COWNRET_{t-1}$ $Analyst > Median$		-2.644***		
		(-12.13)		
$COWNRET_{t-1}$ $Ins.Own > Median$			-1.136***	
			(-8.59)	
$COWNRET_{t-1}$ $IdioVol > Median$				1.423***
				(9.99)
Controls	Yes	Yes	Yes	Yes
IndustryFixed	Yes	Yes	Yes	Yes
N	881,728	881,728	881,728	881,728
Months	420	420	420	420
$Ave.R^2$	0.119	0.121	0.120	0.120

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 12.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE IX: ROBUSTNESS TEST, CROSS-SECTIONAL REGRESSIONS, IN SUB-PERIODS.

Panel A: Historical sub-periods (1982.07-1991.03, 1991.04-1999.12, 2000.01-2008.09 and 2008.10-2017.06)

Dependent variable ×100	RET_t (1)	RET_t (2)	RET_t (3)	RET_t (4)
TimePeriod	1982.07-1991.03	1991.04-1999.12	2000.01-2008.09	2008.10-2017.06
$COWNRET_{t-1}$	-0.022	0.420*	1.559***	0.497***
	(-0.17)	(1.75)	(2.83)	(3.76)
$INDRET_{t-1}$	1.492***	1.763***	0.826**	0.390**
	(5.20)	(6.07)	(2.36)	(2.13)
SIZE	3.600***	5.371***	6.032***	4.014***
	(6.15)	(7.79)	(4.73)	(6.01)
BtoM	1.371***	2.245***	2.530***	0.919***
	(4.61)	(6.34)	(3.04)	(2.63)
GP	1.293***	0.923***	1.456***	0.619**
	(7.97)	(3.84)	(2.94)	(2.49)
AG	-0.483***	-1.403***	-0.752**	-0.492**
	(-2.94)	(-4.46)	(-1.99)	(-2.49)
TURNOVER	-0.156	0.645	-1.778***	-1.958***
	(-0.43)	(1.13)	(-3.31)	(-5.73)
RET_{t-1}	-2.525***	-2.400***	-2.263***	-1.418***
	(-7.37)	(-5.75)	(-3.27)	(-3.40)
MOM	0.536*	0.711**	-0.593	-1.464
	(1.68)	(2.06)	(-1.20)	(-1.42)
Intercept	-1.274	-3.153***	-2.858**	0.789
	(-1.55)	(-6.40)	(-1.99)	(0.89)
IndustryFixed	No	No	No	No
N	146,239	249,732	257,866	227,891
Months	105	105	105	105
Ave.R^2	0.066	0.058	0.071	0.051

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 12.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

Panel B: Three sub-periods (January cycle, February cycle, and March cycle)

Dependent variable ×100	RET_t (1)	RET_t (2)	RET_t (3)	RET_t (4)
TimePeriod	*Full*	*Jan. Cycle*[d]	*Feb. Cycle*[e]	*Mar. Cycle*[f]
$COWNRET_{t-1}$	0.528***	0.585**	0.622**	0.376*
	(2.98)	(2.39)	(2.32)	(1.72)
SIZE	5.089***	5.350***	5.514***	4.404***
	(10.45)	(9.94)	(10.99)	(6.78)
BtoM	2.164***	2.420***	2.296***	1.775***
	(7.75)	(7.12)	(5.85)	(6.49)
GP	1.078***	1.093***	1.203***	0.940***
	(6.48)	(4.29)	(5.19)	(4.92)
AG	-0.784***	-0.952***	-0.705***	-0.695***
	(-5.41)	(-5.05)	(-3.61)	(-4.60)
TURNOVER	-0.976***	-1.135***	-0.390	-1.402***
	(-3.59)	(-2.81)	(-0.80)	(-4.09)
RET_{t-1}	-2.379***	-3.340***	-1.963***	-1.833***
	(-9.02)	(-6.20)	(-6.87)	(-5.82)
MOM	-0.309	-1.039*	-0.931**	1.042***
	(-0.91)	(-1.76)	(-2.51)	(2.64)
Intercept	-1.463*	-1.096	-2.168*	-1.125
	(-1.72)	(-0.98)	(-1.74)	(-1.00)
IndustryFixed	Yes	Yes	Yes	Yes
N	881,728	292,992	295,096	293,640
Months	420	140	140	140
Ave.R^2	0.118	0.126	0.114	0.115

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 4.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.
[d] January cycle indicates the end of first month of each quarter (Jan, Apr, Jul, and Oct) as the relevant forecasting date.
[e] February cycle indicates the end of second month of each quarter (Feb, May, Aug, and Nov) as the relevant forecasting date.
[f] March cycle indicates the end of last month of each quarter (Mar, Jun, Sep, and Dec) as the relevant forecasting date

TABLE X: ROBUSTNESS TEST, MUTUAL FUND & IIA VS. OTHER INSTITUTIONS.

	Mutual Fund & IIA			Other Institutions		
Dependent variable	$RET_{i,t}$	$FIT_{i,q}$	$RET_{i,t}$	$RET_{i,t}$	$FIT_{i,q}$	$RET_{i,t}$
$\times 100$	(1)	(2)	(3)	(4)	(5)	(6)
$COWNRET_{i,t-1}$	0.483**	0.085*		0.258	0.029	
	(2.17)	(1.75)		(1.37)	(0.67)	
$E_{t-1}[FIT_{i,q}]$			5.692**			9.004
			(2.17)			(1.37)
SIZE	4.901***	0.493**	2.096	4.647***	0.520**	-0.036
	(10.1)	(2.42)	(1.58)	(9.65)	(2.44)	(-0.01)
BtoM	2.156***	0.179***	1.140**	2.233***	0.177***	0.641
	(7.48)	(3.23)	(2.36)	(7.66)	(3.15)	(0.56)
GP	1.051***	0.139***	0.262	1.021***	0.144***	-0.279
	(5.46)	(3.61)	(0.77)	(5.26)	(3.76)	(-0.31)
AG	-0.688***	0.027	-0.841***	-0.751***	0.032	-1.037***
	(-3.97)	(0.88)	(-4.19)	(-4.32)	(0.97)	(-3.73)
TURNOVER	-0.967**	0.368***	-3.064**	-1.033***	0.384***	-4.489*
	(-2.41)	(3.05)	(-2.59)	(-2.62)	(3.05)	(-1.66)
$RET_{i,t-1}$	-3.113***	0.094***	-3.649***	-3.083***	0.095***	-3.939***
	(-6.78)	(5.18)	(-6.74)	(-6.75)	(5.11)	(-5.99)
MOM	-0.777	0.367***	-2.866**	-0.714	0.374***	-4.080*
	(-1.41)	(8.45)	(-2.45)	(-1.30)	(8.49)	(-1.66)
Intercept	0.455	-0.434***	1.937	-0.042	-0.216	2.322
	(0.35)	(-2.78)	(1.40)	(-0.04)	(-1.49)	(1.36)
IndustryFixed	Yes	Yes	Yes	Yes	Yes	Yes
N	267,753	267,753	267,753	267,753	267,753	267,753
Quarters	140	140	140	140	140	140
$Ave.R^2$	0.14	0.158	0.14	0.14	0.156	0.14

[a] Parentheses are the newey-west adjusted t-statistics for the time-series average of coefficients using lag 4.
[b] All explanatory variables are assigned to deciles ranging from 0 to 1.
[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.
[d] Relevant forecasting date (t) is the end of first month of each quarter (Jan, Apr, Jul, and Oct).

TABLE XI: ROBUSTNESS TEST, MOMENTUM STRATEGY, BASED ON COWN UNDER DIFFERENT LEVELS OF CONDITIONS.

Panel A: Pearson (Spearman) correlations above (below) the diagonal

Key variables	(1)	(2)	1	2	3	4
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0$	Full	Full		**0.79**	**0.99**	**0.78**
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0.2$	Full	0.2	**0.87**		**0.79**	**0.98**
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0$	1%	Full	**0.99**	**0.87**		**0.79**
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0.2$	1%	0.2	**0.86**	**0.97**	**0.87**	

[a] 5% statistical significance indicated in bold. t-statistics are reported in parentheses.

Panel B: Hedge portfolio returns

Decile	*Excess returns* (%)	*CAPM alpha* (%)	*3-Factor alpha* (%)	*4-Factor alpha* (%)	*5-Factor alpha* (%)	*6-Factor alpha* (%)
Long - Short (*Equal-weights*)						
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0$	0.76***	0.90***	0.83***	0.80***	0.75***	0.74***
	(4.70)	(5.31)	(4.72)	(4.32)	(3.30)	(3.27)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0.2$	0.78***	0.89***	0.84***	0.83***	0.81***	0.80***
	(4.61)	(4.86)	(4.40)	(4.32)	(3.64)	(3.69)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0$	0.69***	0.84***	0.76***	0.73***	0.67***	0.66***
	(4.44)	(5.16)	(4.35)	(3.85)	(2.98)	(2.90)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0.2$	0.78***	0.89***	0.85***	0.84***	0.83***	0.83***
	(4.85)	(5.16)	(4.55)	(4.40)	(3.86)	(3.86)
Long - Short (*Value-weights*)						
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0$	0.42*	0.57**	0.53*	0.35	0.51	0.39
	(1.81)	(2.46)	(1.94)	(1.44)	(1.34)	(1.19)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 0\%, \mathsf{COWN} > 0.2$	0.52**	0.60**	0.61**	0.48*	0.56	0.47
	(2.06)	(2.31)	(2.08)	(1.83)	(1.52)	(1.47)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0$	0.37	0.51**	0.46	0.29	0.42	0.30
	(1.57)	(2.12)	(1.64)	(1.12)	(1.09)	(0.91)
$\mathsf{COWNRET}_{t-1}\mid s_{k,t} > 1\%, \mathsf{COWN} > 0.2$	0.55**	0.64**	0.66**	0.54**	0.67*	0.59*
	(2.18)	(2.57)	(2.20)	(2.13)	(1.80)	(1.87)

[b] t-statistics are reported in parentheses.

[c] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

TABLE XII: ALPHAS OF STRATEGIES WITH DIFFERENT LOOK-BACK AND HOLDING PERIODS.

Panel A: Raw Returns (Equal-weights)

J =	*K* =	1	3	6	12	24	36
Equal-weights				*Excess returns* (%)			
1		0.78***	0.21*	0.20**	0.16***	0.09**	0.06**
		(4.85)	(1.81)	(2.32)	(2.80)	(2.28)	(2.53)
3		0.30*	0.14	0.23*	0.20**	0.10*	0.06
		(1.84)	(1.07)	(1.77)	(2.17)	(1.75)	(1.49)
6		0.44**	0.32*	0.36**	0.26**	0.11	0.06
		(2.50)	(1.74)	(2.46)	(2.12)	(1.43)	(1.05)
12		0.35**	0.23	0.23	0.18	0.06	0.04
		(2.22)	(1.51)	(1.57)	(1.37)	(0.67)	(0.51)
Equal-weights				*4-Factor alpha* (%)			
1		0.84***	0.14	0.11	0.07	0.06**	0.05**
		(4.40)	(0.88)	(1.05)	(1.12)	(2.13)	(2.22)
3		0.19	-0.03	0.09	0.08	0.08	0.05
		(0.95)	(-0.19)	(0.71)	(1.05)	(1.65)	(1.28)
6		0.28	0.15	0.17	0.15*	0.10	0.06
		(1.57)	(0.89)	(1.30)	(1.74)	(1.47)	(0.99)
12		0.15	0.06	0.12	0.13	0.09	0.07
		(1.07)	(0.45)	(1.09)	(1.35)	(0.93)	(0.90)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

Panel B: Industry-Adjusted Returns (Equal-weights)

J =	*K* =	1	3	6	12	24	36
Equal-weights				*Excess returns* (%)			
1		0.67***	0.23	0.23	0.18	0.06	0.07***
		(4.82)	(1.51)	(1.57)	(1.37)	(0.67)	(3.87)
3		0.27*	0.18	0.24**	0.21***	0.12***	0.08**
		(1.96)	(1.64)	(2.25)	(2.75)	(2.73)	(2.55)
6		0.44***	0.33**	0.37***	0.27***	0.15**	0.09**
		(3.04)	(2.20)	(2.88)	(2.73)	(2.41)	(2.05)
12		0.37***	0.25**	0.25**	0.21**	0.11	0.07
		(2.88)	(2.02)	(2.18)	(2.15)	(1.59)	(1.38)
Equal-weights				*4-Factor alpha* (%)			
1		0.73***	0.06	0.12	0.13	0.09	0.07***
		(4.35)	(0.45)	(1.09)	(1.35)	(0.93)	(3.71)
3		0.22	0.08	0.16	0.12*	0.11***	0.08**
		(1.28)	(0.51)	(1.45)	(1.95)	(2.65)	(2.37)
6		0.34**	0.22	0.23**	0.19**	0.14**	0.09**
		(2.29)	(1.56)	(1.98)	(2.53)	(2.36)	(2.02)
12		0.24**	0.14	0.17*	0.18**	0.14*	0.10*
		(2.01)	(1.30)	(1.90)	(2.12)	(1.67)	(1.66)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

Panel C: Raw Returns (Value-weights)

J =	*K* =	1	3	6	12	24	36
Value-weights				*Excess returns* (%)			
1		0.55**	0.24	0.11	0.09	0.03	-0.01
		(2.18)	(1.11)	(0.80)	(1.18)	(0.67)	(-0.44)
3		0.27	0.01	0.10	0.06	-0.01	-0.03
		(1.03)	(0.03)	(0.52)	(0.54)	(-0.18)	(-0.61)
6		0.36	0.31	0.36*	0.11	-0.05	-0.11
		(1.31)	(1.20)	(1.69)	(0.75)	(-0.49)	(-1.05)
12		0.48**	0.34	0.22	0.03	-0.16	-0.19
		(2.08)	(1.56)	(1.20)	(0.18)	(-0.87)	(-0.93)
Value-weights				*4-Factor alpha* (%)			
1		0.54**	0.14	0.02	0.01	-0.01	-0.03
		(2.13)	(0.68)	(0.18)	(0.10)	(-0.23)	(-1.13)
3		0.13	-0.19	-0.06	-0.09	-0.05	-0.06
		(0.55)	(-0.94)	(-0.37)	(-1.13)	(-0.89)	(-1.23)
6		0.19	0.12	0.17	-0.03	-0.09	-0.14
		(0.87)	(0.56)	(0.98)	(-0.25)	(-0.84)	(-1.50)
12		0.30	0.14	0.08	-0.03	-0.14	-0.17
		(1.42)	(0.74)	(0.49)	(-0.19)	(-0.85)	(-1.01)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

Panel D: Industry-Adjusted Returns (Value-weights)

J =	*K* =	1	3	6	12	24	36
Value-weights				*Excess returns* (%)			
1		0.44**	0.34	0.22	0.03	-0.16	0.01
		(2.16)	(1.56)	(1.20)	(0.18)	(-0.87)	(0.35)
3		0.30	0.12	0.15	0.11	0.04	0.01
		(1.44)	(0.65)	(0.93)	(1.12)	(0.82)	(0.16)
6		0.34	0.30	0.34*	0.15	-0.02	-0.07
		(1.60)	(1.40)	(1.90)	(1.14)	(-0.26)	(-0.87)
12		0.53***	0.41**	0.30*	0.14	-0.05	-0.08
		(2.62)	(2.12)	(1.81)	(0.90)	(-0.36)	(-0.59)
Value-weights				*4-Factor alpha* (%)			
1		0.42**	0.14	0.08	-0.03	-0.14	-0.00
		(2.04)	(0.74)	(0.49)	(-0.19)	(-0.85)	(-0.22)
3		0.24	0.03	0.06	0.01	0.00	-0.02
		(1.18)	(0.20)	(0.41)	(0.14)	(0.07)	(-0.46)
6		0.27	0.19	0.21	0.05	-0.05	-0.09
		(1.42)	(1.00)	(1.35)	(0.41)	(-0.58)	(-1.25)
12		0.44**	0.29*	0.19	0.05	-0.06	-0.09
		(2.36)	(1.71)	(1.29)	(0.36)	(-0.43)	(-0.72)

[a] t-statistics are reported in parentheses.
[b] ***, **, or * indicates that the coefficient estimate is different from zero at the 1%, 5%, and 10%, respectively.

CHAPTER 3

COMMON OWNERSHIP LINKAGE AND PEER EFFECTS IN CORPORATE POLICIES

This paper investigates the peer effect of common ownership-linked firms on corporate dividend and investment decisions. We first show that common ownership peer firms are influential in determining U.S. firms' dividend yield and investment capital ratio. Such an effect is distinct from the previously known industry peer effects, more pronounced among more connected firms and firms facing higher uncertainty. Overall, these findings indicate that firms imitate their peers to maintain interest from institutional investors, and/or firms mimic their peers to deal with uncertainty in their decision making.

3.1 Introduction

A growing literature raised a delicate question in corporate finance: Do managers consider other firms' actions when choosing their corporate financial policy? This question challenges the traditional view that firm-specific factors alone determine the optimal corporate policy. Recent empirical evidence suggests that firms consider policies and actions of other firms. For instance, financial decisions made by peers operating in the same industry affect a firm's capital structure (Leary and Roberts, 2014), investment (Foucault and Fresard, 2014; Park et al., 2017), and payout policy (Adhikari and Agrawal, 2018; Grennan, 2019). Managerial decision can be influenced by other executives through educational social interaction (Shue, 2013); and a firm's leverage and equity issuance decisions can be affected by common financial analysts (Gomes et al., 2017).

In this paper, we document a new peer firm effect by identifying an inter-firm connection of common ownership by the same institutional shareholders across industries. We utilize closeness measure of common ownership distance and define peer firms as those connected by the common institutional ownership, but with different 2-digit SIC industry codes[18]. As a result, by design, peer firm effects in this study can be likely intermediated by institutional investors' governance (i.e., voice and exit), rather than industry-specific factors. We investigate whether and how such common ownership-linked peers exert influence on a firm's divided and investment decision making.

When a researcher manages to infer whether the average behavior in some group affects the behavior of members in the group, there are reflection problems that hinder disentangling the impact of peer behaviors from that of peer characteristics (Manski, 1993). Three effects could account for a firm's imitation of its peers: correlated, exogenous, and endogenous effects. First, the correlated effects result from the unobserved common characteristics between the firm and its peers. Second, a focal firm and its peers may be adjusting to change in exogenous factors, referred to as exogenous peer effects or contextual effects. Lastly, the changes to peer firms may influence a firm's behavior, which are endogenous peer effects.

---

[18]In contrast to prior studies focusing on industry peers, my study constructs peer firms with common institutional shareholders with the focal firms, but operating in different industries.

This paper investigates the endogenous effect of peer firms' financial policies. We adopt an instrumental variable (IV) approach (Leary and Roberts, 2014; Adhikari and Agrawal, 2018). We utilize both the idiosyncratic equity shocks and risks of peer firms in identifying the endogenous peer effects. We report results that peer firms have positive causal effects on both a firm's dividend yield and investment capital ratio. Our results are robust to using alternative dividend and investment policy measures, such as dividend payer indicator, dividend payout ratio, and R&D expenses. Our results are consistent with that firm managers take into account the decision of common-ownership-linked peer firms when determining their dividend and investment policy.

Next, we explore potential channels of common ownership peer effects on dividend payment and investment decisions. Lieberman and Asaba (2006) propose rivalry- and information-based motivations for peer firm mimicking. In rivalry-based motivation, firms imitate other firms to maintain competitive parity with rivals. Common ownership peers, by design, do not compete in the product market with the focal firms. However, a focal firm and its common-ownership peers can be subject to the intervention and threat of exit by the same institutional investors. In addition to competitive concerns, firms also need to maintain and cater to the interests from institutional investors. Information-based motivation is applied in uncertain environments where managers may have difficulty to collect information to decide a firm's policy, and so may be more likely to rely on information implicit in the peer firm's policies. Uncertainty is the firm's inability to predict the extent of a particular behavior's consequences due to a lack of information (Milliken, 1987)[19]. For example, managers learn new information from peer firms' stock prices when making financial policy decisions (Foucault and Fresard, 2014). However, stock price informativeness varies systematically across industries (Durnev et al., 2004) and firms of different sizes (Bakke and Whited, 2010). Thus, managers do not always have perfect information on decision-relevant factor, and such environments lead firms to imitate to reduce the decision uncertainty. We utilize the measures of analyst coverage and the probability of informed trading (PIN) as proxies for stock price informativeness. These two motivations are not mutually exclusive.

This research makes several contributions to the literature. First, this paper adds to the literature on peer effects on corporate financial policies (Leary and Roberts, 2014; Park et al., 2017; Adhikari and Agrawal, 2018; Grennan, 2019). To the best of our knowledge, after controlling for the stickiness of dividend policy and the continuity of investment policy, this is the first study that identifies the endogenous peer effects on corporate investment and dividend policies in the U.S. market. Second, this paper explores the role of the common-ownership network as a channel of peer effects in corporate policy. We propose a new closeness-based measure in identifying common-ownership connected firms. Finally, this paper explores how competition pressure and information uncertainty influence firm' mimicking behavior.

The rest of the paper is organized as follows. Section 3.2 presents hypotheses on common ownership peer effects in corporate policy. Section 3.3 discusses the construction of the inter-

---

[19]Milliken (1987) suggested the label "environmental," when attached to the term uncertainty, implies that uncertainty is the organization's external environment.

firm network based on common institutional ownership, with the empirical model and the identification strategy are presented in Section 3.4. Section 3.5 describes the sample selection, variable construction, and the summary statistics. Section 3.6 reports the empirical results as well as the underlying mechanisms of peer effects. Section 3.7 presents a robustness check. Section 3.8 concludes.

3.2 Hypotheses

Previous literature finds some evidence indicative of a peer firm effect on financial policy (Leary and Roberts, 2014; Park et al., 2017; Adhikari and Agrawal, 2018; Grennan, 2019). Adhikari and Agrawal (2018) reported that, when setting dividend and share repurchase policies, U.S. public firms significantly incorporates on the policy changes of their industry peers. Grennan (2019) documents that a one standard deviation increase in peer firm dividend results in a reduced duration between a firm's dividend changes by 1.5 quarters and an increase of dividend payout ratio by 16%. To date, the literature documents the endogenous peer effects in the U.S. firms based on firms operating in the same industry. There is also a peer effect in firm investment decision. Foucault and Fresard (2014) find that firms' investment is related to their peers' stock prices. Similarly, Park et al. (2017) report imitative behavior in investment decisions among U.S. firms[20]. However, so far, earlier studies have not considered dividend smoothing effect, which is prevalent in dividend policy (Lintner, 1956), or continuity of investment policy in their empirical models.

[20]Unlike Park et al. (2017), we use instrumental variables to isolate the variation in industry return.

Previous studies documenting peer effects on corporate financial decisions focus on industry peers. However, inter-firm relationships can be multifaceted, well and beyond being industry competitors. For example, Gomes et al. (2017) find evidence that sell-side analysts may influence the financial policies, such as leverage and equity issuance, of firms that they cover, and peer effects come from firms covered by the same analysts. We identify new peer groups based on the common institutional ownership. Hence, in this setting, a firm and its peers are exposed to competition for and catering to attention from common-owners. In addition, institutional investors, through monitoring and trading, can promote and convey peer firm-related information to the market and other firms in the institutional portfolios. Both the competition and information effects can impose the endogenous peer effect on corporate financial decisions.

3.3 Identification of Common Ownership Linkage

This section describes the identification of common ownership peers. As firms tend to have certain similar characteristics in order to attract shareholders, peer firms can be competing to maintain attention and raise money from a limited set of existing institutional shareholders.

3.3.1 Measuring Common Ownership Closeness

A similar procedure by Jaffe (1986)[21] is used to identify an inter-firm linkage based on common institutional ownership. We first measure the percentage of ownership held by each institutional shareholder for each firm. We construct the vector of institutional ownership structure $S_{i,q} = \left(s_{1,q}, s_{2,q}, ..., s_{\tau,q}, ..., s_{6514,q}\right)$ for each firm i at quarter q, where $s_{\tau,q}$ is a percentage

[21]The framework was pioneered Jaffe (1986) to measure the degree of technological overlap between firms.

of share outstanding owned by an institutional shareholder τ with a rolling average of prior four quarters[22]. The information on quarterly common ownership is from Thomson-Reuters Institutional (13f) Holdings database, previous known as CDA/Spectrum S34[23]. Since this data are known to have reporting error such as unmatched identifier for institution managers, we map the S34 data with the institutional investor classification data provided by Brian Bushee[24], who provide a permanent key to identify institution managers. Also, we exclude 13f institutional investors with fewer than 20 distinct holdings. The final sample consists of 6514 investment managers from July 1982 to June 2017.

We calculate the common ownership proximity measure $\mathsf{COWN}_{ij,q}$ between firm i and j by using the uncentered correlation between these two vectors:

$$\mathsf{COWN}_{ij,q} = \frac{\left(S_{i,q}S'_{j,q}\right)}{\left(S_{i,q}S'_{i,q}\right)^{1/2}\left(S_{j,q}S'_{j,q}\right)^{1/2}} \tag{3.1}$$

The measured value ranges from 0 to 1 and indicates the similarity between firm i and j in their institutional shareholder positions of the common ownership network. The proximity between

[22]To avoid overestimation due to the smaller institutional ownership, we exclude from estimation the , which is less than 1%.

[23]The U.S. Securities and Exchange Commission (SEC) asks for all institutional investment managers who utilize the U.S. mail in their business and exercise investment discretion on over $100 million to report their holdings on Form 13F.

[24]Brian Bushee created a permanent key based on the holdings histories of fund managers with changing investment manager numbers. The data is available on website: http://acct.wharton.upenn.edu/faculty/bushee/IIclass.html

the two firms is higher when there is a larger overlap of institutional investors investing in both firms. That is, the common ownership-linked firms can be in competition for limited funds from the specific institutional investors. Finally, we use the estimated common ownership similarity to construct a common-owner network matrix, $\mathsf{COWN}_{\mathsf{q}} = [\mathsf{COWN}_{\mathsf{ij,q}}]$. We exclude all pairs that belong to the same 2-digit industry. As a result, peer firms are unlikely to share industry characteristics affecting the company's operation, but likely to be subject to investor sentiments affecting the cost of equity capital.

3.3.2 Network Centrality

We examine whether peer effects may differ by a firm's position in the common institutional owner network. The network literature adopts a variety of centrality measures (e.g., degree, closeness, betweenness, and eigenvector centrality) to determine each firm's position in the network. Borgatti (2005) provides guidelines for selecting the appropriate centrality measure[25]. First, the peer effect can simultaneously propagate to connected firms. Second, endogenous peer effects can generate a social multiplier or positive feedback loop (Manski, 1993; Glaeser and Scheinkman, 2003). Thus, the eigenvector centrality can explain the propagation of the peer effects better than other measures such as closeness or betweenness centrality. In addition,

---

[25]Borgatti (2005) notes that shock diffusion occurs via a copy mechanism or move mechanism. Also, in the copy mechanism (replication), it can be assumed whether the duplication is serial or simultaneous. Another attribute is whether the traffic flow follows a geodesic path (the shortest path between two nodes), a path (a sequence in which no link or node is repeated), a trail (a sequence in which no link is repeated) or a walk (an unrestricted sequence of nodes and links). In this study, the peer effects are assumed to have the attributes of the simultaneous replication and the path.

eigenvector centrality measures how connected a firm is to those well-connected firms in the common institutional ownership network.

Eigenvector centrality is defined as the principal eigenvector of the adjacency matrix corresponding to its largest eigenvalue (Bonacich, 1972), as follows:

$$\mathsf{A}\mathsf{c} = \lambda \mathsf{c} \tag{3.2}$$

In this paper, adjacency matrix, A, is defined as the common institutional ownership network, COWN_q. The number λ is an eigenvalue and the corresponding vector c is an eigenvector.

Figure 3 illustrates a sample common institutional ownership network, where nodes represent firms, and edges represent the existence of common institutional owners. While firm B, which has four peers, has a higher degree centrality than firm A (with three peers), firm A has a higher eigenvector centrality than firm B. That is, firm A's peer firms (i.e. firm B, C, and D) have more peers than firm B's peer firms (i.e. firm A, E, F, and G). We hypothesize that firm A, with a higher eigenvector centrality, will be subject to more peer firm effects and compete for funding from a common set of institutional investors.

3.4 Econometric Framework

We develop an econometric model to study the peer firm effects on various corporate financial policies. This section also discusses the identification strategy to estimate the endogenous peer effect.

3.4.1 The Empirical Model

This study first focuses on the common institutional ownership based peer effects on corporate policies, $y_{i,t}$, such as dividend or investment policy. The baseline econometric model to capture the peer effects is in line with the literature on peer effects (Leary and Roberts, 2014; Adhikari and Agrawal, 2018; Grennan, 2019) and is specified as

$$y_{i,t} = \varphi + \rho W_{i*,t} y_t + W_{i*,t} X_{t-1} \gamma + X_{i,t-1} \lambda + \upsilon_i + \nu_t + \varepsilon_{i,t}, \tag{3.3}$$

where the indices i and t correspond to firm and year, respectively. The independent variables of empirical model include the closeness-weighted average outcome of peer group (endogenous effects), the closeness-weighted average characteristics of peer group (contextual effects), and firm-specific characteristics. That is, endogenous effect, ρ, measures the influence of peer firm action and contextual effect, γ', measures the strength of any peer characteristics. y_t is a vector of outcomes for the N firms in the U.S. market. $W_{i*,t}$ is an i^{th} row vector of the N-by-N weight matrix[26] with zeros on the diagonal, and $W_{i*,t} y_t$ denotes peer firms' closeness-weighted average outcome, excluding firm i. The peer firms' corporate policies are measured contemporaneously instead of by a one-year lag, because an insufficient time lag leads to a weaker influence of peer effects. The K-dimensional vectors $W_{i*,t} X_{t-1}$ and $X_{i,t-1}$ represent peer firms' closeness-weighted average and firm-specific characteristics, respectively. υ_i is a firm fixed effect, ν_t is a year fixed effect, and $\varepsilon_{i,t}$ is the firm-year specific error term assumed to be correlated and heteroskedastic.

[26]The weight matrix, W_t, will be discussed in detail in section 3.5.

Thus, regressions are run with heteroscedasticity robust standard errors clustered within firms (Petersen, 2009).

3.4.2 Identification Problem

To identify the endogenous peer effects, we rewrite the equation (3.3) in matrix notation produces as

$$y_t = \varphi\iota_N + \rho W_t y_t + W_t X_{t-1}\gamma + X_{t-1}\lambda + \upsilon + \nu_t\iota_N + \varepsilon_t, \tag{3.4}$$

where $y_t = (y_{1,t}, \ldots, y_{N,t})'$ is a vector of outcome for the N firms, W_t is an N-by-N row-normalized weight matrix with zeros on the diagonal, X_{t-1} is an N-by-K matrix of exogenous variables that appear as both peer firms' closeness-weighted average and firm-specific factors, υ is an N-by-1 vector of firm fixed effects, $\nu_t\iota_N$ is an N-by-1 vector of year fixed effects with ι_N as a vectors of 1s, and ε_t is an N-by-1 vector of residuals. Assuming that $(I - \rho W_t)^{-1}$ is invertible, the reduced form of equation (3.4) is given by

$$y_t = (I - \rho W_t)^{-1}(W_t X_{t-1}\gamma + X_{t-1}\lambda) + (I - \rho W_t)^{-1}(\varphi\iota_N + \upsilon + \nu_t\iota_N + \varepsilon_t), \tag{3.5}$$

As pointed out by Anselin (2003), assuming $\mid \rho \mid < 1$, and the elements of the row-normalized matrix, W_t, are less than one infer that $(I - \rho W_t)^{-1}$ can be written, using a Leontief expansion, as

$$(I - \rho W_t)^{-1} = I + \rho W_t + \rho^2 W_t^2 + \ldots, \tag{3.6}$$

Then, the reduced form can be modified as

$$y_t = (I - \rho W_t)^{-1} W_t X_{t-1}(\gamma + \rho\lambda) + X_{t-1}\lambda + (I - \rho W_t)^{-1}(\varphi\iota_N + \upsilon + \nu_t\iota_N + \varepsilon_t). \tag{3.7}$$

If parameter of $W_t X_{t-1}$ in equation (3.7) is non-zero, then either ρ or γ is non-zero, implying the existence of either endogenous peer effect or contextual effect. That is, there is an identification problem, which is similar to that discussed by Manski (1993) and Leary and Roberts (2014), since ρ (endogenous peer effect) or γ (contextual effect) cannot be separately identified.

3.4.3 Identification Strategy

Several studies propose empirical strategies to address the reflection problem. Instrumental variables (IV) approach is one reliable approach to address this issue. Good instrumental variables need to meet two conditions. First, a valid instrumental variable must be relevant, evaluated by the strength of the correlation between the instrumental variable and the closeness-weighted average outcome of the peer group, $W_{i*,t}y_t$. Second, a valid instrumental variable must be exogenous, with instrumental variable uncorrelated with the error term, $\varepsilon_{i,t}$.

It is empirically challenging to find valid instrumental variables. This paper employs two qualified instrumental variables: peers' idiosyncratic stock return shocks ($\mathsf{Peer\ IdioShock}$) and peers' idiosyncratic risk ($\mathsf{Peer\ IdioRisk}$)[27]. We follow Leary and Roberts (2014) and Adhikari and Agrawal (2018) in constructing the instruments using monthly stock returns from CRSP.

[27] Leary and Roberts (2014) employ the idiosyncratic stock return shocks of peer firms as an instrumental variable, and, Adhikari and Agrawal (2018) use both the idiosyncratic stock return shocks and idiosyncratic risk of peer firms as instrumental variables.

First, idiosyncratic stock return is estimated based on the model with Fama and French (1993) and Carhart (1997) four factors as follows:

$$\begin{aligned} r_{i,t} = \alpha_{i,t} + \beta_{i,t}^{MKT}(MKTRF_t) + \beta_{i,t}^{SMB}(SMB_t) + \beta_{i,t}^{HML}(HML_t) + \beta_{i,t}^{MOM}(MOM_t) \\ + \beta_{i,t}^{SIC2}(SIC2RF_t) + \beta_{i,t}^{COWN}(COWNRF_t) + \eta_{i,t}, \end{aligned} \tag{3.8}$$

where $COWNRF_t$ is the excess return on a common ownership closeness-weighted portfolio of other firms in firm i's common ownership linked peers, $SIC2RF_t$ is the equally weighted portfolio excess return of other firms in firm i's two-digit SIC industry, and $r_{i,t}$ is the return to firm i at month t. The other risk factors are the excess market return ($MKTRF_t$), the size (SMB_t), the value (HML_t), and the momentum (MOM_t). The last term, $\eta_{i,t}$, is intended to remove any common variation in returns across common ownership linked peer firms. Each firm-level regression is run on a rolling 1-year basis using historical monthly returns of prior 60 months, with a minimum of 24 monthly observations. Expected returns are computed using the estimated factor loadings and realized factor returns over the next 12 months[28]. Then, idiosyncratic stock returns are calculated as the residuals from the estimation. Idiosyncratic stock shock ($IdioShock$) is calculated as the geometric mean of the residuals ($\eta_{i,t}$), and idiosyncratic stock risk ($IdioRisk$) is the log volatility of the idiosyncratic returns ($\eta_{i,t}$) during the estimated year..

---

[28]Leary and Roberts (2014) provide an example that the first estimate equation (3.8) using monthly IBM returns from January 1985 through December 1989. Then, based on the estimated equation with monthly IBM returns between January 1990 and December 1990, they can get the idiosyncratic stock returns for 1991. The estimated coefficients in equation (3.8) are constant within a calendar year.

Table XIII reports the summary statistics of factor loadings estimated in equation (3.8). The average number of months per rolling regression is 49. The average adjusted R^2 is roughly 29%. The regressions load negatively on the momentum factor, while positively on market, size, and value factors. The beta of the peer group has the most significant load, which means that the common ownership linked-peer firm has a substantial impact on the stock return. The average idiosyncratic stock return is approximately 40 basis points[29]. After controlling for common factors, instrumental variables derived from the idiosyncratic stock return are supposed to be seldom influenced by the market and other common risks. The instrumental variable is a proxy of the closeness-weighted average of the peer-specific information.

3.5 Variable Construction and Summary Statistics

In this section, we introduce selected firm-specific and peer firm averages variables, describe the primary data sources, and discuss summary statistics.

3.5.1 Firm-specific Factors

Common-owners, both as shareholders and investors, form expectations regarding how firms generate future cash flows and how those cash flows are distributed through corporate investment and corporate payout policies, respectively. To estimate the expectations of common owners, we employ two variables: the investment capital ratio (I_t/K_{t-1}) for investment decision and dividend yield ($DivY_t$) for payout policy.

---

[29]Due to the missing in data cleaning process, the estimated value is non-zero.

Following (Frank and Goyal, 2009), we incorporate a set of other firm-level characteristic variables to control for firm heterogeneity, such as firm size ($Size_t$), market-to-book ratio (MB_t), and sales growth (SG_t). The life-cycle hypothesis posits that larger firms tend to be more mature. Shareholders of the mature firms look for dividends as investment income, rather than investing in growth, compared with the start-up and growth firms. Market-to-book ratio and sales growth are proxies for the level of growth opportunities. Besides, we add a one-year lagged dividend yield and a one-year lagged investment capital ratio to control for the stickiness of dividend policy and the continuity of investment policy, respectively.

3.5.2 Peer Firm Average Variables

The peer firm average variables are constructed as a common-ownership closeness-weighted sum of the corresponding firm-specific factors across all peer firms. Denoted as $W_{i*,t}y_t$, the endogenous effects presented to firm i is

$$W_{i*,t}y_t = \frac{\sum_{i \neq j} COWN_{ij,q-1} \times y_{j,t}}{\sum_{i \neq j} COWN_{ij,q-1}} \tag{3.9}$$

where $q-1$ is the quarter prior to the last quarter of the fiscal year t[30]. Thus, $W_{i*,t}y_t$ captures common-ownership-linked peers' actions on investment and dividends. The weight matrix, W_t,

[30] Peer firms have various end-months of the fiscal year, so the fiscal year's peer firm average variables vary across firms. For example, in 2017, if a firm's end month of the fiscal year is in May, we use $COWN$ for the 1st quarter of 2017 and peer action or characteristics from April 2016 to May 2017 to compute the peer average.

is row-normalized so that each element $\mathsf{COWN}_{ij,q}$ represents the share of influence of firm j on the firm i.

Similarly, the contextual effects, $W_{i*,t}X_t$, represent the common ownership-linked peers' characteristics, including firm size ($\mathsf{Peer\ Size}_t$), market-to-book ratio ($\mathsf{Peer\ MB}_t$), sales growth ($\mathsf{Peer\ SG}_t$), as well as one year lagged peer firms' characteristics. Formally, the closeness-weighted contextual effects of common ownership-linked peers for each focal firm i at year t is defined as

$$W_{i*,t}X_t = \frac{\sum_{i\neq j} \mathsf{COWN}_{ij,q-1} \times X_{j,t}}{\sum_{i\neq j} \mathsf{COWN}_{ij,q-1}} \tag{3.10}$$

When constructing the peer firm average variables, we restrict the measure to be those with at least ten institutional shareholders with more than 1% of shares. In our sample, each institutional shareholder hold at least 20 distinct holdings. As a result, each firm in the sample has more than or equal to 20 peer firms. These restrictions are consistent with the previous empirical studies of institutional investors Coval and Stafford (2007). Besides, we use only $\mathsf{COWN}_{ij,q}$ which is required to be higher than the first quartile for each year, to focus on the peer effect of adjacent pairs

3.5.3 Data Sources and Summary Statistics

We collect data used in this study from the CRSP/Compustat merged database and monthly CRSP database for the period 1988 to 2017, excluding financial firms (SIC codes 6000-6999), government entities (SIC codes above 9000) and utilities (SIC codes 4900-4999). The sample is limited to U.S. firms with CRSP common stock traded on NYSE/AMEX/NASDAQ, and with at least 10 institutional shareholders. From the CRSP/Compustat merged database, we obtain annual information on a variety of accounting variables. In addition, we construct the idiosyncratic stock returns using the equation (3.8) with the monthly returns from CRSP database. Panel A of Table XIV and Panel A of Table XV presents the descriptive statistics. To mitigate the influence of extreme observations, we winsorize all continuous variables at 1% and 99% levels. After data cleaning and merging, the final two samples consist of 2,725 unique firms representing 21,898 firm-year observations in Panel A of Table XIV (related to the dividend policy), and of 2,840 distinct firms representing 23,210 firm-year observations in Panel A of Table XV (related to the investment policy). In the sample for dividend policy (for investment policy), there are, on average, 730 (749) firms per year, and each firm is connected to about 7.6% (9.3%) of the firms in the Compustat through the common institutional ownership.

Panel B in Table XIV and Panel B in Table XV report the results of the correlation analysis. A firm's investment rate (I_t/K_{t-1}) is positively correlated with its peer firms' average investment ($\mathsf{Peer}\ I_t/K_{t-1}$). The firm's dividend yield, DivY_t, is also positively correlated with its peer firms' average dividend yield ($\mathsf{Peer\ DivY}_t$). Both are significant at a 5% level. Thus, the correlation analysis indicates that a firm's financial policies are positively associated with its endogenous peer effects in the common ownership network.

3.6 Empirical Results

In this section, we perform the empirical analysis to test proposed hypotheses.

3.6.1 Peer Effects in Corporate Financial Policies

Table XVI is the result of reduced-form estimation of equation (3.7). The first two columns present results for dividend yield, and the next two columns report results for investment capital ratio. Columns (2) and (4) include one year lagged terms of firm variables and of peer firms. All control variables are one-year-lagged.

The results in Columns (1) and (2) indicate that the dividend yield is negatively associated with the weighted average peer firm risk. Likewise, the results in Columns (3) and (4) show that the investment capital ratio is positively associated with the weighted average peer firm risk. Also, Columns (1) and (3) find that the dividend yield is positively associated with the weighted average peer firm equity shocks, and the investment capital ratio is negatively associated with the weighted average peer firm equity shocks. As discussed in section 3.4.2, although this reduced form would be insufficient for identifying the endogenous peer and contextual effects separately, the reduced-form result points to the existence of either endogenous peer or contextual effects.

The effects of one year lagged peer firms' policies are stronger than those of other peer characteristics. The effects of other peer firm characteristics are not as robust and have a smaller impact on the dividend yield and investment capital ratio. It suggests that peer-firms' financial policy can be the primary channel through which peer firms influence a firm's financial policies.

Table XVII reports IV-2SLS estimates using the average peer firm shock and risk as instrumental variables. The Hansen's J statistic in Column (1) and (4) indicates that the overidentifying restriction is not valid, with all other models passing the standard tests for instrument validity. Columns (1) and (4) show that, without controlling for peer firm average and firm-specific characteristics, the corporate financial policies are strongly related to the endogenous peer effects. After adding the peer firm average and firm-specific characteristics in Columns (2) and (5), the coefficient of endogenous peer effect on dividend yield increases, and the coefficient of endogenous peer effect on investment rate decreases. Thus, it is likely to find endogenous peer effects on a firm's dividend-paying decision instead of the contextual ones. It suggests that the peer effect of a dividend-paying decision depends mainly on the actions of peer firms rather than peer characteristics. On the contrary, the firm's investment decision not only depends on the peers' choices but also on its growth opportunities.

Since Lintner (1956), it has been well documented that dividends are sticky and that firms are reluctant to reduce the level of dividends. To capture such a persistence of the firm's policies, we add the lagged values of the firm-specific and peer firm average outcomes as control variables in Columns (3) and (6). With the lagged outcome variables, the endogenous peer effects are considerably reduced in magnitude, but are still significant. In terms of statistical significance, results in Column (3) imply that, ceteris paribus, a one standard deviation increase in the average peer dividend yield, is associated with an increase of 20.8% ($= 0.728 \times 0.004/0.014$) in firm's dividend yield. Also, results in Column (6) indicate that, ceteris paribus, a one standard deviation increases in the average peer investment capital ratio leads to a 14.2% ($= 0.296 \times 0.063/0.131$) increase in the firm's investment capital ratio.

Overall, the results in Tables XVI and XVII support our hypothesis that there exists peer effects among common institutional ownership linked firms. We find that firm managers' investment decisions are sensitive to the level of investment ratio of peer firms sharing common institutional owners. Likewise, when firms determine the amount of dividend, they pay more attention to the dividend policy decisions of their peer-firms, more than the other dividend-paying determinants.

3.6.2 Heterogeneity in the Peer Effects on Corporate Financial Policies

We now turn to investigate the heterogeneity of the peer effect on corporate financial policies. We first investigate whether firms' heterogeneity in peer connection affects the strength of peer influence. We calculate a firm's eigenvector centrality to measure the firm's competitiveness for limited funds from the common institutional owners. Based on the centrality measures, firms are divided into three groups: high-, moderate-, and low-centrality firms. As discussed in section 3.3.2, the high-centrality firms are those connected to those highly connected firms in the common ownership network.

As a starting point to investigate the heterogeneity of the peer effect, we perform univariate comparisons of firm-specific characteristics in the two groups. Table XVIII lists the tests that estimate the significance and magnitude of difference in the firm-specific characteristic, including ownership characteristics and three financial decision variables, such as payout, investment, and financing policies. The analysis uses one observation per firm, obtained by averaging all available sample observations.

The high-centrality firms have higher institutional ownership but a lower concentration of institutional ownership. As percentage of institutional ownership has been used as a proxy for measuring information asymmetry between managers and shareholders (O'Brien and Bhushan, 1990), the high-centrality firms are likely to have low information asymmetry.

Since the institutions have a relative advantage in monitoring firms and ensuring firms are well managed, firms can pay dividends to attract certain institutional investors (Allen et al., 2000). Grinstein and Michaely (2005) find that, although institutional investors prefer dividend-paying firms, they avoid investing firms that pay very high dividends. Consistent with Allen et al. (2000), the fraction of dividend-paying firms ($\mathsf{D\_Div_t}$) among the high-centrality firms is 8.5% more than that of the low-centrality firms. The difference is statistically significant and close to a 16% average dividend-paying rate. Also, the differences in dividend payout ratio ($\mathsf{DivPay_t}$) and dividend yield ($\mathsf{DivY_t}$) is statistically significant but relatively small. For the other payout policies, such as repurchase and total payout, the high-centrality firms show more aggressive payout policies.

Panousi and Papanikolaou (2012) demonstrate that an increase of institutional ownership helps mitigate managerial underinvestment caused by firm-specific risk. Table XVIII shows that the high-centrality firms with better managerial diversity have a higher investment-to-capital ratio ($\mathsf{I_t/K_{t-1}}$). Also, high levels of their characteristics ($\mathsf{MB_t}$ and $\mathsf{SG_t}$) are indicative of more profitable investment opportunities. On the contrary, the low-centrality firms are young, small, and R&D intensive, and are characterized by both high leverage and high cash holdings.

The univariate tests show the heterogeneities in not only the firm characteristics in each group but also in institutional investor preference investing in those firms. In other words, institutional investors can hold high-centrality stocks expecting relatively higher investment and dividend policies.

The results of IV-2SLS regressions for subsamples sorted by the eigenvector centrality are presented in Table XIX. Columns (1), (2), and (3) display the heterogeneity of endogenous peer effects on dividend yields for subsamples with high-, moderate-, low-centrality. In Column (1), a one standard deviation increase in the average peer dividend yield results in a 34.7% ($= 1.504 \times 0.003/0.013$) increase in the dividend yield of high-centrality firms and a 24.3% ($= 0.679 \times 0.005/0.014$) increase in the dividend yield of moderate-centrality firms. That is, the endogenous peer effect on dividend decision is strongly significant only in the high-centrality firms. Similarly, in Columns (4), (5), and (6), we estimate the regressions of investment-to-capital ratio in the three subsamples. A one standard deviation increase in the average peer investment-to-capital ratio is associated with a 64.4% ($= 1.484 \times 0.059/0.136$) increase in investment rate in the high-centrality firms and an 26.2% ($= 0.497 \times 0.066/0.125$) increase in investment rate in the moderate-centrality firms. Thus, the peer effects on dividend payment and investment decisions are stronger among firms that compete more fiercely for limited funds managed by common institutional owners.

3.6.3 The Role of Financial Constraints

The previous section demonstrates the existence of peer effects in corporate financial decisions through the common institutional ownership network, and the variation of those peer effects by the firm's centrality of the network. As discussed in section 3.3, high-centrality firms raising capital from the common institutional investors can face a more competitive environment. That is, such a firm's demand for raising capital can be the source of the peer effects. Hence, to avoid the loss of interests and attention of these common institutional investors, firms facing financial constraints are more likely to experience pressure and mimic peer firms' policies. We now examine the role of financial constraints in strengthening the peer effects.

Three measures of financial constraints are used: firm asset size, credit rating, and WW index (Whited and Wu, 2006). Small firms have less fixed assets to be used as collateral and are too unknown to obtain external financing (Luo, 2011), so we use firms' asset size as the primary measure to categorize firms into financially constrained and less-constrained groups. All firms are ranked by their asset size each year and those in the bottom half of the distribution are classified as financially constrained. Next, we use credit rating. A firm with a S&P long-term rating is assigned as less constrained firm. Unrated firms are classified as constrained firms. Last, based on the WW index, constrained firms (less-constrained) are those with above (below) median WW index.

In Panel A of Table XX, Columns (1) through (6) show that less-constrained firms are more likely to mimic investment decisions than constrained firms. Contrastively, Panel B in Table XX show that constrained firms are more likely to mimic investment decisions than less-constrained firms. In all columns, instrumental variables are valid. The results thus support the role of financial constraints in catalyzing the peer effect on only corporate investment decisions, but not on dividend payment.

3.6.4 Information Environment

Following the analysis of Adhikari and Agrawal (2018), we employ two proxy variables to measures information uncertainty. The first variable is the peer closeness-weighted average analyst coverage, measured by the average monthly number of analysts providing current fiscal year earnings estimates. The lower value of the peer average analyst coverage, the less information on the peer firms is revealed to the market. The second variable is the peer closeness-weighted average of the probability of informed trading (PIN)[31], which is developed by Easley et al. (1996). The more information uncertainty is associated with higher levels of informed trading.

Table XXI presents evidence on the effects of information uncertainty on both financial policies. Peer effect on corporate financial decisions are more pronounced for firms with more uncertain information environment. Thus, lack of informativeness in peers' stock prices leads firms to imitate in order to reduce uncertainty in financial decisions.

3.7 Robustness

Firms can potentially be subject to different types of peer effects. As a first robustness check, we construct an alternative peer groups. The first set, $\{\mathsf{SIC2}\}$, is the peer group defined by two-digit SIC industry groups, which is used in Leary and Roberts (2014). Columns (1) and (2) in Table XXII show that firms have relatively less or no industry peers influence on firms' dividend and investment. The next set, $\{\mathsf{COWN}\} \cap \{\mathsf{SIC2}\}$, is defined by intersecting the same SIC industry and common-ownership affiliation. In the case of dividend policy, Column (3) reports a more significant peer influence, indicating presence of both industry and common-ownership peer effects on dividend policy. The third set as is the baseline, $\{\mathsf{COWN}\} - \{\mathsf{SIC2}\}$, excluding the same industry firms from common-ownership peers. The last set, $\{\mathsf{COWN}\}$, consists of all common-ownership linked peers. The results in Columns (5) through (8) reveal

---

[31] The data is available on the website: http://scholar.rhsmith.umd.edu/sbrown/pin-data

that, regardless of controlling for industry peer influence, there are endogenous peer effects on corporate policies in the common-ownership network.

We provide additional robustness check using three alternative proxies for corporate financial policies. We use two variables to measure the dividend policy of a firm: dividend payer ($\mathsf{D\_Div_t}$) and the dividend payout ratio ($\mathsf{DivPay_t}$). Dividend payer ($\mathsf{D\_Div_t}$) is an indicator that equals one if, given fiscal year, a manager distributes cash dividend to their shareholders and zero otherwise. Hence, peer dividend payer ($\mathsf{Peer\ D\_Div_t}$) is the percentage of dividend-paying peer firms. Column (1) in Table XXIII reports the IV-Probit regression result to estimate a peer influence on the dividend payment decision. Holding other variables constant at their means, the estimated marginal effect of peer influence on the likelihood of a firm paying dividends is 0.94. It means that a firm with all dividend-paying peers is approximately 100% dividend payers, whereas a firm with no dividend-paying peers is rare to pay any dividend. Next, Column (2) presents IV-2SLS regression results using the dividend payout ratio. A one standard deviation increase in peer average dividend payout ratio leads to an increase in a firm-level dividend payout ratio by 16.9% ($= 0.406 \times 0.044/0.106$) higher. Finally, we estimate the IV-2SLS regression using R&D to Assets ($\mathsf{R\&D_t/AT_{t-1}}$) as an alternative measure of firm investment. Column (3) shows that a one standard deviation increase in peer firms' R&D investments is associated with a 3.9% ($= 0.199 \times 0.013/0.067$) increase in firm's R&D investments. Therefore, all the robustness tests are consistent with the main results.

3.8 Conclusion

This paper examines whether there exist significant common ownership peer effects on a firm's financial policies. We demonstrate that peer firms are influential in determining firms' dividend yield and investment capital ratio in the US market. The given effect is above and beyond the industry peer effects documented in the literature. We also show that the peer effect on both financial policies is more pronounced among firms with higher eigen-centrality in the common ownership network, and that the peer effect on investment policy is stronger for firms facing greater financial constraints. Both cross-sectional tests support that firms tend to imitate their competitors to cater to their common institutional investors. Furthermore, the peer effect on corporate policy decisions is more pronounced for firms with high information uncertainty, consistent with that firms mimic peer firms to maintain reputation and to deal with uncertainty in their decision.

This paper contributes to the growing literature on corporate peer effects in three ways. First, this paper proposes a new peer firm identification based on common institutional ownership. Second, this paper finds endogenous peer effects on corporate investment and dividend policies in the U.S. market. This study also fills a gap in prior literature that such peer effects are robust and significant after controlling for the stickiness of dividend policy and the continuity of investment policy. Lastly, this study provides evidence that catering to the institutional investors is important in driving the peer effects on corporate investment and dividend policies.

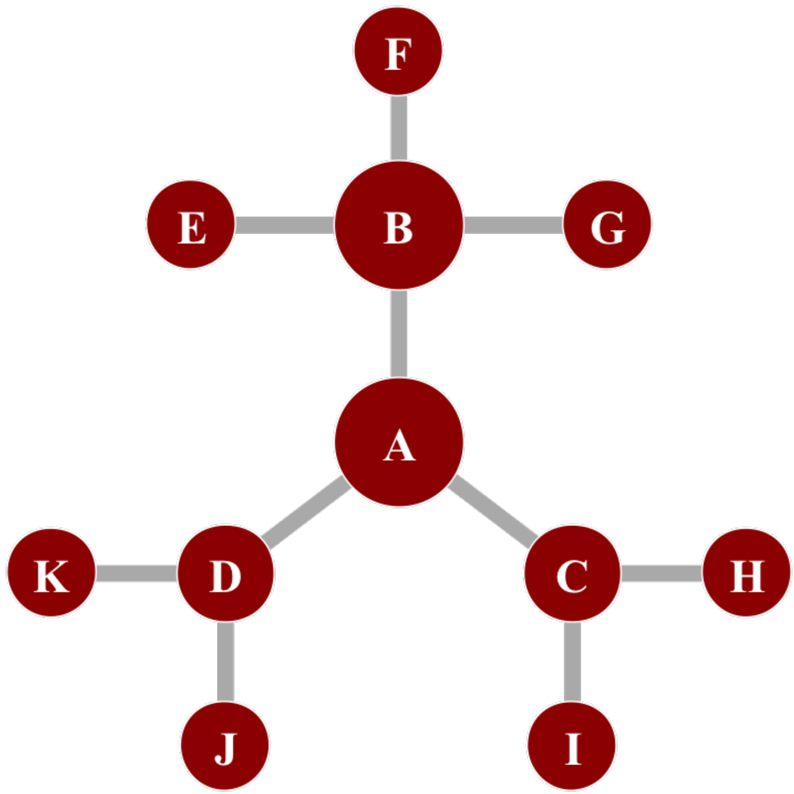

Figure 3: Hypothetical Common-Owners Network

TABLE XIII: STOCK RETURN FACTOR REGRESSION RESULTS.

	Mean	Median	S.D.
$\hat{\alpha}_{i,t}$	0.004	0.004	0.022
$\hat{\beta}_{i,t}^{MKT}$	0.189	0.246	2.146
$\hat{\beta}_{i,t}^{SMB}$	0.088	0.034	1.807
$\hat{\beta}_{i,t}^{HML}$	-0.012	0.024	1.188
$\hat{\beta}_{i,t}^{MOM}$	0.004	0.023	0.784
$\hat{\beta}_{i,t}^{SIC2}$	0.427	0.350	0.909
$\hat{\beta}_{i,t}^{COWN}$	0.423	0.366	1.706
Observation per Regression	49	54	13
R^2	0.390	0.379	0.161
Adjusted R^2	0.290	0.280	0.190
Monthly Return	0.012	0.009	0.127
Expected Monthly Return	0.016	0.016	0.091
Idiosyncratic Monthly Return	-0.004	-0.005	0.123

TABLE XIV: SUMMARY STATISTICS BASED ON DIVIDEND POLICIES.

Panel A: Sample statistics

Key variables	Mean	S.D.	Q1	Median	Q3
Peer Firm Averages[a]					
Peer $DivY_t$	0.010	0.004	0.007	0.009	0.012
Peer D_Div_t	0.507	0.127	0.417	0.497	0.592
Peer $DivPay_t$	0.071	0.044	0.049	0.065	0.091
Peer $Size_{t-1}$	2.567	0.753	2.025	2.651	3.083
Peer MB_{t-1}	1.777	0.452	1.461	1.746	2.024
Peer SG_{t-1}	0.198	0.208	0.103	0.164	0.237
Peer $IdioShock_{t-1}$	-0.010	0.008	-0.013	-0.008	-0.005
Peer $IdioRisk_{t-1}$	0.106	0.029	0.087	0.097	0.118
Firm-Specific Factors					
$DivY_t$	0.010	0.014	0.000	0.003	0.017
D_Div_t	0.528	0.499	0.000	1.000	1.000
$DivPay_t$	0.072	0.106	0.000	0.017	0.119
$Size_{t-1}$	2.569	1.466	1.507	2.446	3.509
MB_{t-1}	1.640	1.218	0.891	1.267	1.943
SG_{t-1}	0.104	0.217	0.001	0.078	0.176
$IdioShock_{t-1}$	-0.009	0.039	-0.028	-0.006	0.012
$IdioRisk_{t-1}$	0.107	0.057	0.067	0.093	0.131
Cross-sectional Stat.					
COMPUSTAT Firms	4,885	992	3,931	4,752	5,657
Sample Firms	730	268	566	741	984
Ave.Peers per Year	369	107	330	393	425
Sample Characteristics					
Firms	2,725				
Observations	21,898				

[a] The peer firm averages are constructed as the common ownership closeness weighted average across all its peer firms in the other two-digit SIC industries.
[b] All continues variables are winsorized at the 1% and 99% levels.

Panel B: Pearson correlation matrix

		Firm Specific Factors					*Peer Firm Averages*				
Key variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$DivY_t$	(1)										
$DivY_{t-1}$	(2)	**0.87**									
$Size_{t-1}$	(3)	**0.18**	**0.14**								
MB_{t-1}	(4)	**-0.14**	**-0.17**	**0.29**							
SG_{t-1}	(5)	**-0.20**	**-0.24**	**0.08**	**0.25**						
Peer $DivY_t$	(6)	**0.32**	**0.32**	**0.20**	**-0.12**	**-0.15**					
Peer $DivY_{t-1}$	(7)	**0.33**	**0.35**	**0.18**	**-0.15**	**-0.19**	**0.63**				
Peer $Size_{t-1}$	(8)	**0.15**	**0.14**	**0.68**	**0.18**	0.01	**0.30**	**0.35**			
Peer MB_{t-1}	(9)	**-0.12**	**-0.14**	**0.37**	**0.39**	**0.20**	**-0.21**	**-0.33**	**0.48**		
Peer SG_{t-1}	(10)	**-0.19**	**-0.20**	**0.12**	**0.21**	**0.18**	**-0.33**	**-0.46**	**0.11**	**0.55**	

[c] 5% statistical significance indicated in bold.

TABLE XV: SUMMARY STATISTICS BASED ON INVESTMENT POLICIES.

Panel A: Sample statistics

Key variables	Mean	S.D.	Q1	Median	Q3
Peer Firm Averages[a]					
Peer I_t/K_{t-1}	0.187	0.063	0.143	0.173	0.214
Peer $R\&D_t/AT_{t-1}$	0.042	0.013	0.034	0.042	0.049
Peer $Size_{t-1}$	2.586	0.770	2.033	2.672	3.111
Peer MB_{t-1}	1.774	0.446	1.465	1.750	2.019
Peer SG_{t-1}	0.192	0.207	0.096	0.159	0.233
Peer $IdioShock_{t-1}$	-0.009	0.008	-0.013	-0.007	-0.005
Peer $IdioRisk_{t-1}$	0.105	0.029	0.086	0.096	0.115
Firm-Specific Factors					
I_t/K_{t-1}	0.153	0.131	0.072	0.116	0.187
$R\&D_t/AT_{t-1}$	0.038	0.067	0.000	0.006	0.049
$Size_{t-1}$	2.561	1.510	1.479	2.446	3.530
MB_{t-1}	1.639	1.227	0.885	1.267	1.943
SG_{t-1}	0.103	0.216	0.000	0.076	0.173
$IdioShock_{t-1}$	-0.010	0.039	-0.028	-0.007	0.012
$IdioRisk_{t-1}$	0.107	0.057	0.067	0.093	0.131
Cross-sectional Stat.					
COMPUSTAT Firms	3,637	651	3,032	3,799	4,051
Sample Firms	749	49	596	775	1,007
Ave.Peers per Year	337	109	265	358	404
Sample Characteristics					
Firms	2,840				
Observations	23,210				

[a] The peer firm averages are constructed as the common ownership closeness weighted average across all its peer firms in the other two-digit SIC industries.
[b] All continues variables are winsorized at the 1% and 99% levels.

Panel B: Pearson correlation matrix

		Firm Specific Factors					*Peer Firm Averages*				
Key variables		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I_t/K_{t-1}	(1)										
I_{t-1}/K_{t-2}	(2)	**0.67**									
$Size_{t-1}$	(3)	**0.10**	**0.06**								
MB_{t-1}	(4)	**0.38**	**0.31**	**0.30**							
SG_{t-1}	(5)	**0.40**	**0.40**	**0.09**	**0.25**						
Peer I_t/K_{t-1}	(6)	**0.28**	**0.29**	**0.17**	**0.30**	**0.22**					
Peer I_{t-1}/K_{t-2}	(7)	**0.27**	**0.31**	**0.12**	**0.27**	**0.19**	**0.66**				
Peer $Size_{t-1}$	(8)	**0.05**	**0.05**	**0.68**	**0.19**	**0.02**	**0.16**	**0.14**			
Peer MB_{t-1}	(9)	**0.27**	**0.28**	**0.39**	**0.39**	**0.20**	**0.75**	**0.57**	**0.49**		
Peer SG_{t-1}	(10)	**0.22**	**0.24**	**0.12**	**0.21**	**0.17**	**0.66**	**0.49**	**0.11**	**0.54**	

[c] 5% statistical significance indicated in bold.

TABLE XVI: PEER EFFECTS IN CORPORATE FINANCIAL POLICIES: REDUCED-FORM ESTIMATES.

Dependent variable	$DivY_t$ (1)	$DivY_t$ (2)	I_t/K_{t-1} (3)	I_t/K_{t-1} (4)
Peer Firm Averages[c]				
Peer $IdioShock_{t-1}$	0.090***	-0.011	-0.723***	0.039
	(3.93)	(-0.70)	(-3.25)	(0.21)
Peer $IdioRisk_{t-1}$	-0.124***	-0.023***	0.501***	0.269***
	(-6.66)	(-2.82)	(3.52)	(2.68)
Peer $DivY_{t-1}$		0.098***		
		(3.42)		
Peer I_{t-1}/K_{t-2}				0.082***
				(3.53)
Peer $Size_{t-1}$	0.000	-0.001***	-0.006*	-0.003
	(0.10)	(-3.37)	(-1.87)	(-1.34)
Peer MB_{t-1}	-0.004***	-0.000	0.039***	0.005*
	(-7.07)	(-0.74)	(9.07)	(1.66)
Peer SG_{t-1}	-0.002***	-0.000	0.018***	0.004
	(-2.92)	(-0.69)	(3.78)	(1.19)
Firm Specific Factors				
$IdioShock_{t-1}$	-0.002	0.004***	-0.042*	0.204***
	(-1.18)	(2.65)	(-1.78)	(10.32)
$IdioRisk_{t-1}$	-0.057***	-0.013***	0.286***	0.095***
	(-17.99)	(-8.61)	(11.21)	(5.40)
$DivY_{t-1}$		0.778***		
		(67.76)		
I_{t-1}/K_{t-2}				0.508***
				(53.07)
$Size_{t-1}$	0.001***	0.001***	0.003**	0.002***
	(5.79)	(9.28)	(2.51)	(3.09)
MB_{t-1}	-0.001***	-0.000***	0.028***	0.017***
	(-5.28)	(-3.65)	(16.83)	(16.40)
SG_{t-1}	-0.008***	-0.000	0.171***	0.069***
	(-14.54)	(-1.47)	(24.47)	(14.48)
YearFixed	Yes	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes	Yes
N	21,898	21,898	23,210	23,210
$Ave.R^2$	0.20	0.68	0.28	0.52

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] The peer firm averages are constructed as the common ownership closeness weighted average across all its peer firms in the other two-digit SIC industries.

TABLE XVII: PEER EFFECTS IN CORPORATE FINANCIAL POLICIES: IV-2SLS ESTIMATES.

Dependent variable	$DivY_t$ (1)	$DivY_t$ (2)	$DivY_t$ (3)	I_t/K_{t-1} (4)	I_t/K_{t-1} (5)	I_t/K_{t-1} (6)
Instrumented Dependent						
Peer $\widehat{DivY_t}$	1.663***	1.856***	0.728**			
	(9.31)	(8.81)	(2.56)			
Peer $\widehat{I_t/K_{t-1}}$				0.930***	0.590***	0.296**
				(14.97)	(4.91)	(2.54)
Peer Firm Averages						
Peer $DivY_{t-1}$			-0.222			
			(-1.63)			
Peer I_{t-1}/K_{t-2}						0.015
						(0.36)
Peer $Size_{t-1}$		-0.002***	-0.001***		-0.001	-0.001
		(-3.31)	(-3.52)		(-0.23)	(-0.34)
Peer MB_{t-1}		0.001	0.000		-0.013	-0.018*
		(1.14)	(1.36)		(-1.00)	(-1.79)
Peer SG_{t-1}		-0.000	0.000		0.006	-0.000
		(-0.58)	(0.03)		(1.16)	(-0.08)
Firm Specific Factors						
$DivY_{t-1}$			0.768***			
			(62.64)			
I_{t-1}/K_{t-2}						0.507***
						(52.89)
$Size_{t-1}$		0.001***	0.001***		0.002*	0.002**
		(5.26)	(6.98)		(1.81)	(2.53)
MB_{t-1}		-0.001***	-0.000**		0.028***	0.017***
		(-4.42)	(-2.54)		(16.79)	(16.45)
SG_{t-1}		-0.007***	-0.000		0.166***	0.067***
		(-13.29)	(-1.30)		(24.20)	(14.25)
$IdioShock_{t-1}$	0.000	-0.000	0.005***	0.078**	-0.033	0.202***
	(0.10)	(-0.17)	(3.24)	(3.09)	(-1.39)	(10.22)
$IdioRisk_{t-1}$	-0.062***	-0.051***	-0.012***	0.314***	0.270***	0.093***
	(-14.29)	(-16.44)	(-7.56)	(11.19)	(10.40)	(5.31)
1^{st} stage Instrumental Variables						
Peer $IdioShock_{t-1}$	0.086***	0.035***	0.009*	-3.544***	-0.623***	-0.269***
	(17.51)	(6.34)	(1.88)	(-34.66)	(-9.36)	(-4.36)
Peer $IdioRisk_{t-1}$	-0.104***	-0.070***	-0.026***	0.622***	1.019***	0.835***
	(-32.71)	(-18.74)	(-9.13)	(12.29)	(23.79)	(22.19)
YearFixed	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes	Yes	Yes	Yes
IndustryFixed	No	No	No	No	No	No
N	21,898	21,898	21,898	23,210	23,210	23,210
Adjusted R^2(2^{nd}Stage)	0.19	0.20	0.68	0.13	0.28	0.51
K − P rk LM Stat.	387.94***	332.17***	96.54***	23.37***	383.01***	345.67***
K − P rk Wald F Stat.	812.04***	243.86***	52.09***	348.24***	373.27***	275.46***
Hansen J Stat.	8.58***	1.16	1.38	7.87***	2.71	0.42

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.

TABLE XVIII: EIGENVECTOR CENTRALITY AND FIRM-SPECIFIC FACTORS: UNIVARIATE EVIDENCE.

		Eigenvector Centrality			
	ALL	High	Low	H–L	(H–L)/ALL
Eigenvector Centrality	0.026	0.033	0.019	0.015***	56%
Ave. Peer in Sample Period	432	585	278	307***	71%
Payout Policy					
D_Div_t	0.528	0.571	0.486	0.085***	16%
$DivY_t$	0.010	0.011	0.010	0.001***	9%
$DivPay_t$	0.072	0.075	0.069	0.006***	9%
D_Rep_t	0.586	0.615	0.557	0.058***	10%
$RepY_t$	0.020	0.022	0.018	0.004***	19%
$RepPay_t$	0.198	0.211	0.184	0.027***	14%
$TotalY_t$	0.031	0.033	0.029	0.004***	14%
$TotalPay_t$	0.285	0.297	0.272	0.025***	9%
Investment Policy					
I_t/K_{t-1}	0.153	0.161	0.146	0.015***	9%
$R\&D_t/AT_{t-1}$	0.038	0.038	0.040	-0.002***	-5%
Financing Policy					
$BookLev_t$	0.227	0.227	0.227	0.000	0%
$MarketLev_t$	0.208	0.203	0.213	-0.010***	-5%
Ownership Characteristics					
IO HHI	0.052	0.046	0.059	-0.012***	-23%
IO	0.773	0.785	0.761	0.025***	3%
Other Characteristics					
Age_t	25.576	27.663	23.487	4.176***	16%
$Size_t$	2.601	3.045	2.156	0.889***	34%
MB_t	1.619	1.658	1.581	0.077***	5%
SG_t	0.093	0.098	0.089	0.009***	9%

[a] The null hypothesis is that the difference is zero. Significance at 10%, 5%, and 1% is denoted with *, **, and ***, respectively.

TABLE XIX: HETEROGENEITY IN THE PEER EFFECTS ON CORPORATE FINANCIAL POLICIES.

Dependent variable	$DivY_t$			I_t/K_{t-1}		
Eigenvector Centrality	High	Moderate	Low	High	Moderate	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Dependent						
Peer $\widehat{DivY_t}$	1.504***	0.679*	0.273			
	(3.15)	(1.70)	(0.51)			
Peer $\widehat{I_t/K_{t-1}}$				1.484**	0.497**	0.241
				(2.54)	(2.02)	(1.40)
1st stage Instrumental Variables						
Peer $IdioShock_{t-1}$	0.042***	0.035***	0.007	-0.299**	-0.491***	-0.269***
	(2.88)	(3.46)	(1.17)	(-2.18)	(-3.94)	(-3.27)
Peer $IdioRisk_{t-1}$	-0.063***	-0.038***	-0.016***	0.642***	0.807***	0.666***
	(-7.70)	(-6.55)	(-4.59)	(10.23)	(14.19)	(14.05)
PeerFirmAverages	Yes	Yes	Yes	Yes	Yes	Yes
FirmSpecificFactors	Yes	Yes	Yes	Yes	Yes	Yes
YearFixed	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes	Yes	Yes	Yes
N	7,432	7,434	7,032	7,883	7,891	7,436
Adjusted $R^2(2^{nd}Stage)$	0.68	0.68	0.66	0.53	0.53	0.47
$K-P$ rk LM Stat.	72.76***	59.23***	28.05***	118.83***	212.93***	172.94***
$K-P$ rk Wald F Stat.	40.36***	31.51***	14.51**	62.80***	135.50***	112.14***
Hansen J Stat.	0.31	1.47	1.15	0.52	0.14	0.03

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.

TABLE XX: ROLE OF FINANCIAL CONSTRAINTS.

Panel A: Dividend policies

Dependent variable	$\mathsf{DivY_t}$					
Financial Constraints	Firm Size (Asset)[d]		Credit Rating[e]		WW Index[f]	
	Small	Large	Unrated	Rated	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Dependent						
Peer $\widehat{\mathsf{DivY_t}}$	0.562	0.851**	0.794**	0.905**	0.686	0.837**
	(1.38)	(2.28)	(2.11)	(2.18)	(1.53)	(2.33)
1st stage Instrumental Variables						
Peer $\mathsf{IdioShock_{t-1}}$	-0.000	0.029***	0.001	0.026***	0.005	0.016**
	(-0.01)	(3.16)	(0.07)	(3.05)	(0.84)	(1.96)
Peer $\mathsf{IdioRisk_{t-1}}$	-0.024***	-0.029***	-0.027***	-0.025***	-0.021***	-0.033***
	(-6.81)	(-6.15)	(-7.50)	(-5.12)	(-5.88)	(-7.57)
PeerFirmAverages	Yes	Yes	Yes	Yes	Yes	Yes
FirmSpecificFactors	Yes	Yes	Yes	Yes	Yes	Yes
YearFixed	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes	Yes	Yes	Yes
N	10,954	10,944	11,964	9,934	10,915	10,927
Adjusted R^2(2^{nd}Stage)	0.66	0.68	0.66	0.67	0.67	0.63
K − P rk LM Stat.	47.52***	57.52***	57.64***	44.01***	38.74***	67.24***
K − P rk Wald F Stat.	25.39***	30.94***	30.03***	25.35***	20.74***	34.62***
Hansen J Stat.	0.00	2.34	1.17	0.20	0.14	0.89

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.
[d] Based on the firm asset size, constrained firms are defined as small firms.
[e] Based on the bond rating, constrained firms are defined as unrated firms.
[f] Based on the WW index, constrained firms are those in the top at the median.

Panel B: Investment policies

Dependent variable	I_t/K_{t-1}					
Financial Constraints	Firm Size (Asset)[d]		Credit Rating[e]		WW Index[f]	
	Small	Large	Unrated	Rated	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
Instrumented Dependent						
Peer $\widehat{I_t/K_{t-1}}$	0.369**	0.185	0.539***	-0.089	0.445***	0.084
	(2.47)	(1.02)	(3.41)	(-0.49)	(2.68)	(1.07)
1st stage Instrumental Variables						
Peer $\mathrm{IdioShock}_{t-1}$	-0.198**	-0.285***	-0.193**	-0.423***	-0.323***	-0.338***
	(-2.43)	(-2.74)	(-2.38)	(-3.32)	(-3.27)	(-2.94)
Peer $\mathrm{IdioRisk}_{t-1}$	0.856***	0.850***	0.862***	0.786***	0.985***	0.948***
	(17.54)	(14.57)	(17.88)	(13.16)	(16.73)	(16.45)
PeerFirmAverages	Yes	Yes	Yes	Yes	Yes	Yes
FirmSpecificFactors	Yes	Yes	Yes	Yes	Yes	Yes
YearFixed	Yes	Yes	Yes	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes	Yes	Yes	Yes
N	11,613	11,597	13,147	10,063	11,568	11,588
Adjusted $R^2(2^{nd}\mathrm{Stage})$	0.47	0.58	0.49	0.57	0.52	0.61
$K-P$ rk LM Stat.	222.20***	157.29***	227.16***	144.67***	176.91***	139.61***
$K-P$ rk Wald F Stat.	165.63***	124.80***	171.05***	113.20***	121.66***	125.95***
Hansen J Stat.	0.10	0.26	0.01	2.83*	1.76	0.09

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.
[d] Based on the firm asset size, constrained firms are defined as small firms.
[e] Based on the bond rating, constrained firms are defined as unrated firms.
[f] Based on the WW index, constrained firms are those in the top at the median.

TABLE XXI: INFORMATION ENVIRONMENT.

Dependent variable	$DivY_t$				I_t/K_{t-1}			
Information Uncertainty	Peer Average Analyst Coverage[d]		Peer Average Prob. of Informed Training[e]		Peer Average Analyst Coverage[d]		Peer Average Prob. of Informed Training[e]	
	Low (Uncertainty)	High (Certainty)	High (Uncertainty)	Low (Certainty)	Low (Uncertainty)	High (Certainty)	High (Uncertainty)	Low (Certainty)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrumented Dependent								
Peer $\widehat{DivY_t}$	0.604*	0.246	0.873**	0.001				
	(1.74)	(0.58)	(2.45)	(0.00)				
Peer $\widehat{I_t/K_{t-1}}$					0.504***	-0.085	0.410**	0.177
					(3.52)	(-0.35)	(2.27)	(0.85)
1 st ***stage Instrumental Variables***								
Peer $IdioShock_{t-1}$	0.004	0.024**	-0.004	0.045***	-0.065	-0.069	-0.032	-0.046
	(0.66)	(2.25)	(-0.82)	(4.39)	(-0.72)	(-0.68)	(-0.23)	(-0.13)
Peer $IdioRisk_{t-1}$	-0.027***	-0.022***	-0.317***	-0.024***	0.869***	0.900***	0.789***	0.810***
	(-8.19)	(-3.64)	(-8.40)	(-4.09)	(18.44)	(15.12)	(14.93)	(10.79)
PeerFirmAverages				All	Yes			
FirmSpecificFactors				All	Yes			
YearFixed				All	Yes			
FirmFixed				All	Yes			
N	10,954	10,944	7,367	7,373	11,613	11,597	7,475	7,484
Adjusted $R^2(2^{nd}Stage)$	0.61	0.74	0.60	0.73	0.45	0.56	0.44	0.59
$K-P$ rk LM Stat.	70.47***	27.93***	66.94***	45.60***	241.91***	177.43***	180.43***	97.77***
$K-P$ rk Wald F Stat.	38.93***	13.55**	35.91***	24.22***	175.08***	118.47***	118.97***	68.87***
Hansen J Stat.	0.09	7.55***	0.05	2.40	0.08	0.06	0.01	1.11

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.

[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.

[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.

[d] Firm have a more uncertain information environment if the firm's peer average number of analyst coverage is below at the median.

[e] Firm have a more uncertain information environment if the firm's peer average probability of informed trading is above at the median.

TABLE XXII: DIFFERENT SETS OF PEER FIRMS.

Definition of Peers:	{SIC2}[d]		{COWN} ∩ {SIC2}[e]		{COWN} − {SIC2}[f]		{COWN}[g]	
Dependent variable:	$DivY_t$	I_t/K_{t-1}	$DivY_t$	I_t/K_{t-1}	$DivY_t$	I_t/K_{t-1}	$DivY_t$	I_t/K_{t-1}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instrumented Dependent								
Peer $\widehat{DivY_t}$	0.547		0.769*		0.728**		0.860***	
	(0.07)		(1.80)		(2.56)		(0.29)	
Peer $\widehat{I_t/K_{t-1}}$		0.047		-0.193		0.296**		0.288***
		(0.32)		(-1.10)		(2.54)		(2.58)
1st stage Instrumental Variables								
Peer $IdioShock_{t-1}$	0.0004*	0.106**	0.002	-0.241***	0.009*	-0.269***	0.008	-0.243***
	(1.68)	(2.31)	(0.55)	(-2.94)	(1.88)	(-4.36)	(1.61)	(-3.49)
Peer $IdioRisk_{t-1}$	-0.0002*	0.263***	-0.008***	0.302***	-0.026***	0.835***	-0.026***	0.855***
	(-1.93)	(5.78)	(-3.79)	(7.26)	(-9.13)	(22.19)	(-9.39)	(23.44)
PeerFirmAverages				All	Yes			
FirmSpecificFactors				All	Yes			
YearFixed				All	Yes			
FirmFixed				All	Yes			
N	22,169	22,725	12,569	12,790	21,898	23,210	21,917	23,240
Adjusted R^2(2^{nd}Stage)	0.68	0.51	0.72	0.49	0.68	0.51	0.68	0.52
K − P rk LM Stat.	8.22**	34.96***	17.29***	63.47***	96.54***	345.67***	98.83***	345.29***
K − P rk Wald F Stat.	4.12	17.77**	8.78*	34.35***	52.09***	275.46***	52.25***	283.45***
Hansen J Stat.	8.84***	1.87	2.78*	1.19	1.38	0.42	2.82*	1.23

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.
[d] {SIC2} is two-digit SIC industry groups.
[e] {COWN} ∩ {SIC2} is an intersection between the same SIC industry and common-ownership linked affiliation.
[f] {COWN} − {SIC2} is the exclusion of the same industry firms in common-ownership linked peers.
[g] {COWN} consists of all common-ownership linked peers.

TABLE XXIII: EFFECT OF PEER FIRMS ON OTHER PAYOUT POLICIES AND INVESTMENT DECISIONS.

Dependent variable	D_Div_t	$DivPay_t$	$R\&D_t/AT_{t-1}$
Model	IV Probit	IV-2SLS	IV-2SLS
	(1)	(2)	(3)
Instrumented Dependent			
Peer $\widehat{D\_Div_t}$	6.181***		
	(12.27)		
Peer $\widehat{DivPay_t}$		0.406***	
		(3.75)	
Peer $R\&\widehat{D_t/AT_{t-1}}$			0.199***
			(3.36)
1st stage Instrumental Variables			
Peer $IdioShock_{t-1}$	0.037***	-0.425***	0.095***
	(6.88)	(-4.87)	(4.15)
Peer $IdioRisk_{t-1}$	-0.073***	-0.604***	0.437***
	(-27.01)	(-12.44)	(30.42)
PeerFirmAverages	Yes	Yes	Yes
FirmSpecificFactors	Yes	Yes	Yes
YearFixed	Yes	Yes	Yes
FirmFixed	Yes	Yes	Yes
N	21,898	21,888	23,210
Adjusted $R^2(2^{nd}Stage)$	-	0.64	0.89
$K-P$ rk LM Stat.	-	143.26***	516.77***
$K-P$ rk Wald F Stat.	-	77.49***	463.19***
Hansen J Stat.	-	3.57	0.38
Wald Test of Exogeneity	52.69***	-	-

[a] Heteroskedasticity-robust t-statistics are clustered by firm in parentheses.
[b] *, **, and *** represent that the coefficient estimate is different from zero at the 10%, 5% and 1% levels, respectively.
[c] **, and *** represent that K-P rk Wald F statistics significance is less than 15% or 10% levels, respectively.

CITED LITERATURE

Adhikari, B. K. and Agrawal, A. (2018). Peer influence on payout policies. *Journal of Corporate Finance*, 48:615–637.

Aivazian, V. A., Ge, Y., and Qiu, J. (2005). The impact of leverage on firm investment: Canadian evidence. *Journal of Corporate Finance*, 11(1-2):277–291.

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, 84(3):488–500.

Ali, U. and Hirshleifer, D. (2020). Shared analyst coverage: Unifying momentum spillover effects. *Journal of Financial Economics*, 136(3):2499–2536.

Allen, F., Bernardo, A. E., and Welch, I. (2000). A theory of dividends based on tax clienteles. *The Journal of Finance*, 55(6):2499–2536.

Almeida, H., Campello, M., and Jr., A. F. G. (2010). Measurement errors in investment equations. *The Review of Financial Studies*, 23(9):3279–3328.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The cross-section of volatility and expected returns. *The Journal of Finance*, 61(1):259–299.

Angrist, Joshua, D. and Lang, K. (2004). Does school integration generate peer effects? evidence from boston's metco program. *American Economic Review*, 94(5):1613–1634.

Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, 26(2):153–166.

Antón, M., Ederer, F., Giné, M., and Schmalz, M. C. (2018). Common ownership, competition, and top management incentives. *Ross School of Business Paper*, (1328).

Antón, M. and Polk, C. (2014). Connected stocks. *The Journal of Finance*, 69(3):1099–1127.

Azar, J., Raina, S., and Schmalz, M. C. (2019). Ultimate ownership and bank competition. *Available at SSRN*, (2710252).

Azar, J., Schmalz, M. C., and Tecu, I. (2018). Anticompetitive effects of common ownership. *The Journal of Finance*, 73(4):1513–1565.

Backus, M., Conlon, C., and Sinkinson, M. (2019). Common ownership in america: 1980-2017. *NBER Working Paper*, (No. w25454).

Badrinath, S. G., Kale, J. R., and Noe, T. H. (1995). Of shepherds, sheep, and the cross-autocorrelations in equity returns. *The Review of Financial Studies*, 8(2):401–430.

Baker, M. and Wurgler, J. (2004). A catering theory of dividends. *The Jounal of Finance*, 59(3):1125–1165.

Bakke, T.-E. and Whited, T. M. (2010). Which firms follow the market? an analysis of corporate investment decisions. *The Review of Financial Studies*, 23(5):1941–1980.

Baltas, N. and Kosowski, R. (2013). Momentum strategies in futures markets and trend-following funds. *Paris December 2012 Finance Meeting EUROFIDAI-AFFI Paper*.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009). Why do us firms hold so much more cash than they used to?. *The Journal of Finance*, 64(5):1985–2021.

Baumol, W. J. (1952). The transactions demand for cash: An inventory theoretic approach. *The Quarterly Journal of Economics*, 66(4):545–556.

Bereskin, F., Byun, S. K., Officer, M. S., and Oh, J.-M. (2018). The effect of cultural similarity on mergers and acquisitions: Evidence from corporate social responsibility. *Journal of Financial and Quantitative Analysis*, 53(5):1995–2039.

Bertrand, M., Luttmer, E. F., and Mullainathan, S. (2000). Network effects and welfare cultures. *The Quarterly Journal of Economics*, 115(3):1019–1055.

Bhattacharya, S. (1979). Imperfect information, dividend policy, and" the bird in the hand" fallacy. *The Bell Journal of Economics*, 10(1):259–270.

Black, F. and Scholes, M. (1974). The effects of dividend yield and dividend policy on common stock prices and returns. *Journal of Financial Economics*, 1(1):1–22.

Bloom, N., Schankerman, M., and Reenen, J. V. (2013). Identifying technology spillovers and product market rivalry. *Econometrica*, 81(4):1347–1393.

Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology*, 2(1):113–120.

Borgatti, S. P. (2005). Centrality and network flow. *Social networks*, 27(1):55–71.

Brav, A., Graham, J. R., Harvey, C. R., and Michaely, R. (2005). Payout policy in the 21st century. *Journal of Financial Economics*, 77(3):483–527.

Brennan, M. J., Jegadeesh, N., and Swaminathan, B. (1993). Investment analysis and the adjustment of stock prices to common information. *The Review of Financial Studies*, 6(4):799–824.

Brickley, James A., R. C. L. and Jr, C. W. S. (1988). Ownership structure and voting on antitakeover amendments. *Journal of Financial Economics*, 20:267–291.

Bushee, B. J. (2004). Identifying and attracting the "right" investors: evidence on the behavior of institutional investors. *Journal of Applied Corporate Finance*, 16(4):28–35.

Card, D. and Rothstein, J. (2007). Racial segregation and the black–white test score gap. *Journal of Public Economics*, 91(11-12):2158–2184.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of Finance*, 52(1):57–82.

Chahyadi, C. S. and Salas, J. M. (2012). Not paying dividends? a decomposition of the decline in dividend payers. *Journal of Financial Economics*, 36(2):443–462.

Chan, L. K., Jegadeesh, N., and Lakonishok, J. (1996). Momentum strategies. *The Journal of Finance*, 51(5):1681–1713.

Chen, H. J. and Chen, S. J. (2012). Investment-cash flow sensitivity cannot be a good measure of financial constraints: Evidence from the time series. *Journal of Financial Economics*, 103(2):393–410.

Chen, S. and Ma, H. (2017). Peer effects in decision-making: Evidence from corporate investment. *China journal of accounting research*, 10(2):167–188.

Chen, X., Harford, J., and Li, K. (2007). Monitoring: Which institutions matter?. *Journal of Financial Economics*, 86(2):279–305.

Chen, Y.-W., Chan, K., and Chang, Y. (2019). Peer effects on corporate cash holdings. *International Review of Economics & Finance*, 61:213–227.

Chevalier, J. and Ellison, G. (1997). Risk taking by mutual funds as a response to incentives. *Journal of Political Economy*, 105(6):1167–1200.

Chordia, T., Subrahmanyam, A., and Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?. *Journal of Accounting and Economics*, 58(1):41–58.

Cohen, L. and Frazzini, A. (2008). Risk taking by mutual funds as a response to incentives. *The Journal of Finance*, 63(4):1977–2011.

Cohen, L. and Lou, D. (2012). Complicated firms. *Journal of Financial Economics*, 104(2):383–400.

Col, B., Liao, R., and Zeume, S. (2020). Corporate inversions: Going beyond tax incentives. *The Review of Corporate Finance Studies*, 9(1):165–206.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

DeAngelo, H., DeAngelo, L., and Stulz, R. M. (2006). Dividend policy and the earned/-contributed capital mix: a test of the life-cycle theory. *Journal of Financial Economics*, 81(2):227–254.

DeLong, J. B., Shleifer, A., Summers, L. H., and Waldmann, R. J. (1990). Positive feedback investment strategies and destabilizing rational speculation. *The Journal of Finance*, 45(2):379–395.

DeVault, L., Sias, R., and Starks, L. (2019). Sentiment metrics and investor demand. *The Journal of Finance*, 74(2):985–1024.

Dittmar, A. and Mahrt-Smith, J. (2007). Corporate governance and the value of cash holdings. *Journal of Financial Economics*, 83(3):599–634.

Dixit, A. K., Dixit, R. K., and Pindyck, R. S. (1994). Investment under uncertainty. *Princeton university press.*

Durnev, A., Morck, R., and Yeung, B. (2004). Value-enhancing capital budgeting and firm-specific stock return variation. *The Journal of Finance*, 59(1):65–105.

Easley, D., Kiefer, N. M., O'hara, M., and Paperman, J. B. (1996). Liquidity, information, and infrequently traded stocks. *The Journal of Finance*, 51(4):1405–1436.

Easley, D. and O'hara, M. (1987). Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19(1):69–90.

Erickson, T. and Whited, T. M. (2012). Treating measurement error in tobin's q. *The Review of Financial Studies*, 25(4):1286–1329.

Fama, E. F. and French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33(1):3–56.

Fama, E. F. and French, K. R. (2001). Disappearing dividends: changing firm characteristics or lower propensity to pay?. *Journal of Financial Economics*, 60(1):3–43.

Fama, E. F. and French, K. R. (2015). A five-factor asset pricing model. *Journal of Financial Economics*, 116(1):1–22.

Fama, E. F. and MacBeth, J. D. (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy*, 81(3):607–636.

Foley, C. F., Hartzell, J. C., Titman, S., and Twite, G. (2007). Why do firms hold so much cash? a tax-based explanation. *Journal of Financial Economics*, 86(3):579–607.

Foucault, T. and Fresard, L. (2014). Learning from peers' stock prices and corporate investment. *Journal of Financial Economics*, 111(3):554–577.

Fowler, J. H. and Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the framingham heart study. *British Medical Journal*, 337.

Frank, M. Z. and Goyal, V. K. (2009). Capital structure decisions: which factors are reliably important? *Financial management*, 38(1):1–37.

Frazzini, A. and Lamont, O. A. (2008). Dumb money: Mutual fund flows and the cross-section of stock returns. *Journal of Financial Economics*, 88(2):299–322.

Gao, G. P., Moulton, P. C., and Ng, D. T. (2017). Institutional ownership and return predictability across economically unrelated stocks. *Journal of Financial Intermediation*, 31:45–63.

Georgopoulou, A. and Wang, J. (1990). The trend is your friend: Time-series momentum strategies across equity and commodity markets. *Review of Finance*, 21(4):1557–1592.

Glaeser, Edward L., B. I. S. and Scheinkman, J. A. (2003). The social multiplier. *Journal of the European Economic Association*, 1(2-3):345–353.

Gomes, A. R., Gopalan, R., Leary, M. T., and Marcet, F. (2017). Analyst coverage networks and corporate financial policies. *Available at SSRN*.

Graham, J. R. and Kumar, A. (2006). Do dividend clienteles exist? evidence on dividend preferences of retail investors. *The Journal of Finance*, 61(3):1305–1336.

Grennan, J. (2019). Dividend payments as a response to peer influence. *Journal of Financial Economics*, 131(3):549–570.

Griffin, J. M., Harris, J. H., Shu, T., and Topaloglu, S. (2011). Who drove and burst the tech bubble? *The Journal of Finance*, 66(4):1251–1290.

Grinstein, Y. and Michaely, R. (2005). Institutional holdings and payout policy. *The Journal of Finance*, 60(3):1389–1426.

Grossman, S. J. and Miller, M. H. (1988). Liquidity and market structure. *The Journal of Finance*, 43(3):617–633.

Grullon, G., Michaely, R., and Swaminathan, B. (2002). Are dividend changes a sign of firm maturity?. *The Journal of Business*, 75(3):387–424.

Ham, H., Cho, H., Kim, H., and Ryu, D. (2019). Time-series momentum in china's commodity futures market. *Journal of Futures Markets*, 39(12):1515–1528.

Han, S. and Qiu, J. (2007). Corporate precautionary cash holdings. *Journal of Corporate Economics*, 13(1):43–57.

Harford, J. (1999). Corporate cash reserves and acquisitions. *The Journal of Finance*, 54(6):1969–1997.

Harford, J., Mansi, S. A., and Maxwell, W. F. (2008). Corporate governance and firm cash holdings in the us. *Journal of Financial Economics*, 87(3):535–555.

Harris, L. and Gurel, E. (1986). Price and volume effects associated with changes in the s&p 500 list: New evidence for the existence of price pressures. *The Journal of Finance*, 41(4):815–829.

He, J. J. and Huang, J. (2017). Product market competition in a world of cross-ownership: Evidence from institutional blockholdings. *The Review of Financial Studies*, 30(8):2674–2718.

He, J. J., Huang, J., and Zhao, S. (2019). Internalizing governance externalities: The role of institutional cross-ownership. *Journal of Financial Economics*, 134(2):400–418.

Hennessy, C. A., Levy, A., and Whited, T. M. (2007). Testing q theory with financing frictions. *Journal of Financial Economics*, 83(3):691–717.

Higgins, R. C. (1972). The corporate dividend-saving decision. *Journal of Financial and Quantitative Analysis*, 7(2):1527–1541.

Ho, H. (2003). Dividend policies in australia and japan. *International Advances in Economic Research*, 9(2):91–100.

Hoberg, G. and Phillips, G. (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy*, 124(5):1423–1465.

Hoberg, G. and Prabhala, N. R. (2009). Dividend policy, risk, and catering. *The Review of Financial Studies*, 22(1):79–116.

Hong, H., Lim, T., and Stein, J. C. (2000). Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. *The Journal of Finance*, 55(1):265–295.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of Finance*, 54(6):2143–2184.

Hou, K. (2007). Industry information diffusion and the lead-lag effect in stock returns. *The Review of Financial Studies*, 20(4):1113–1138.

Ippolito, R. A. (1992). Consumer reaction to measures of poor quality: Evidence from the mutual fund industry. *The Journal of Law and Economics*, 35(1):45–70.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D evidence from firms' patents, profits and market value. *The American Economic Review*, 76(5):984–1001.

Jank, S. (2012). Mutual fund flows, expected returns, and the real economy. *Journal of Banking & Finance*, 36(11):3060–3070.

Jegadeesh, N. (1990). Evidence of predictable behavior of security returns. *The Journal of Finance*, 45(3):881–898.

Jegadeesh, N. and Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, 48(1):65–91.

Jensen, M. C. (1986). Agency costs of free cash flow, corporate finance, and takeovers. *The American Economic Review*, 76(2):323–329.

Jiang, Z., Kim, K. A., a. L. E., and Yang, S. (2013). Share repurchases, catering, and dividend substitution. *Journal of Corporate Finance*, 21:36–50.

Joo, C., Yang, I., and Yang, T. (2016). Peer group effect in firm cash holding policy: Evidence from korean manufacturing firms. *Asia-Pacific Journal of Financial Studies*, 45(4):535–573.

Jung, M. J. (2013). Investor overlap and diffusion of disclosure practices. *Review of Accounting Studies*, 18(1):167–206.

Kaplan, S. N. and Zingales, L. (1997). Do investment-cash flow sensitivities provide useful measures of financing constraints?. *The Quarterly Journal of Economics*, 112(1):169–215.

Kogan, L., Dimitris Papanikolaou, A. S., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics*, 132(2):665–712.

Kostovetsky, L. and Manconi, A. (2020). Common institutional ownership and diffusion of innovation. *Available at SSRN 2896372*.

Kwon, H. J. (2016). Executive compensation under common ownership. *Department of Economics, University of Chicago*.

Kyle, A. S. (1992). Continuous auctions and insider trading. *Econometrica: Journal of the Econometric Society*, 53(6):1315–1335.

Lang, L., Ofek, E., and Stulz, R. (1996). Leverage, investment, and firm growth. *Journal of Financial Economics*, 40(1):3–29.

Leary, M. T. and Michaely, R. (2011). Determinants of dividend smoothing: Empirical evidence. *The Review of Financial Studies*, 24(10):3197–3249.

Leary, M. T. and Roberts, M. R. (2014). Do peer firms affect corporate financial policy?. *The Journal of Finance*, 69(1):139–178.

Lee, C. and Swaminathan, B. (2000). Price momentum and trading volume. *The Journal of Finance*, 55(5):2017–2069.

Lee, C. M., Sun, S. T., Wang, R., and Zhang, R. (2019). Technological links and predictable returns. *Journal of Financial Economics*, 132(3):76–96.

Lehmann, B. N. (1990). Fads, martingales, and market efficiency. *The Quarterly Journal of Economics*, 105(1):1–28.

Lewellen, J. and Lewellen, K. (2016). Investment and cash flow: New evidence. *Journal of Financial and Quantitative Analysis*, 51(4):1135–1164.

Li, W. and Lie, E. (2006). Dividend changes and catering incentives. *Journal of Financial Economics*, 80(2):293–308.

Liang, L. (2016). Common ownership and executive compensation. *University of Texas at Dallas Working Paper*.

Lieberman, M. B. and Asaba, S. (2006). Why do firms imitate each other? *Academy of Management Review*, 31(2):366–385.

Lintner, J. (1956). Distribution of incomes of corporations among dividends, retained earnings, and taxes. *The American Economic Review*, 46(2):97–113.

Lo, A. W. and MacKinlay, A. C. (1990). When are contrarian profits due to stock market overreaction?. *The Review of Financial Studies*, 3(2):175–205.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies*, 25(12):3457–3489.

Luo, M. (2011). A bright side of financial constraints in cash management. *Journal of Corporate Finance*, 17(5):1430–1444.

Manski, C. F. (1993). Identification of endogenous social effects: The reflection problem. *The Review of Economic Studies*, 60(3):531–542.

Mas, A. and Moretti, E. (2009). Peers at work. *American Economic Review*, 99(1):112–45.

McCabe, G. M. (1979). The empirical relationship between investment and financing: a new look. *Journal of Financial and Quantitative Analysis*, 14(1):119–135.

Menzly, L. and Ozbas, O. (2010). Market segmentation and cross-predictability of returns. *The Journal of Finance*, 65(4):1555–1580.

Miller, M. H. and Orr, D. (1966). A model of the demand for money by firms. *The Quarterly Journal of Economics*, 80(13):413–435.

Miller, M. H. and Rock, K. (1985). Dividend policy under asymmetric information. *The Journal of Finance*, 40(4):1031–1051.

Milliken, F. J. (1987). Three types of perceived uncertainty about the environment: State, effect, and response uncertainty. *Academy of Management review*, 12(1):133–143.

Moskowitz, T. J. and Grinblatt, M. (1999). Do industries explain momentum?. *The Journal of Finance*, 54(4):1249–1290.

Moskowitz, T. J., Ooi, Y. H., and Pedersen, L. H. (2012). Time series momentum. *Journal of Financial Economics*, 104(2):228–250.

Mueller, D. C. (1972). A life cycle theory of the firm. *The Journal of Industrial Economics*, 20(3):199–219.

Mulligan, C. B. (1997). Scale economies, the value of time, and the demand for money: Longitudinal evidence from firms. *Journal of Political Economy*, 105(5):1061–1079.

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, 5(2):147–175.

Nofsinger, J. R. and Sias, R. W. (1999). Herding and feedback trading by institutional and individual investors. *The Journal of Finance*, 54(6):2263–2295.

O'Brien, P. C. and Bhushan, R. (1990). Analyst following and institutional ownership. *Journal of Accounting Research*, 28:55–76.

Opler, T., Pinkowitz, L., Stulz, R., and Williamson, R. (1999). The determinants and implications of corporate cash holdings. *Journal of Financial Economics*, 52(1):3–46.

Ozoguz, A., Rebello, M. J., and Wardlaw, M. (2018). Information, competition, and investment sensitivity to peer stock prices. *SMU Cox School of Business Research Paper*, pages 18–24.

Panousi, V. and Papanikolaou, D. (2012). Investment, idiosyncratic risk, and ownership. *The Journal of Finance*, 67(3):1113–1148.

Park, K., Yang, I., and Yang, T. (2017). The peer-firm effect on firm's investment decisions. *The North American Journal of Economics and Finance*, 40:178–199.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

Qiu, J. and Wan, C. (2015). Technology spillovers and corporate cash holdings. *Journal of Financial Economics*, 115(3):558–573.

Rantapuska, E. (2008). Ex-dividend day trading: Who, how, and why?: Evidence from the finnish market. *Journal of Financial Economics*, 88(2):355–374.

Rock, E. B. and Rubinfeld, D. L. (2018). Antitrust for institutional investors. *Antitrust Law Journal*, 82(1):221–278.

Rozeff, M. S. (1982). Growth, beta and agency costs as determinants of dividend payout ratios. *Journal of financial Research*, 5(3):249–259.

Semov, S. (2017). Common ownership, competition and firm financial policy. *Working Paper*.

Shue, K. (2013). Executive networks and firm policies: Evidence from the random assignment of mba peers. *The Review of Financial Studies*, 26(6):1401–1442.

Sias, R. W., Starks, L. T., and Titman, S. (2006). Changes in institutional ownership and stock returns: Assessment and methodology. *The Journal of Business*, 79(6):2869–2910.

Stoll, H. R. (1978). The supply of dealer services in securities markets. *The Journal of Finance*, 33(4):1133–1151.

Tobin, J. (1969). A general equilibrium approach to monetary theory. *Journal of Money, Credit and Banking*, 1(1):15–29.

Warther, V. A. (1995). Aggregate mutual fund flows and security returns. *Journal of Financial Economics*, 39(2-3):209–235.

Whited, T. M. and Wu, G. (2006). Financial constraints risk. *The Review of Financial Studies*, 19(2):531–559.

APPENDICES

Appendix A. Brief definitions and sources of main variables.

Chapter 2: Common Ownership Linkage and Return Predictability

Variable	Definition
RET_t	Monthly holding period return at end of current month t. [*Source from* CRSP]
$\mathsf{COWNRET}_t$	*Common ownership momentum*, defined as the closeness-weighted return of a focal firm's common ownership-linked firms. For each focal firm i at month t the $\mathsf{COWNRET}_{i,t}$ is calculated as $$\mathsf{COWNRET}_{i,t} = \frac{\sum_{i \neq j} \mathsf{COWN}_{i,j,q-1} \times \mathsf{RET}_{j,t}}{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1}}$$ where $\mathsf{RET}_{j,t}$ is return of peer firm j at month t which belong to quarter q, and $\mathsf{COWN}_{ij,q-1}$ is defined as the degree of common ownership closeness between firm i and j at the end of prior quarter $q-1$. $$\mathsf{COWN}_{ij,q} = \frac{\left(S_{i,q} S'_{j,q}\right)}{\left(S_{i,q} S'_{i,q}\right)^{1/2} \left(S_{j,q} S'_{j,q}\right)^{1/2}}$$ where $S_{i,q} = \left(s_{1,q}, s_{2,q}, ..., s_{\tau,q}, ..., s_{6514,q}\right)$ is a vector of institutional ownership structure in firm i at quarter q, and then $s_{k,q}$ is a percentage of share outstanding owned by institutional shareholder k on a rolling average of prior 4 quarters. [*Source from* CRSP / Thomson Reuters (S34)]
INDRET_t	*Industry Momentum*, defined as the value-weighted average industry return based on CRSP 2-digit SIC code (Moskowitz and Grinblatt, 1999). [*Source from* CRSP]
$\mathsf{SUPPRET}_t$ $\mathsf{CUSTRET}_t$	Following Menzly and Ozbas (2010), *Supplier Return*, defined as the return on the portfolio of supplier industries of focal firm i at time t, and *Customer Return*, defined as the return on the portfolio of customer industries of focal firm i at time t. [*Source from* CRSP / BEA Input-Output data]

Variable	Definition
$\mathsf{PCRET_t}$	Following Cohen and Lou (2012), *Pseudo-conglomerate Return*, defined as equally-weighted returns of its pseudo-conglomerate portfolio for each conglomerate firm i at time t. The pseudo-conglomerate portfolio consists of the conglomerate firm's segments constructed from standalone firms in corresponding industries. [*Source from* CRSP / COMPUSTAT (Customer Segment file)]
$\mathsf{TECHRET_t}$	Following Lee et al. (2019), Technology-linked Return defined as the closeness-weighted return of a focal firm's technology-linked firms. For each focal firm i at month t the $\mathsf{TECHRET}_{i,t}$ is calculated as $$\mathsf{TECHRET}_{i,t} = \frac{\sum_{i \neq j} \mathsf{TECH}_{i,j,t} \times \mathsf{RET}_{j,t}}{\sum_{i \neq j} \mathsf{TECH}_{ij,t}}$$ where $\mathsf{TECH}_{ij,t}$ is defined as the degree of technology closeness between firm i and j at month t. $$\mathsf{TECH}_{ij,t} = \frac{\left(T_{i,t} T'_{j,t}\right)}{\left(T_{i,t} T'_{i,t}\right)^{1/2} \left(T_{j,t} T'_{j,t}\right)^{1/2}}$$ where $T_{i,q} = \left(T_{i1,t}, T_{i2,t}, ..., T_{i\tau,t}, ..., T_{i427,t}\right)$ is a vector of firm i's proportional share of patents across 427 USPTO technology class at time t. [*Source from* CRSP Google patent data (provided by Kogan et al. (2017))]
RET_{t-1}	*Short-term Reversal*, defined as the monthly holding period return at end of previous month $t-1$ (Jegadeesh and Titman, 1993). [*Source from* CRSP]
MOM	*Medium-term Momentum*, defined as the cumulative return from month $t-12$ to $t-2$ (Chan et al., 1996). [*Source from* CRSP]
SIZE	*Firm Size*, defined as the market capitalization at the end of last month measured in logarithm. [*Source from* CRSP]

Variable	Definition
BtoM	*Book-to-Market*, defined as the ratio of total book value of equity to total market capitalization. [*Source from* CRSP / COMPUSTAT]
AG	*Asset Growth*, defined as assets at the end of y minus assets at the end of $y-1$. [*Source from* COMPUSTAT]
GP	*Gross Profitability*, defined as revenue minus cost of goods sold scaled by assets. [*Source from* COMPUSTAT]
$\mathsf{TURNOVER}$	*Share Turnover*, computed as the monthly share trading volume divided by the share outstanding and then average across month $t-12$ to $t-1$ (Lee and Swaminathan, 2000). [*Source from* CRSP]
$\mathsf{Ins.Own}$	*Institutional Ownership*, defined as the percentage of outstanding shares owned by 13F institutions at the end of the prior quarter $q-1$ (Badrinath et al., 1995). [*Source from* Thomson Reuters (S34)]
$\mathsf{Analyst}$	*Analyst Coverage*, defined as the number of analysts covering the firm at end of previous month $t-1$ (Brennan et al., 1993). [*Source from* I/B/E/S]

Variable	Definition
$\mathsf{IdioVol}$	*Idiosyncratic Volatility*, calculated as $$\mathsf{IdioVol} = \sqrt{var(\varepsilon_{i,t})}$$ where $\varepsilon_{i,t}$ is the error term from the Fama and French (1993) three factor regression. The regression is estimated monthly with more than 10 daily observations (Ang et al., 2006). [*Source from* CRSP]

Chapter 3: Common Ownership Linkage and Peer Effects in Corporate Policies

Variable	Definition
DivY_t	Dividend Yield, computed as the cash dividends divided by market value of equity. [*Source from* CRSP]
$\mathsf{D\_Div}_t$	Dividend Payer, equals one if the firm distributes a cash dividend in the current year t, and zero otherwise. [*Source* CRSP]
DivPay_t	Dividend Payout, computed as the cash dividends divided by total assets. [*Source from* CRSP]
$\mathsf{I}_t/\mathsf{K}_{t-1}$	Investment to Capital Ratio, defined as the ratio of cumulative investment over a one-year period to the beginning-of-the-year capital stock. [*Source from* Compustat]
$\mathsf{R\&D}_t/\mathsf{AT}_{t-1}$	R&D to Assets, defined as the R&D spending divided by lagged assets. [*Source from* Compustat]
Size	Firm Size, computed as the logarithm of total sales (Leary and Roberts, 2014). [*Source from* Compustat]

Variable	Definition
MB	Market-to-Book Ratio, market value of assets divided by the book value.
SG	Sales Growth, defined as the percentage growth in sales in a given year. [*Source from* Compustat]
$\mathsf{Peer\ DivY}_t$	*Common Ownership-Linked Peers' Dividend Yield*, defined as the closeness-weighted dividend yield of a focal firm's common ownership-linked firms. For each focal firm i at fiscal year t the $\mathsf{Peer\ DivY}_{i,t}$ is calculated as $$\mathsf{Peer\ DivY}_{i,t} = \frac{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1} \times \mathsf{DivY}_{j,t}}{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1}}$$ where q is the quarter prior to the last quarter of the fiscal year t. [*Source from* CRSP / Thomson Reuters (S34)]
$\mathsf{Peer}\ I_t/K_{t-1}$	*Common Ownership-Linked Peers' Investment to Capital Ratio*, defined as the closeness-weighted investment to capital ratio of a focal firm's common ownership-linked firms. For each focal firm i at fiscal year t the $\mathsf{Peer}\ I_{i,t}/K_{i,t-1}$ is calculated as $$\mathsf{Peer}\ I_{i,t}/K_{i,t-1} = \frac{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1} \times I_{j,t}/K_{j,t-1}}{\sum_{i \neq j} \mathsf{COWN}_{ij,q-1}}$$ where q is the quarter prior to the last quarter of the fiscal year t. [*Source from* Compustat / Thomson Reuters (S34)]

Appendix B. Measuring flows of 13f institution.

To measure the institutional flow-induced trading, we use the following method, which is inspired by Griffin et al. (2011) and DeVault et al. (2019). They note that the institutional investors' demand ($\triangle InstD_{i,q}$) consists of three components; changes in holdings due to flow-induced trading or flow-induced net buying ($FIT_{i,q}$), net active buying by institution ($NActBuy_{i,q}$), and passive changes in ownership ($Passive_{i,q}$). We begin by calculating the fund flow ratio[27] of 13f institution k at the end of quarter q, which is defined as (identical to Griffin et al.'s equation (IA.4) and DeVault et al.'s equation (IA.1))

$$FlowRatio_{k,q} = \frac{\sum_{i=1}^{N_q} P_{i,q} H_{ik,q}}{\sum_{i=1}^{N_q} P_{i,q-1} H_{ik,q-1}(1 + R_{i,q})}, \tag{B1}$$

where $P_{i,q}$ is the price of stock i at the end of q, R_q is the return on stock i, N_q is the number of stock in the market, and $H_{ik,q}$ is the number of shares of stock i held by 13f institution k. After winsorizing the estimated flow ratio at the 5% and 95% level[28], we then decompose quarterly demand of 13f institution k in stock i at the end of quarter q into flow-induced net buying ($FIT_{ik,q}$), net active buying ($NActBuy_{ik,q}$), and passive trading ($Passive_{ik,q}$).

---

[27] Griffin et al. (2011) use different fund flow ratios between mutual funds and 13f institutions other than mutual funds. For mutual funds, they use total net asset value instead of the holdings ($P_{i,q} H_{ik,q}$). In this paper, we adopt the unified framework for measuring fair value of the 13f institutional demand.

[28] As Griffin et al. (2011) point out, outliers can occur when an institution shift funds from non-equity holdings to equity holdings.

The flow-induced net buying for 13f institution k in stock i at the end of quarter q is given by (identical to Griffin et al.'s equation (IA.5) and DeVault et al.'s equation (IA.2))

$$\mathsf{FIT}_{ik,q} = \frac{(P_{i,q-1}H_{ik,q-1}) \times (1 + R_{i,q}) \times (\mathit{FlowRatio}_{k,q} - 1)}{P_{i,q}S_{i,q}}, \tag{B2}$$

where $S_{i,q}$ is the number of shares outstanding for stock i at the end of quarter q. Following Griffin et al. (2011) and DeVault et al. (2019), we winsorize $\mathsf{FIT}_{ik,q}$ at the 99.9% level.

The net active buying for 13f institution k in stock i at the end of quarter q is given by (identical to Griffin et al.'s equation (IA.6) and DeVault et al.'s equation (IA.4))

$$\mathit{NActBuy}_{ik,q} = \frac{P_{i,q}H_{ik,q} - (P_{i,q-1}H_{ik,q-1}) \times (1 + R_{i,q}) \times (\mathit{FlowRatio}_{k,q})}{P_{i,q}S_{i,q}}. \tag{B3}$$

The passive trading for 13f institution k in stock i at the end of quarter q is given by (identical to DeVault et al.'s equation (IA.6))

$$\mathit{Passive}_{ik,q} = \frac{(P_{i,q-1}H_{ik,q-1}) \times (1 + R_{i,q}) - P_{i,q}H_{ik,q-1}}{P_{i,q}S_{i,q}}. \tag{B4}$$

If there is no dividend payment in a given quarter (i.e, $P_{i,q} = P_{i,q-1} \times (1 + R_{i,q})$), then passive trading is zero.

Summing equations (B2), (B3), and (B4) across institutions yield the institutional demand shock ($\triangle \mathrm{InstD}_{i,q}$) and its three components (flows, manager's decision, and passive) for stock i at the end of quarter q (identical to DeVault et al.'s equation (IA.8)) as

$$\mathrm{FIT}_{i,q} = \sum_{i=1}^{K_q} \mathrm{FIT}_{ik,q}, \tag{B5}$$

$$\mathrm{NActBuy}_{i,q} = \sum_{i=1}^{K_q} \mathrm{NActBuy}_{ik,q}, \tag{B6}$$

$$\mathrm{Passive}_{i,q} = \sum_{i=1}^{K_q} \mathrm{Passive}_{ik,q}, \tag{B7}$$

$$\triangle \mathrm{InstD}_{i,q} = \mathrm{FIT}_{i,q} + \mathrm{NActBuy}_{i,q} + \mathrm{Passive}_{i,q}, \tag{B8}$$

where K_q is the number of institution in the market at quarter q.

VITA

NAME	Haesung Kim
EDUCATION	B.S., Statistics, Iowa State University, Magna Cum Lauda, Ames, IA, 2010
	M.S., Statistics, University of Chicago, Chicago, IL, 2012
	Exchange Student, Northwestern University, Evanston, IL, 2016
	Ph.D., Business Administration, University of Illinois at Chicago, Chicago, IL, 2020
RESEARCH	Common Ownership Links and Return Predictability
	Common Ownership Links and Peer Effects in Corporate Policies
TEACHING	**Teaching Assistant**, The University of Illinois at Chicago Corporate Finance (FIN 520; FIN 320) International Corporate Finance (FIN 442) Investments (FIN 510; FIN 310) Advanced Investments (FIN 594) Introduction to Finance (FIN 300) Asset Management (FIN 455) Business Forecasting (IDS 476) Business Analytic Statistics (IDS 575) Statistics Software in Business (IDS 462) Statistics for Management (IDS 570)
	Lab Instructor, The University of Illinois at Chicago Business Statistics (IDS 270)
	Teaching Assistant, The University of Chicago Elementary Statistics (STAT 20000)

EXPERIENCE	Research Assistant, Department of Finance in the University of Illinois at Chicago, Chicago, IL, January 2014 – December 2016
	Research Associate, Economic Research Institute in the Bank of Korea, Seoul, South Korea, September 2012 – August 2013
	Associate, POSCO, Seoul, South Korea, June 2012 – August 2012
	Internship, SAS Korea, Seoul, South Korea, June 2010 – August 2010
HONERS	Business School Fellowship, The University of Illinois at Chicago, 2013 – 2019
	Tuition Remission Scholarship, The University of Chicago, 2010 – 2012
	Undergraduate Scholarship, Iowa State University, 2008 – 2010
	Phi Beta Kappa
SKILLS	Computer Skills: R, SAS, Stata, Python
	Actuarial Exam: Passed Exams P (Probability), FM (Financial Mathematics)
MEMBERSHIP	Financial Management Association
	American Finance Association