Common Ownership and Stock Return Comovement

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Abstract

Comovement in stock returns is an important determinant of market risk and stability. This study shows that increased common ownership between same-industry firms leads to greater comovement in their stock returns. The results are robust after controlling for time trends and various empirical specifications. The effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their products. These findings are consistent with previous studies, which suggest that comovement at the market level is due to blurred firm boundaries. Common ownership serves as a mechanism for joint control across firms, allowing coordination in firm activities, efficient resource allocation, and cross-monitoring. Thus, the market considers firms with common ownership relevant and correlated in fundamentals.

Keywords: common ownership; return comovement; corporate governance.

1. Introduction

Over the last decades, same-industry firms have progressively shared blockholders, i.e., a common ownership structure. In 2014, more than 60% of publicly listed companies in the United States had this structure (He & Huang, 2017). The growing popularity of common ownership demonstrates that depicting firms as autonomous decision-makers in the product market may no longer adequately represent their strategic interactions. Indeed, prior research indicates that large common blockholders can influence the performance and investment choices of same-industry firms in their portfolios (Koch, Panayides, & Thomas, 2021). While the existing literature focuses almost entirely on the performance of commonly owned firms, there has been little emphasis devoted to the role of common ownership in influencing return comovement. Given the substantial growth in common ownership and that it remains largely unregulated, it is critical for both academics and policymakers to understand the economic consequences of the structure, particularly its implications for return comovement and systematic risk.

Comovement in stock returns is a fundamental component of the market's risk and stability. It is crucial to determine the efficiency of the cross-sectional diversification and management of systematic risk, thus affecting firms' cost of capital. Comovement also impacts the level of systemic risk through the way shocks are transmitted among stocks in the markets. High comovement in returns reflects a high level of systematic variation or a low level of firm-specific information compounded into stock prices (Roll, 1988). Common ownership allows blockholders to exert influence on the corporate decisions of a group of firms potentially binding their performance together and reducing individual firm-specific information incorporated in prices. Can common ownership between same-industry firms increases comovement in stock returns?

There are several reasons why common ownership is likely to impact comovement between stock returns. For example, common ownership can foster fundamental correlation among commonly owned firms by reducing information asymmetry and facilitating coordination, thereby tying their potential earnings together (He & Huang, 2017). Chemmanur, Shen, and Xie (2016) discover a high number of co-patents and mutual citations among same-industry firms with common owners. Moreover, common ownership affects how a firm discloses its earnings information in relation to other firms with the same common owners, potentially creating correlations in news about firm performance (Massa & Žaldokas, 2017; Park, Sani, Shroff, & White, 2019). Despite these reasons, research on how common ownership impacts comovement is scarce. Edmans, Levit, and Reilly (2014) theoretically prove that common ownership between any two firms in the same or different industries allows blockholders to choose between a balanced or unbalanced exit when faced with liquidity shocks, affecting stock prices of both retained and sold firms in the same or opposite directions. Common owners are more likely to follow imbalanced exit, and thus causing negative return comovement when the agency problem is severe or liquidity shocks are infrequent.

Motivated by Edmans et al. (2014)'s study, this study empirically tests whether common ownership can impact comovement in stock returns even in the absence of liquidity shocks and agency concerns. Moreover, this study differs from other studies by solely investigating the effects of common ownership on comovement in returns between same industry firms. I question whether there is excessive comovement in returns between firms in the same industry with and without this structure. I first identify all pairs of firms in the same industry that share no or at least one common owner from 1990 to 201 for the US public firms. I then follow Gilje, Gormley, and Levit (2020) to measure common ownership effects in any firm pairs with common owners, which depends on the importance of each firm in the common owners' portfolio and the proportion of that common owner's ownership in each firm. The measure captures the attention and knowledge of common owners to the firm pairs and how much firm managers care about the common owners' preferences.

I construct two measures for pairwise comovement between two firms with common ownership following Morck, Yeung, and Yu (2000)'s method and adjusting for a within-US study. The first measure observes the number of days that stock prices of each pair of firms move in the same direction and divide it by the total number of days in which both firms move in either direction. If the two firms always move in the same (opposite) direction, the measure equals one (zero). The second measure is the correlation coefficient between the returns of two paired firms. While the first comovement measure captures time-period-specific shocks and depends on the number of days where two returns move in the same direction, the second correlation measure reveals both the direction and magnitude of the two returns' movement.

Given that each observation in the sample contains a pair of firms, unobservable firm effects can cause the errors to be correlated across pairs. I address this problem by applying the non-parametric bootstrapping estimation method by Krackhardt (1988) to determine the significance of estimated coefficients. Firms with common ownership are also more likely to share an overall trend caused by unobserved reasons, overestimating the degree of comovement attributable to the effects of common ownership. For example, increased supplier-customer relationships may cause firms' fundamentals to be correlated when common ownership is present. Thus, I do the trend correction for long-run trends by detrending the data on firm-level returns (K. H. Chan, Hayya, &

Ord, 1977; Khanna & Thomas, 2009). There are other reasons why the returns of two firms could be correlated, whether they share common ownership. For instance, two firms operating in the same industry may be exposed to the same sources of materials and product demands, as well as legal and political risks. These common factors may blur firm boundaries, reducing firm-specific information incorporated in stock returns. Using common industry effects, I attempt to account for the possibility that firms may share fundamentals even if the common ownership between them does not exist.

My multivariate ordinary least-squares (OLS) analysis shows that firm pairs with common ownership experience significantly higher comovement in returns than firm pairs without common ownership. The result is robust to alternative empirical specifications after removing the trends in the data of the pairs and controlling for unobserved variables that may affect the pair's comovement. It is consistent with the idea that the market views common ownership as a mechanism for common owners exercise joint control across firms. A firm pair with common ownership is predicted to move in the same direction 3.5% more often than a pair without common ownership. In addition, when firm pairs share common ownership, their returns are 7% more correlated than when they do not.

While I am interested in whether common ownership influences comovement in returns, comovement in returns may also influence the likelihood of common ownership. For instance, institutional investors may target same-industry firms with a high correlation in stock returns to create common ownership. To overcome the reverse causality concerns, I implement a difference-in-differences (DID) analysis around the mergers of large financial institutions as an external shock to firms' common ownership levels (Lewellen & Lowry, 2021). The mergers create a significant shift in the level of common ownership between a firm pair in the same industry, whose each firm is block-held by one party before the merger. Thus, the treatment sample consists of firms whose ownership linkages with same-industry firms are likely to increase just because of the merger. On the other hand, the control sample consists of other block-held firms in the same institution's portfolio that are unlikely to experience such changes. I find evidence that treatment firms, relative to control firms, experience an approximately five to ten percent larger increase in return comovement surrounding the institution mergers, which rules out the mechanical effect of common ownership.

Several mechanisms could contribute to the increase in return comovement. I find that the effect of common ownership on pairwise comovement is stronger between firms with less product similarity. While common ownership may help in product space, it may hinder innovation.

Commonly owned firms selling similar products are less willing to invest in innovation for the fear that their advanced products will negatively impact the business of other firms with common owners. Employing such a tool may well be in the interest of undiversified shareholders (and consumers) but costly for common owners. Common ownership may thus create more binding value between firms with different products or firms close in the technology space, increasing their comovement in returns. On the other hand, firms with similar products generate less value from innovation collaboration; thus, their stock prices may be less correlated.

My findings are important for both market participants and policymakers. The U.S.'s Council of Economic Advisers considered common ownership a rising concern for the economy[1]. Elhauge (2015) states that block-holding multiple firms within the same industry promotes anticompetitive effects and thus should be prohibited. Posner, Scott Morgan, and Weyl (2016) and Schmalz (2018) propose a policy restricting institutions' ownership in a sector to a certain percentage or to a single large stake in only one firm. However, it could be premature to enact such policies as numerous papers find no discernible effect of common ownership on industry competition (Kennedy, O'Brien, Song, & Waehrer, 2017; Koch et al., 2021; Patel, 2018; Rock & Rubinfeld, 2018). My finding that common ownership increases comovement in returns may deepen the U.S. government's current concerns on the market impacts of common ownership. The increasing likelihood of shocks spreading across stocks due to common ownership may impact systemic risk and the propensity for flash crashes. Comovement in returns also affects systematic risk and expected return premiums. Comovement between firms with common ownership can raise firm costs of capital and impact the real economy through their investment levels. If all firms are eventually controlled by a single institution, the impact of common ownership on market stability should be obvious.

This study also adds to the literature on pairwise comovement in stock returns. My study is consistent with previous research, which suggests that comovement at the market level is caused by correlated fundamentals and blurred firm boundaries (Bertrand, Mehta, & Mullainathan, 2002; Khanna & Thomas, 2009). Common ownership acts as a mechanism for joint control across firms. Firms with common ownership are considered relevant by the market, possibly because they allow for coordination in firm activities, efficient resource allocation, and cross-monitoring (He & Huang, 2017; Morck et al., 2000). This study also adds to the body of knowledge about the impact

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[1] https://obamawhitehouse.archives.gov/sites/default/files/page/files/20160414_cea_competition_issue_brief.pdf
http://www.oecd.org/competition/common-ownership-and-its-impact-on-competition.htm

of ownership structure on institutional selling. Compared to large separate institutional ownership in a single firm, common owners with selling options between good and bad firms can create incremental effects on stock prices (Edmans, Levit, & Reilly, 2019). Finally, comovement in returns between commonly owned firms can provide new trading opportunities for individual investors who follow a specific trading style, such as trading by categories, and seek to invest in a small group of firms with similar characteristics (Barberis & Shleifer, 2003; Barberis, Shleifer, & Wurgler, 2005; Wahal & Yavuz, 2013).

2. Related literature and hypotheses

There is considerable literature studying the effects of common ownership; see Schmalz (2018) for a more detailed summary. Thus, this section only reviews papers directly related to my empirical investigation about the effect of common ownership on comovement, then proceeds to develop hypotheses.

2.1 Comovement in returns

The extent to which stock returns comove determines the effectiveness of diversification strategy and portfolio or market risk. Comovement affects asset prices, required returns, and the cost of capital. Thus, its determinants have been widely studied.

Stock returns reflect new market-wide and firm-specific information. High comovement in returns can be attributed to either a high level of market-wide information (systematic variation) or a low level of firm-specific information (firm-specific variation) capitalized into stock prices (Roll, 1988). In frictionless economies with rational investors, stock prices equal rationally forecasted cash flows discounted at an appropriate rate for their risks. Thus, any market-wide return comovement must result from the correlation in the news about fundamental values such as the same cash-flow stream (Barberis et al., 2005) or correlated macro discount factors (Campbell, Polk, & Vuolteenaho, 2010; Li, 2002; Pindyck & Rotemberg, 1993). High fundamentals correlation is common in undiversified low-income economies where listed firms may concentrate in a few industries. An industry event or rumours such as leadership succession within a controlling family can potentially affect the entire economy. An economy depends disproportionately on a few large firms, which are the suppliers and customers of most other listed firms can also ensure a high level of return comovement. Emerging markets experience higher comovement in returns than developed markets due to uncertain protection of private property rights, which reduces firm-specific information incorporated into stock prices (Morck et al., 2000).

Firm fundamentals may also converge due to blurred boundaries between firms, reducing the amount of firm-specific information in prices (Barberis et al., 2005). Blurred boundaries occur when two or more businesses are not entirely segregated. Control pyramids, family holdings, and business groups are all common ways to exercise joint control over business activities (Bertrand et al., 2002; La Porta, Lopez-De-Silanes, & Shleifer, 1999). Weaker protection for public investors may encourage income shifting between controlled firms via non-arm's-length transactions for goods, services, or capital at inflated prices, causing their earnings to be interdependent. Khanna and Thomas (2009) show that firm-specific variation within a country can be attributed to the variance between firms within the same industry and ownership networks through three mechanisms of joint control: equity interlocks, director interlocks, and individual owners. These ties between firms are associated with either decreased transparency at the firm level or increased correlation in firm fundamentals. They allow firms to pool their resources together, create the supplier-customer relationship, or facilitate inter-organizational coordination, enabling firms to share common cash flow rights (Johnson, La Porta, Lopez-de-Silanes, & Shleifer, 2000). These connections enhance ownership network-specific information when pricing individual firms' stocks while simultaneously reducing firm-specific residuals, thereby improving the overall fit of the regression equation.

On the other hand, comovement in returns might simply be the consequence of numerous market frictions, inadequate assimilation of information in prices, or sentiment. These factors cause stock prices to temporarily diverge from fundamentals and impact the degree of comovement. Adding a firm to an index, for example, tends to raise its degree of return comovement even if its fundamentals stay the same (e.g., (Barberis et al., 2005; Claessens & Yafeh, 2013). Investors may group stocks into different categories based on their market capitalization or industry characteristics and allocate funds to specific groups to simplify portfolio decisions (L. K. C. Chan, Lakonishok, & Swaminathan, 2007; Fodor, Jorgensen, & Stowe, 2021). Suppose some of these investors are noise traders with correlated sentiments, and their trading affects prices. As they move funds from one category to another, it will create a demand for all stocks in the new category, resulting in comovement (Barberis & Shleifer, 2003). The comovement can also result from the habitat view when many investors prefer to trade on a specific subset of all available stocks due to transaction costs, insufficient information, or restricted regulation (Wahal & Yavuz, 2013). These investors may create a common factor in stock returns of these subset firms, leading to comovement in returns. Another reason for the comovement could attribute to the information diffusion that certain equities reflect market-wide information more rapidly than others (K. Chan & Chan, 2014; K. Chan & Hameed, 2006).

My contribution to this literature is in showing that common ownership has a significant impact on return comovement and that this impact is consistent with correlation in fundamentals or trading demands.

2.2. The effect of common ownership on comovement

Much of the prior studies focus on the anti-competitive effects of common ownership. They show that common owners are more likely to reduce competition and motivate coordination among commonly owned firms to increase their combined portfolio value. He and Huang (2017) discover that firms with common ownership grow market share significantly faster and engage in more explicit collaborations through joint ventures, strategic alliances, and acquisitions with other commonly owned firms. Chemmanur et al. (2016) investigate the role of common ownership in forming strategic alliances between industry peers and find a greater number of co-patenting patents among commonly owned firms. Kostovetsky and Manconi (2018) find that firms receive more citations among firms that share common owners around the Russell 1000/2000 index boundary or the mergers of their financial institution, indicating the facilitation of innovation diffusion among their portfolio firms. This paper examines whether increased coordination among commonly owned firms bides their earnings together, thus increasing their return comovement.

Park et al. (2019) investigate information disclosure among commonly owned firms and find that common ownership can lead to more earnings disclosure, thus higher market liquidity measured by Amihud (2002)'s approach and lower bid-ask spread. Disclosure is higher with the larger proportion of same-industry firms who share common owners. More firm-specific information released to the market can reduce the market return variation. However, Park et al. (2019) also find that firms disclose more when one of the commonly-owned firms experiences temporary (and exogenous) loss of public information from analyst coverage due to, for example, a broker closure or merger. Massa and Žaldokas (2017) show that lenders in commonly owned firms learn common owners' behaviour to make decisions. These findings suggest a potential correlation in earning news and thus returns among commonly owned firms. This paper adds to this literature on common ownership effects by investigating whether more information disclosure and potential correlated news among common ownership impact their comovement in returns.

Prior studies have investigated the institutional-based comovements in stock returns between firms in the same portfolio. For example, AntÓN and Polk (2014) find that price pressure following liquidity shocks of mutual funds during the 2003 trading scandal results in excessive comovement among large firms in the same portfolio, consistent with (Coval & Stafford, 2007; Lou, 2012). Fricke and Savoie (2017) extend AntÓN and Polk (2014)'s study to a larger set of funds and small firms and find consistent results. Jotikasthira, Lundblad, and Ramadorai (2012) demonstrate that liquidity shocks to mutual funds cause comovement between the markets they invest in. Gao, Moulton, and Ng (2017) provide empirical evidence of return predictability across firms with the same institutional ownership. According to Bartram, Griffin, Lim, and Ng (2015), a company's stock return is greater when institutional investors have strong returns on overseas stocks. These preceding studies mainly show that correlation in different firms in the same common fund portfolio is primarily due to fund flow shocks. My research differs from the prior studies in that it focuses on the effects of institutional investors on portfolio firms in the same industry. The effects of common ownership on firms in the same industry are expected to result from a deeper understanding of the common owners in that industry, which may cause a correlation in fundamentals between firms. I also examine if common ownership can impact stock prices even when there are no liquidity shocks to fund flows.

Edmans et al. (2014) theoretically prove that common ownership can affect return comovement of commonly owned firms, even when their fundamentals are independent. Assume that liquidity shocks force common owners to sell a portion of their portfolio. If the common owners choose a balanced exit and sell both firms, the prices of both firms will fall. In contrast, if common owners choose an unequal exit, the value of the sold firm decreases while the value of the retained firm increases. In general, the correlation is positive in the case of a balanced exit and negative when the probability of an imbalanced exit is sufficiently high. The direction of comovement depends on the probability of an imbalanced exit determined by the severity of the agency problem. If the blockholder uses a balanced exit strategy, the firm of a working manager is sold if the other manager is slack, lowering the incentive for the first manager to work. If the blockholder uses an imbalanced exit strategy, the firm of a working manager will not be sold in the liquidity shock of the blockholder, but only the other firm, increasing the incentive for the first manager to work. Whether the common owners choose a balanced or imbalanced exit, the comovement of these firms' returns will be affected. Motivated from this study, this paper empirically tests whether common ownership impacts comovement in returns between same-industry firms.

2.3. Hypothesis development

Common ownership is more likely to increase comovement for several reasons. First, common ownership is a mechanism for blockholders to execute joint control across firms, facilitating coordination. By serving on the boards of directors of both firms, common owners can mitigate information asymmetry, lowering the risk of expropriation due to incomplete contracts and aligning the incentives of both parties. Coordination can happen in the form of strategic alliances, intercorporate resource allocation, or research and development (He & Huang, 2017). Such coordination allows commonly owned firms to reduce production and distribution costs, eliminate duplication of research and development efforts, and improve product market competitiveness. These strategic benefits for all contracting parties create a potential correlation in their projected earnings; as a result, increasing comovement in returns of these firms.

Second, firms are likely to issue more earnings and capital expenditure forecasts when one of its commonly owned firms experiences a temporary (and exogenous) loss of public information from analyst coverage due to, for example, a broker closure or merger. It implies that the earnings of one commonly owned firm can have implications on the earnings of other firms with the same common owners. In other words, there is a potential correlation in earnings news among commonly owned firms. Moreover, high earnings announcements resulting from common ownership are associated with increased stock liquidity of all these firms (Park et al., 2019). An increase in liquidity comovement is likely to be followed by an increase in return comovement, and vice versa. The reason is that many determinants of liquidity comovement are also determinants of return comovement. Besides, a loss in market liquidity tends to raise future expected market returns, resulting in a negative concurrent market return. This higher liquidity comovement will lead to high return comovement.

Third, common ownership can affect comovement in stock returns through their exit strategy. The price of both firms will fall if the common owners choose a balanced exit and sell both firms. Moreover, it also pulls down the performance of both commonly owned firms as the firm of a working manager is sold even if he works hard when the other manager is slack, reducing his incentive to work (Edmans et al., 2014). Based on the discussion above, my first hypothesis is as follows.

H1A. Common ownership between pairs of same-industry firms increases comovement in returns of the pairs.

On the other hand, common owners can choose an unbalanced exit. Common owners will sell the firms of slacked managers only and retain the firms of working managers upon their liquidity shocks. This option reduces the value of the sold firm while increasing the value of the retained firm, creating negative relation in their stock returns. Thus, the alternative hypothesis is as follows.

H1B. Common ownership between pairs of same-industry firms reduces comovement in returns of the pairs.

3. Data selection and summary statistics

I collect data from several sources and construct a sample for U.S. firms from 1990 to 2019 to investigate the effects of common ownership on pairwise correlation in stock returns. To identify which firm has common ownership each year, I first extract data on institutional blockholders and industry concentration from Thomson Financials 13F database. The common ownership data is then merged with the stock price data from CRSP to estimate the pairwise correlation.

3.1. Common ownership data

I obtain the data on institutional holdings mainly from Refinitiv (formerly known as Thomson Reuters). For the period from 1990 to March 2013, I collect data from the Refinitiv 13F Institutional Holdings dataset and supplement missing information with raw data from EDGAR's 13F filings. Since 2010, Refinitiv's legacy systems, which generate Mutual Fund and 13F ownership data, began losing and corrupting data.[2] WRDS worked with Refinitiv to correct the data deficiencies and incorporate them into the WRDS SEC Analytics Suite – 13F Holdings dataset. Therefore, I rely on this data source for the June 2013 – 2015 period.

I clean the data following several criteria. First, I filter out cases where a manager reports multiple positions in the same stock on the same report date and use only the holdings with the latest filing date. Second, I identify the ten largest institutions each year using the 13F data on total assets under management. Refinitiv records institutional holdings at the institution level.[3] For each of these institutions, I check for missing quarters – quarters in which the institution should own shares, but Refinitiv does not show it – and supplement them using the raw 13F data provided on EDGAR.[4] Additionally, I confirm that the holdings of these ten largest institutions are consistent between the Refinitiv Institutional 13F Holdings dataset and the WRDS SEC Analytics Suite – 13F Holdings dataset for the matching year of 2013. This step ensures that no significant change in holdings occurs between the end of the Thomson data and the start of the WRDS data. For institutions not included in the top ten largest, holdings are carried forward one quarter in cases where the institution misses a reporting period to make up for reporting gaps (Griffin & Xu, 2009).

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[2] See information on the WRDS website regarding problems of this data in the recent years: https://wrds-www.wharton.upenn.edu/pages/support/research-wrds/research-guides/research-note-regarding-thomson-reuters-ownership-data-issues/.

[3] Refinitiv reports the ownership for the holdings typically above 10,000 shares or $200,000 and excludes cases which are potential confidentiality issues, unmatched to a master security file, and have more than one manager share control.

[4] As discussed in Lowry, Rossi, and Zhu (2019), EDGAR only contains 13F filings for 1999 and later, thus restricting this process to this period. This step led to the data supplement of Barclay in 2003Q4, AXA in 2003Q4, Mellon in 2008Q4, JP Morgan in 2008Q3, and Blackrock in 2010Q1 and Q2.

Third, I aggregate institutional holdings at the fund-family level to match the institutional feature of voting and governance among member funds following Azar, Schmalz, and Tecu (2018). The aggregation ensures that the incentives of all members in a fund family are consistent and align with their investors' incentives.[5] Forth, I compute each manager's holdings in a firm by aggregating holdings of that manager in all stocks with the same six-digit CUSIP. Last, institutional investors are defined as block-holders if they hold at least 5% of firm outstanding shares. An institutional investor is considered as a common owner when it simultaneously holds blocks of shares in more than one firm in the same three-digit SIC codes from CRSP (following Lewellen and Lowry (2021) at a given point in time (as defined by He and Huang (2017)).

3.2. Pairwise common ownership

Common ownership is formed among same-industry firms with at least one institutional shareholder who holds a minimum of five percent ownership in both firms. Figure 1 depicts a common ownership formation scenario. Assume the market has two industries (X and Y) and four institutional investors (A-D). Firms are designated by the letters X1 through X4, as well as Y1 and Y2. An arrow indicates that an institutional investor owns at least 5% of a firm. The lack of an arrow indicates no direct ownership of more than 5% between the institution and a specific firm. Thus, there are three pairs of common ownership in industry X: those between firms X1-X2, X1-X3, and X2-X3, and none in industry Y. Four pairs with non-common ownership are X1-X4, X2-X4, and X3-X4 in industry X, and Y1 – Y2 in industry Y.

[Insert Figure 1 about here]

To measure the effects of common owners on a pair of firms, I apply the measure of Gilje et al. (2020). Assuming there are I common owners between two firms A and B. First, I measure the effect of all common owners on firm A in relation to firm B. I form a product of three components: Firm A's proportion in the portfolio of common owner i, the stakes of common owner i in firm A and in firm B. Then, I aggregate the products across all common owners between two firms to get the measure for firm A.

$$GGl(A,B) = \sum_{i=1}^{I} \beta_{i,A} * \alpha_{i,A} * \alpha_{i,B} \quad (1)$$

where $\beta_{i,A}$ represents the proportion of firm A in common owner i's portfolio. $\alpha_{i,A}$ and $\alpha_{i,B}$ represent owner i's ownership percentages in each firm. I compute the ownership percentages using blockholdings only since blockholders have feasible channels to affect managers' utility (via

[5] These family funds include Fidelity, Invesco, Capital Research, Merrilyn, and Blackrock

voting, stock selling, or negative public statements). The proportion of firm A in common owner i's portfolio is computed as $\alpha_{i,A}\bar{v}_j/(Y_i + \sum_{m=1}^{M} \alpha_{i,m}\bar{v}_m)$, where M is the number of firms in common owner i's portfolio; $\bar{v}$ is firm market value; and $Y_i \geq 0$ captures non-traded assets, T-bills, or any other assets of common owner i. Thus, $\beta_{i,A}$ measures the weight of firm A in the portfolio of investor i.

Second, I follow the same procedure to compute the effect of all common owners on firm B in relation with firm A as:

$$GGl(B, A) = \sum_{i=1}^{I} \beta_{i,B} * \alpha_{i,A} * \alpha_{i,B} \quad (2)$$

Last, the pairwise common ownership is measured as the average effect of all common owners on the pair of firms A and B:

$$\text{PairGGL} = \frac{1}{2}\big(GGl(A, B) + GGl(B, A)\big) = \frac{1}{2}\sum_{i=1}^{I} \alpha_{i,A} * \alpha_{i,B} * (\beta_{i,A} + \beta_{i,B}) \quad (3)$$

PairGGL is first computed using quarterly data and then averaged across four quarters in a fiscal year to get the annual measure.

A high degree of common ownership between firm pairs implies close attention of common owners to the performance of the firms in pairs and great attention of those firms' managers to common owners' references. The measure accounts for comprehensive attention between common owners and firm management. The primary advantage of this measure over He and Huang (2017)'s and Lewellen and Lowry (2021)'s measures is that it is not predicated on the assumption that investors are fully attentive to managers' actions or $\beta = 1$. Common owners pay more attention to firms representing a large proportion in their portfolios. Less attentive investors will not shift managerial efforts, as so for firm decisions. Similarly, firm managers care more about the preferences of common owners who hold more shares in their firms. The ownership of common owner i in firm B representing the knowledge common owner I can acquire from owning another same-industry firm.

3.3. Pairwise comovement

I construct the first measure of pairwise comovement between two firms by following Morck et al. (2000)'s method and adjusting for within-US study. In particular, I observe the number of days that stock prices of each pair of firms move in the same direction and divide it by the total number of days in which both firms move in either direction. Considering two firms i and j, the stock comovement is given as

$$f_{i,j} = \frac{\sum_t \left(n_{i,j,t}^{up} + n_{i,j,t}^{down}\right)}{T_{i,j}} \quad (4)$$

where $n_{i,j,t}^{up}$ ($n_{i,j,t}^{down}$) is equal to one if both returns are positive (negative) for day t, and 0 otherwise; and $T_{i,j}$ is the number of days in a fiscal year in which both returns move in any direction. Thus, $f_{i,j}$ is equal to one (zero) if the two firms always move in the same (opposite) directions. Besides, I exclude days where either return stays the same to avoid any bias caused by non-trading of illiquid stocks as mentioned in Morck et al. (2000).

The second measure is the correlation coefficient between the returns of two paired firms as:

$$C_{i,j} = \frac{Cov(i,j)}{\sqrt{Var(i).Var(j)}} \quad (5)$$

where $Cov(i,j)$ is the covariance between the daily returns of firm i and j for all days in a year. $Var(i)$ and $Var(j)$ is the variances of firm i's and firm j's daily returns. Similarly, I exclude days where either return remains unchanged to make it consistent with the first measure.

The first measure of pairwise comovement, $f_{i,j}$, expectedly captures time-period-specific shocks and depends on the number of days where two returns move alongside. The pairwise correlation coefficient, $C_{i,j}$, reveals both the direction and magnitude of the two returns' movement. As a result, a significant time trend affecting both firms uniformly can exaggerate the overall comovement, causing their prices to move in the same direction over time. To address this concern, I use simple linear regression to detrend the returns data (Khanna & Thomas, 2009). For each firm, I find the value of its average trend over the year and measure the difference between the actual daily return and the predicted daily return using the estimated trend and the previous day's price. The detrend data capture the deviation in daily stock prices of a firm from its own underlying trend. Finally, I use this detrended return to construct two pairwise comovement measures defined above, denoted $f_{i,j}^d$ and $C_{i,j}^d$. The main results with the dependent variable are based on the returns data without detrending, $f_{i,j}$ and $C_{i,j}$, and are robust using detrended data.

3.4. Control variables

I control for variables that affect the co-movement between a pair of firms, including product similarity, analyst coverage, market value, industry concentration, industry volatility, and industry size. Industry volatility and industry size are constructed at industry level, while other variables are constructed at pair level.

First, pair product similarity is a continuous variable equal to the similarity in products between two firms. I use the similarity score from (Hoberg & Phillips, 2016) to capture the extent to which a firm produces similar products to their competitor[6]. The pairwise similarity score between firm i and firm j is equal to one minus the cosine distance of vector Vi and Vj, where Vi is the vector of firm i's product description reported in its annual 10-K report. Intuitively, the score is higher when firm i and j use more of the same words. Firms with high product similarity are more likely to be correlated in stock returns because they are more likely to subject to the same source of variation.

Second, analysts typically cover similar firms in the same industry to lower their marginal cost of information gathering and the firm's investment opportunity (Bhushan, 1989). Analysts will choose not to cover a company if it has marginal costs and poor growth prospects. These analyst coverages are also expected to provide effective coverage in monitoring managerial behaviour and providing adequate information to investors. As a result, firms with a higher number of analysts in common are more likely to have synchronous returns. Third, like An and Zhang (2013), I control for the effects of firm size which is the average market capitalization of two firms. Firms with similar size are likely to have higher comovement.

Forth, pair industry concentration is the Herfindahl-Hirschman Index, proxy for the level of industry concentration. A more concentrated industry faces less competition and higher correlation in stock returns (more likely to correlate in fundamentals). Roll (1992) finds that high industry or firm concentration, as captured by such Herfindahl indices, contributes to the high volatility of certain stock market indices. Fifth, industry volatility is the standard deviation of returns for each 3-digit SIC industry. Industry volatility reflects the return comovement of stocks in that industry with the market. High industry volatility is likely to associate with high pairwise comovement (K. Chan, Hameed, & Kang, 2013). Sixth, as in Morck et al. (2000), I control for industry size by including the logarithmic number of stocks within a 3-digit SIC industry.

According to Khanna and Thomas (2009), director overlap - the number of directors seating on the boards of both firms divided by the average size of two boards – positively affects their pairwise comovement. They suggest that director interlocks facilitate coordination across firms by reducing hold-up problems and fostering growth. However, I do not include this variable in the model because such interlocking directorates are prohibited under the Antitrust laws if firms compete. The pairs of firms in the sample are from the same industry, so mainly subject to these laws. Empirically, the same industry firms in the sample with common directors are less than 1%.

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6 Product similarity data is available at https://hobergphillips.tuck.dartmouth.edu

3.5. Summary statistics

Table 1 shows the summary statistics. The data set contains 2,922,925 pairwise observations where the two firms have at least one common institutional owner from 1990 to 2019. The comovement measure is truncated in [0,1], while the correlation is bounded from -1 to 1. On average, firms are more likely to move in the same direction. A medium pair of firms in the sample moves in the same direction 55.2 percent of the time and has a correlation coefficient of 0.111, comparable with those of Morck et al. (2000). After removing the average trend in stock return of both firms over the year, the comovement and correlation for a median firm in the sample are 0.606 and 0.282, respectively.

[Insert Table 1 about here]

The sample contains 293 3-digit SIC industries and a total of 10,498 firms. Each year, these firms generate 19,137 firm pairs with common ownership and 78,947 firm pairs without common ownership. However, there is a high skewness in the distribution of firm pairs across industries. Industries with the highest number of firms, such as computer and data processing services, drugs, and electronic components and accessories, also have the largest number of firm pairs. Table 2 provides the list of industries with the greatest number of firm pairs. A typical industry has 36 firms, resulting in 65 firm pairs with common ownership and 269 without common ownership. On average, the ratio of firm pairs with and without common ownership in an industry is one-fourth.

[Insert Table 2 about here]

To facilitate the interpretation of PairGGL as a relative measure, I rescale PairGGL to have a mean of 1 (rescale by its sample average) for all pair firms with common ownership. Thus, a value of one indicates the average level of incentives, and a value of two represents twice the average level of incentives. An average firm pair in the sample has a PairGGL measure equal to one with a standard deviation of 4.731, respectively. Pairs of firms in the 99th percentile have a PairGGL of 38.265. Panel B shows that overall, firm pairs with common ownership on average have higher comovement and correlation than firm pairs without common ownership.

The average market capitalization, industry concentration and product similarity of an average firm pair are 3,809 million dollars, 0.0165, and 7.7%, respectively. An average firm pair operates in an industry with a volatility of 0.065 and a log number of firms of 5.884. Industry volatility reflects the return comovement of stocks in that industry with the market. High industry volatility is likely to associate with high pairwise comovement (K. Chan et al., 2013).

4. Empirical results

4.1. Logistic transformation

Since the dependent variables, comovement measures $f_{i,j}$ and $f_{i,j}^{d}$, are truncated on $[0,1]$, I follow Morck et al. (2000) to transform these measures using a logistic transformation, avoiding the econometric issue of data that are potentially censored at the boundaries. I also use the same method to transform the other dependent variables, correlation $C_{i,j}$ and $C_{i,j}^{d}$ that are bounded on [-1,1]. In robustness analyses, I confirm that transforming correlation measures using logistic transformation makes no significant difference from the Fisher transformation applied in Li (2002).

I estimate different specifications of the following equation:

$$PairwiseComovement = \alpha_0 + \alpha_1 CommonOwnership_{i,j} + \alpha_2 Controls_{i,j}$$

$$+IndFE_{i,j} + TimeFE_{i,j} + \varepsilon_{i,j} \quad (6)$$

where $PairwiseComovement$ measures are the log transformation of $f_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}$ or $C_{i,j}^{d}$. $CommonOwnership_{i,j}$ is PairGGL measuring common ownership effect on firm managerial incentives between two firms i and j. PairGGL is computed by aggregating the effects of all common institutional owners between two firms who hold at least 5% ownership in each firm. Control variables include pair product similarity, pair industry concentration, pair MV, pair analyst coverage, industry volatility, and industry size, which are explained in the next section. The model also controls for year and industry fixed effects. The standard errors are clustered by industry to control for the possible correlation in residuals between pairs of firms in the same industry.

Because any common owner of this firm-pair could be common owner of other firm-pair as well, the error terms for these firm-pair observations will be correlated and bias the coefficient estimators. Thus, I apply the non-parametric bootstrapping method to determine the significance of estimated coefficients. The method creates a new dataset by sampling with replacement of the original dataset which is then used to obtain another set of estimators. When the sample size gets larger, the distribution of sample means approximates a normal distribution regardless of the population's distribution.

The specific procedure includes creating an empirical distribution for each of the coefficients under a null hypothesis that common ownership does not affect pairwise comovement. I then compare the estimated coefficient from the OLS regression to the empirically generated distribution. The empirical distribution of coefficient estimates under this null is produced as follows. First, I construct a matrix where its rows and columns are the 1st and 2nd firms in each pair. The matrix elements are the dependent variable observations of comovement for each pair. The rows and columns of the matrix are then rearranged with the same permutation. The dependent variable observations are reassigned to the independent variables. This technique preserves any dependency between elements in the same row or column (firm-level effects) but removes the predicted relationship between the dependent and independent variables. Following that, the coefficient for each variable is computed using the new permutation. For each regression, I perform 100 permutations. The computed coefficient under the alternative hypothesis of a significant relationship is explained in the following manner. I assert that there is a significant correlation between the two variables given the error structure if the coefficient is located sufficiently far within one tail of the distribution generated by the null, and the independent variable can explain some of the observed variation in the dependent variable.

This approach is conceptually like traditional hypothesis testing, except that instead of imposing a theoretical distribution centered on the estimated coefficient, the actual data are utilized to generate a distribution centered on the null. Rather than asking whether zero is substantially different from the predicted coefficient based on theoretical distribution characteristics, I question if my estimated coefficient is significantly different from the center of the empirical distribution under the null. For evaluating hypotheses in multiple regression analysis utilizing pair-level data, this technique outperforms standard least squares (Krackhardt, 1988). An alternate technique would be to add firm fixed effects, although this would diminish the estimation's efficiency. Another option is to employ a generalized least squares technique, which would entail placing some structure on the covariance matrix. A third option is to assume independence in OLS and cluster the mistakes by company in the pair (P.Ciarlini & Pavese, 1994).

4.2. OLS regression results

Tables 3 to 5 present the results on the effects of common ownership on pairwise correlation. I first divide the sample into two groups with and without common ownership to observe the difference of common ownership effects between two groups on comovement. Table 3 shows that a firm pair with common ownership is predicted to move in the same direction 3.5% more often than a pair without common ownership. In addition, when firm pairs share common ownership, their returns are 7% more correlated than when they do not.

[Table 3 is about here]

Table 4 reports the OLS regression results estimating Equation (1). Columns (1) and (3) show the linear relationship between common ownership and pairwise comovement measures.

Columns (2) and (4) add control variables that may affect the likelihood of common ownership in both firms and the pairwise comovement. All regression models include the industry fixed and year fixed effect to control constant effects across industry and year. The standard errors are clustered by industry and year. The main independent variable, PairGGL, is winsorized at the first and 99th percentiles to reduce the effect of outliers in all tables.

[Table 4 is about here]

The coefficients of PairGGL across four regression models show that common ownership between a pair of same industry firms is positively associated with both measures of pairwise comovement, supporting hypothesis 1A. In terms of economic magnitude, a one-unit increase in PairGGL (or incentives level) will increase 0.3% comovement and a 0.4% correlation in stock returns of firms in a pair. A pair of firms with similar products, large size, and more analyst coverage are more likely to comove in stock return than firms with low product similarity, small size, and less analyst coverage. However, firm pairs in highly concentrated industries are less likely to comove than firm pairs in low industry concentration.

Table 5 shows that the positive relationship between common ownership and pairwise comovement is robust at a 1% significant level after controlling for the common trend in stock returns between two firms.

[Table 5 is about here]

4.3. Endogeneity issue

While the results show that common ownership increases comovement in returns, comovement in returns may also influence the likelihood of common ownership, causing reserve causality issue. For instance, institutional investors may proactively target same-industry firms with a high correlation in stock returns to create common ownership. Moreover, unobservable firm characteristics may also affect the likelihood of common ownership that, at the same time, determine the comovement in stock returns for commonly owned firms, resulting in a spurious correlation between the two.

To address these potential endogeneity biases, I implement a difference-in-differences (DID) analysis around the mergers of large financial institutions as an external shock to firms' common ownership levels (He & Huang, 2017). The mergers between financial institutions often occur for reasons unrelated to the fundamentals of their portfolio firms; thus, it could be used as an external shock to the firm's common ownership level. Although some firms may have common ownership before the merger, Lewellen and Lowry (2021) show that institution mergers cause substantial and lasting increases in the level of common ownership for the pairs of affected firms. New common owners also have new and different effects on managerial incentives compared to current common owners in those firms. It is less likely that other common owners in those firms before the mergers exit the firms during the mergers. Thus, mergers between financial institutions can serve a strong instrument to identify the effect of common ownership on firm performance as well as return comovement.

Prior studies also apply three other approaches to address the endogeneity issues, which are the Blackrock/BGI merger, additions to the S&P500 index, and reconstitutions of Russell 1000/2000 indices. However, these approaches are likely not appropriate to use as an exogenous shock to the common ownership level due to obvious concerns about endogenous index inclusion. Moreover, being added to the S&P500 index affects many types of institutional ownership in firms, which is inherently difficult to distinguish. Index additions allow index-tracking institutions to increase their ownership in the added firms, raising the firm's total institutional ownership and common ownership with other portfolio firms but reducing the ownership of other blockholders. On the other hand, Russell index reconstitutions are more transparent and based on market capitalization alone, thus causing fewer endogenous issues about index inclusion. However, Lewellen and Lowry (2021) find that the reconstitutions do not affect the level of common ownership, which disqualifies them as an instrument for this study. Russell reconstitutions are more likely to affect the holdings of mutual funds that track the Russell indices rather than 13F institutions (Schmidt & Fahlenbrach, 2017).

I construct both treatment and control groups around the financial institution mergers. The treatment group contains pairs of firms in the same industry (the same 3-digit SIC industry); each firm is block-held by one institution before the merger announcement. I use the same list of mergers from Lewellen and Lowry (2021). Thus, there are 51 mergers from 1990 to 2010 satisfying the condition. The treatment group consists of 1,588 firms collectively from 51 mergers (firms in which both partners hold a block are deleted), forming 1,277 firm pairs with common ownership (combinations). After requiring that ownership data is available in the years prior to the effective date of the merger, these numbers drop to 1,142 pairs in the period of one year before and after the mergers, 846 in the period of two years before and after the merger, and 841 in the period of three years before and after the merger.

I construct the control group by forming a control pair for each treatment pair. I first construct pair of firms in the same merger but belong to two different industries (2000 firm pairs). Then I match these firm pairs to a treatment pair based on their average market capitalization.

Moreover, one of the firms in the control pair is in the same industry as the treatment pair (thus, the control pair is from a different merger with the treatment pair). Each treatment pair can have up to three control pairs with replacement based on its nearest average market capitalization. This matching process ensures that both treatment pairs and control pairs experience the same effect from a merger or a new combined institution. However, the treatment group consists of firms in the same industry, whereas the control group consists of firms from two different industries. The control group consists of 2,000 firm pairs in which the target holds 1,000 firms and the acquirer holds 1,000 firms. Figure 2 illustrates the construction of both groups.

[Insert Figure 2 about here]

The number of control pairs reduces after computing their comovement measures. Dependent variables are the measures of comovement in stock returns of each pair and are the average of one year, two years, or three years of data before and after the mergers. All control variables are computed in the same way as the dependent variable. The short window allows to observe the effect more accurate without too much noise that is irrelevant to the events. On the other hand, the long window allows to capture meaningful changes in returns comovement in response to the exogenous changes in common ownership.

[Insert Table 6 about here]

Table 6 shows the results without control variables in panel A and with control variables in panel B. The regressions include firm and year fixed effects for one-year data in columns 1 and 2, and only firm fixed effects in columns 3 to 6 as the data are averaged for two years and three years around the institution mergers. The inclusion of firm fixed effects in the DiD estimation framework largely mitigates the concern about time-invariant industry-specific effects (to the extent that firms do not switch industries) and omitted variables that are correlated with both returns comovement and common ownership. I cluster standard errors at the firm level.

Moreover, the settings also allow me to observe the excessive comovement between same-industry firms and different-industry firms those shares the same common owners. The mergers create a significant shift in the level of common ownership between a firm pair in the same industry, where each firm is block-held by one party before the merger. Thus, the treatment sample consists of firms whose ownership linkages with same-industry firms are likely to increase just because of the merger. On the other hand, the control sample consists of other block-held firms in the same institution's portfolio that are unlikely to experience such changes. I find evidence that treatment firms, relative to control firms, experience an approximately five to ten percent larger increase in return comovement surrounding the institution mergers, which rules out the mechanical effect of common ownership.

5. Robustness tests and further analysis

5.1. Tobit regression

Since my dependent variables ($f_{i,j}$, $C_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}^{d}$) are truncated, I apply the Tobit regression following Khanna and Thomas (2009) to conduct the robustness test for the relationship between common ownership and pair-wise comovement. The advantage of this method over the logistic transformation (Morck et al., 2000) and the Fisher transformation Li (2002), is that it allows to include observations on either boundary. I re-estimate different specifications of the equation (6):

$$Pairwisecomovement = \alpha_0 + \alpha_1 CommonOwnership_{i,j} + \alpha_2 Controls_{i,j} + \varepsilon_{i,j} \quad (7)$$

where $PairwiseComovement$ measures are the log transformation of $f_{i,j}$, $f_{i,j}^{d}$, $C_{i,j}$ or $C_{i,j}^{d}$. $CommonOwnership_{i,j}$ is a pairwise common ownership between two firms i and j as computed in Section 3.2. Control variables are defined the same as in Equation (6). The regression includes $IndustryConcentration_{i,j}$ measured by the Herfindahl-Hirschman Index to proxy for the level of industry concentration. Firms within the same industry are more likely to correlate in fundamentals. However, adding an industry fixed effect in the Tobit model may cause biased estimates. Thus, I include this variable to proxy for the effect of different industry on price comovement. A more concentrated industry has less competition and higher correlation in stock returns. αs are vectors of estimated coefficients, and $\varepsilon_{i,j}$ is a pairwise error term.

[Table 7 is about here]

Table 7 shows that the results are robust and consistent with the main finding that common ownership is associated with positive comovement in stock returns between a pair of commonly owned firms.

5.2. Product Similarity

The increase in comovement due to common ownership is consistent with several possible mechanisms. One channel through which common ownership could increase comovement in returns is through correlation in earnings news (Massa & Žaldokas, 2017; Park et al., 2019). The second channel is through the exit effects of common owners on the stock returns of both firms in pairs (Edmans et al., 2014). Common ownership can also increase the return comovement by motivating the coordination between firms in a pair. Chemmanur et al. (2016) show that common ownership encourages more explicit collaborations between firms through strategic alliances with a greater number of co-patenting patents and citations among these firms.

This section investigates the third channel, whether common ownership is more likely to increase comovement through coordination between a pair of firms in relation to the level of product similarity. Pairwise common ownership may affect comovement between firms that are in the same industry but not close in product space. When firms are closer in the technology space, technology spillovers among commonly owned firms within the same industry may have more pronounced benefits as the larger the number of firms can benefit from the technological innovations. When innovation lowers marginal costs in the industry so much as to increase industry output, common ownership may even increase welfare.

However, when commonly owned firms are closer in product space, common ownership may instead harm innovation. The reason is that firms whose shareholders own stakes in other same-industry firms selling similar products are less willing to invest in innovation because doing so would steal business away from those other firms. Furthermore, when technological spillovers are relatively small, there is no free-riding problem that common ownership can mitigate. In that case, innovation is a costly tool that improves firm productivity and steals business from competitors, which is more favourable for undiversified shareholders (and consumers) than common owners. In such a situation, more common ownership leads to lower innovation, lower output, and lower welfare. Thus, common ownership may create more binding value between firms with less similarity in their products, positively affecting comovement in their returns. In contrast, firms with high product similarity create less value from innovation collaboration. Therefore, they may have less comovement in stock prices.

[Insert Table 8 about here]

[Insert Table 9 about here]

Tables 8 and 9 show the effects of common ownership on pairwise comovement in relation to their product similarity. While table 8 uses the interaction term between the common ownership measure PairGGL and Pair_product_similarity, table 9 divides the sample into two subsamples containing firms with high and low product similarity. Table 8 shows that the effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their products. This negative relationship implies that the higher product similarity, the less effect of common ownership on pairwise comovement. Table 8 demonstrates that the effect is stronger in firm pairs with low product similarity than in high product similarity.

6. Conclusion

Comovement in returns is an important determinant of market risk and stability. My main finding is that increased common ownership leads to greater comovement in returns. In terms of economic magnitude, a one-unit increase in PairGGL (or incentives level) will increase 0.3% comovement and a 0.4% correlation in stock returns of firms in a pair. This is consistent with the idea that the market views common ownership as a mechanism to exercise joint control. The results are robust after controlling for time trends and various empirical specifications. The effect of common ownership on pairwise comovement is more pronounced between firms with less similarity in their product. This negative relationship implies that the higher product similarity, the less effect of common ownership on pairwise comovement. My study is consistent with previous studies, which suggest that comovement at the market level is due to correlated fundamentals and blurred firm boundaries (Bertrand et al., 2002; Khanna & Thomas, 2009). Common ownership serves as a mechanism for joint control across firms. The market considers firms with common ownership relevant, possibly because it allows for coordination in firm activities, efficient resource allocation, and cross-monitoring (He & Huang, 2017; Morck et al., 2000).

My findings are important for both market participants and policymakers. My result that common ownership leads to increased comovement in returns may deepen the U.S. government's current concerns on the market impacts of common ownership. The increasing likelihood of shocks spreading across stocks due to common ownership may impact systemic risk and the propensity for flash crashes. Moreover, comovement in returns is a source of systematic risk that affects expected return premiums. Therefore, high comovement between firms with common ownership can raise their cost of capital and influence the actual economy through their investment levels. If all firms eventually become collectively controlled by a single institution, the impact of common ownership on market stability should become readily obvious.

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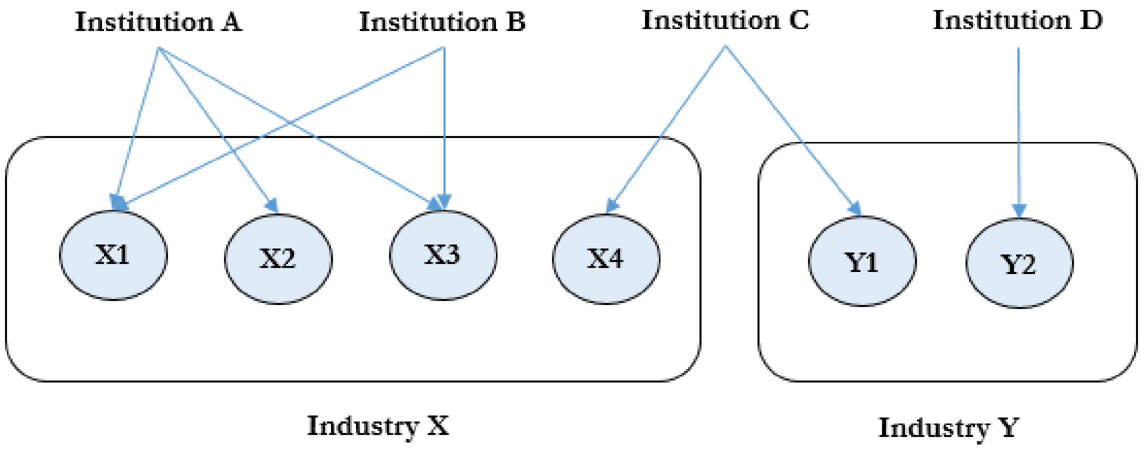
Figures and tables

Figure 1: Sample Construction of Common Ownership

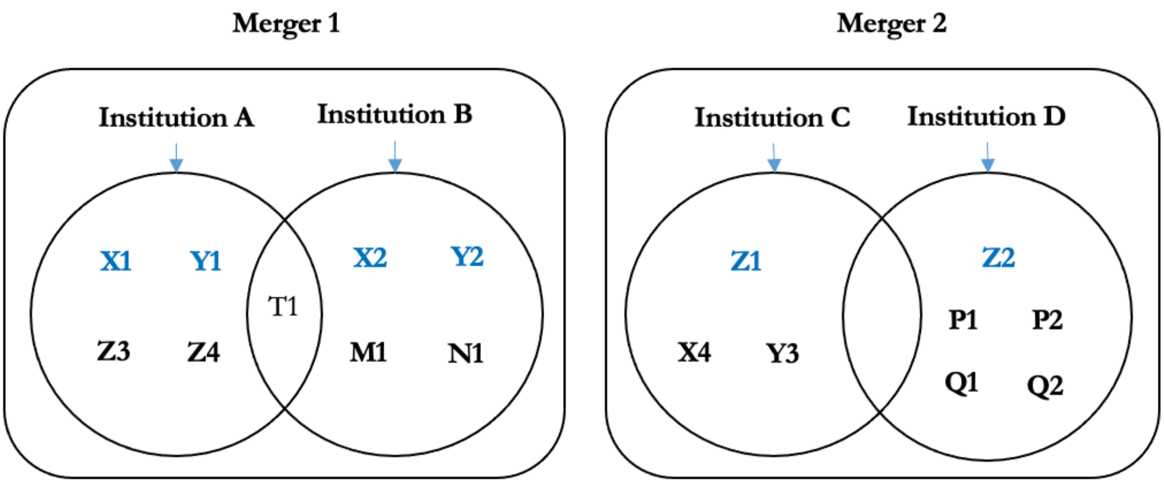
Figure 1 illustrates the sample construction for common ownership. Assume the market has two industries (X and Y) and four institutional investors (A-D). Firms are designated by the letters X1 through X4, as well as Y1 and Y2. An arrow indicates that an institutional investor owns at least 5% of a firm. The lack of an arrow indicates no direct ownership of more than 5% between the institution and a specific firm. Thus, there are three pairs of common ownership in industry X: those between firms X1-X2, X1-X3, and X2-X3, and none in industry Y. Four pairs with non-common ownership are X1-X4, X2-X4, and X3-X4 in industry X, and Y1 – Y2 in industry Y.



Pair-level analyses:
X1 – X2: common owner A
X1 – X3: common owner A and B
X2 – X3: common owner A

Figure 2: Sample Construction of Common Ownership in Institution Mergers

Figure 2 shows the sample construction of common ownership through the institution mergers. Take example of two institution mergers. Merger 1 is between institution A and B, **whereas** merger 2 is between institution C and D. Firms are noted X1, X2, …, Q2 which are block-held by these four institutions. X1 and X2 are two firms in the same industry X. Thus, there are 3 treatment pairs from two merger 1 and 2. The sample of control pairs is constructed by matching two firms in the same merger but not in the treatment pairs. Each control pair is held by one institutional investor and not in the same industry as the other firm. There are twelve possible control pairs from the two mergers. Each treatment pair is matched with at most three control pairs based on its average market capitalization and where one firm in the control pair belongs to the same industry as the treatment pair (thus the control pair is from different merger with the treatment pair).



Control pairs sample

Merger 1:	Merger 2:
Z3 – M1	X4 – P1
Z3 – N1	X4 – P2
Z4 – M1	X4 – Q1
Z4 – N1	X4 – Q2
	Y3 – P1
	Y3 – P2
	Y3 – Q1
	Y3 – Q2

Treatment pairs	**Control pairs**
X1 – X2	X4 – P1
	X4 – P2
	X4 – Q1
Y1 – Y2	Y3 – P1
	Y3 – Q1
	Y3 – Q2
Z1 – Z2	Z3 – M1
	Z3 – N1
	Z4 – N1

Table 1: Summary Statistics

Panel A shows the summary statistics of all variables, and Panel B shows the main statistics of comovement measures for firm pairs with and without common ownership. F is the measure of return comovement which is equal to one (zero) if the two firms always move in the same (opposite) directions. C is the measure of correlation in return between pairs of firms. Fd and Cd is the detrended measures of f and C reusing simple linear regression to remove the value of its average trend over the year. F_log, C_log, fd_log, and Cd_log are the logistic transformation of f, fd, C, and Cd respectively. PairGGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry.

Panel A:	N	Mean	Std	Min	P1	P10	P50	P90	P99	Max
f	2,922,925	0.561	0.061	0.339	0.448	0.491	0.552	0.643	0.741	0.939
fd	2,922,925	0.575	0.253	0.000	0.063	0.202	0.606	0.890	0.986	1.000
c	2,922,925	0.139	0.147	-0.662	-0.107	-0.017	0.111	0.332	0.618	0.980
cd	2,922,925	0.211	0.485	-0.962	-0.804	-0.509	0.282	0.807	0.929	0.995
f_log	2,922,925	0.249	0.258	-0.668	-0.207	-0.035	0.208	0.589	1.051	2.739
fd_log	2,922,925	0.420	1.509	-16.11	-2.704	-1.371	0.429	2.089	4.272	16.118
c_log	2,922,925	0.289	0.326	-1.594	-0.214	-0.033	0.223	0.691	1.444	4.613
cd_log	2,922,925	0.568	1.275	-3.940	-2.221	-1.124	0.579	2.239	3.303	6.053
PairGGL	2,922,925	1.000	4.731	0.000	0.000	0.000	0.000	0.978	38.265	38.265
Pair_product_similarity	2,628,433	0.077	0.070	0.000	0.000	0.000	0.062	0.173	0.298	0.955
Pair_ind_concentration	2,922,925	0.165	0.125	0.010	0.032	0.050	0.124	0.344	0.562	1.000
Pair_MV (mil)	2,821,355	3,809	16,859	1.857	14.599	76.529	547.01	5,480	75,672	1,060,239
Pair_analyst_coverage	2,922,925	0.083	0.129	0.000	0.000	0.000	0.000	0.267	0.533	1.000
Ind_volatility	2,922,886	0.065	0.041	0.000	0.014	0.027	0.057	0.135	0.179	1.375
Ind_size	2,922,925	5.884	1.060	0.000	2.639	4.489	5.951	7.040	7.153	7.153

Panel B:	Firm pairs with C/O			Firm pairs without C/O		
	N	Mean	Std	N	Mean	Std
f	554,517	0.600	0.065	2,368,408	0.551	0.056
fd	554,517	0.569	0.238	2,368,408	0.577	0.256
c	554,517	0.223	0.164	2,368,408	0.119	0.135
cd	554,517	0.220	0.488	2,368,408	0.209	0.484

Table 1. continued

Panel C: Correlation coefficients									
Variables	**f_log**	**fd_log**	**c_log**	**cd_log**	**Pair GGL**	**Pair_ Ind_ HHI**	**Pair_ MV**	**Pair_ analyst_ coverage**	**Ind_ Volatility**
f_log	1								
fd_log	0.099	1							
c_log	0.840	0.107	1						
cd_log	0.203	0.714	0.234	1					
PairGGL	0.175	0.002	0.175	0.026	1				
Pair_ind_HHI	-0.397	0.010	-0.385	-0.037	-0.124	1			
Pair_MV	0.102	-0.025	0.120	-0.010	0.235	-0.11	1		
Pair_analyst_ coverage	0.441	0.029	0.445	0.085	0.199	-0.332	0.124	1	
Ind_Volatility	-0.121	0.055	-0.097	0.094	-0.059	0.101	-0.060	-0.082	1
Ind_size	-0.217	-0.043	-0.249	-0.075	-0.072	0.108	-0.061	-0.151	0.348

All correlation coefficients in the table are significant at 1% level (p<0.01)

Table 2: Firm Pairs by Industry

This table shows the list of 25 industries with largest number of firm pairs with and without common ownership in the sample.

No.	3-digit SIC	Description	No of firms	No of firm pairs with C/O	No of firm pairs without C/O
1	737	Computer and Data Processing Services	1,175	3,403	24,197
2	283	Drugs	583	2,194	10,130
3	367	Electronic Components and Accessories	395	1,632	6,589
4	384	Medical Instruments and Supplies	381	699	3,534
5	366	Communications Equipment	338	298	2,128
6	357	Computer and Office Equipment	313	314	2,172
7	738	Miscellaneous Business Services	276	227	1,086
8	131	Crude Petroleum and Natural Gas	269	284	1,482
9	481	Telephone Communications	229	99	683
10	382	Measuring and Controlling Devices	189	384	1,106
11	138	Oil and Gas Field Services	171	149	277
12	873	Research and Testing Services	160	166	583
13	581	Eating and Drinking Places	154	210	535
14	809	Health and Allied Services, NEC	131	24	136
15	874	Management and Public Relations	118	56	188
16	371	Motor Vehicles and Equipment	107	152	350
17	491	Electric Services	95	160	263
18	701	Hotels and Motels	77	21	69
19	355	Special Industry Machinery	71	66	194
20	799	Miscellaneous Amusement, Recreation Services	70	14	118
21	483	Radio and Television Broadcasting	69	32	78
22	596	Nonstore Retailers	69	10	53
23	331	Blast Furnace and Basic Steel Products	66	77	101
24	356	General Industrial Machinery	66	67	195
25	369	Miscellaneous Electrical Equipment and Supplies	64	8	68
Total		293 industries	10,498	19,137	78,947
Mean			36	65	269
Median			9	2	3

Table 3: OLS Regression of Comovement on Common Ownership - Dummy Variable

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, where as C, and C_log is the logistic transformation of correlation C in their stock returns. PairGGL_dummy is the measures of common ownership which equal to one if there is at least one common owner between two firms in the pairs and zero otherwise. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	f_log	**fd_log**	**c_log**	**cd_log**
	(1)	(2)	(3)	(4)
PairGGL_dummy	0.097***	0.035***	0.104***	0.070***
	(19.445)	(3.356)	(11.586)	(3.668)
Pair_product_similarity	0.293***	1.119***	0.312***	0.975***
	(4.774)	(3.745)	(3.019)	(4.666)
Pair_ind_concentration	-0.498***	0.162	-0.605***	-0.164
	(-6.389)	(1.317)	(-6.136)	(-1.189)
Pair_MV	0.000*	-0.000***	0.000***	0.000
	(1.661)	(-4.982)	(2.747)	(-1.372)
Pair_analyst_coverage	0.524***	0.323***	0.675***	0.616***
	(11.365)	(5.676)	(8.253)	(7.063)
Ind_volatility	0.133	1.697*	0.188	1.490*
	(1.208)	(1.947)	(1.198)	(1.655)
Ind_size	-0.007	0.064	-0.012	0.068
	(-0.280)	(0.864)	(-0.278)	(0.954)
Constant	0.280**	-0.203	0.349	-0.032
	(2.092)	(-0.550)	(1.533)	(-0.096)
Observations	2,602,250	2,602,250	2,602,250	2,602,250
Adjusted R-squared	0.426	0.088	0.457	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Industry	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Table 4: OLS Regression of Comovement on Common Ownership

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, where as C, and C_log is the logistic transformation of correlation C in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	f_log		**c_log**	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.008***	0.003***	0.010***	0.004***
	(22.941)	(12.291)	(19.931)	(11.060)
Pair_product_similarity		0.295***		0.310***
		(7.369)		(5.243)
Pair_ind_concentration		-0.556***		-0.667***
		(-18.607)		(-17.222)
Pair_MV		0.000***		0.000***
		(2.917)		(7.442)
Pair_analyst_coverage		0.557***		0.706***
		(29.173)		(24.238)
Ind_volatility		0.142		0.197
		(1.468)		(1.243)
Ind_size		-0.009		-0.013
		(-0.745)		(-0.712)
Constant	0.241***	0.311***	0.279***	0.380***
	(25.282)	(4.496)	(20.223)	(3.431)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.215	0.412	0.256	0.448
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Industry and Year	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Table 5: OLS Regression of Comovement on Common Ownership – Detrended Data

This table shows the effects of PairGGL on two detrended measures of pairwise comovement, comovement fd_log and correlation Cd_log. Fd_log is the logistic transformation of comovement fd in stock returns of firm pair, where as Cd_log is the logistic transformation of correlation C in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

	fd_log		**cd_log**	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.004***	0.002***	0.009***	0.005***
	(6.645)	(4.565)	(10.379)	(7.123)
Pair_product_similarity		1.114***		0.964***
		(5.445)		(5.788)
Pair_ind_concentration		0.143		-0.202
		(1.290)		(-1.418)
Pair_MV		-0.000***		-0.000**
		(-4.368)		(-2.537)
Pair_analyst_coverage		0.328***		0.625***
		(5.745)		(13.478)
Ind_volatility		1.700*		1.496
		(1.837)		(1.567)
Ind_size		0.064		0.069
		(0.903)		(1.016)
Constant	0.417***	-0.196	0.559***	-0.019
	(6.101)	(-0.443)	(8.892)	(-0.044)
Observations	2,922,915	2,602,250	2,922,915	2,602,250
Adjusted R-squared	0.082	0.088	0.103	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Industry and Year	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Table 6: DiD Analysis of Institution Mergers

This table shows the DiD analysis results. In panel A and B, *Treat* equals one for Treatment Pairs and equal zero for Control Pairs. *After* is an indicator for year 1 in model (1) and (2); an indicator for year 1 and 2 in model (3) and (4); and an indicator for year 1 to 3 in model (5) and (6). The regressions include deal fixed effects and year fixed effects. In model (1) and (2) the dependent variables are the pairwise comovement measures computed in year -1 and year 1 around the mergers. In model (3) and (4), the dependent variables are the average 2-year pairwise comovement measures before and after the mergers. In model (5) and (6), the dependent variables are the average 3-year pairwise comovement measures before and after the mergers. All the control variables in Panel B are computed in the same way with the dependent variable. The model controls for firm and year fixed effects. The standard errors are clustered by firm.

	f_log11	**c_log11**	**f_log22**	**c_log22**	**f_log33**	**c_log33**
Panel A:	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	0.050*	0.105***	0.094***	0.108***	0.051*	0.056
	(1.817)	(2.720)	(2.854)	(2.654)	(1.813)	(1.504)
Treat	-0.041	-0.106*	-0.003	0.055	0.033	0.054
	(-0.778)	(-1.702)	(-0.079)	(0.625)	(0.917)	(0.888)
Post	-0.029	-0.084	0.100***	0.139***	0.129***	0.168***
	(-0.579)	(-1.497)	(6.830)	(7.484)	(8.204)	(8.568)
Constant	0.439***	0.631***	0.361***	0.445***	0.331***	0.412***
	(9.784)	(10.378)	(11.233)	(8.778)	(11.237)	(9.620)
Observations	2,488	2,488	1,862	1,862	1,828	1,828
Adjusted R-squared	0.670	0.747	0.729	0.764	0.717	0.732
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N
Cluster by Firm	Y	Y	Y	Y	Y	Y
Bootstrapping (times)	500	500	500	500	500	500

	f_log11	**c_log11**	**f_log22**	**c_log22**	**f_log33**	**c_log33**
Panel B:	(1)	(2)	(3)	(4)	(5)	(6)
Treat*Post	0.074**	0.157***	0.110***	0.132***	0.070**	0.093***
	(2.235)	(4.195)	(3.646)	(3.690)	(2.406)	(2.622)
Treat	-0.097*	-0.196***	-0.057	-0.034	-0.027	-0.046
	(-1.660)	(-2.912)	(-1.311)	(-0.397)	(-0.692)	(-0.743)
Post	-0.037	-0.103	0.085***	0.108***	0.119***	0.148***
	(-0.626)	(-1.447)	(4.697)	(4.319)	(6.041)	(5.592)
Pair_product_similarity	0.549***	0.590**	0.648***	0.987***	0.653***	1.012***
	(2.664)	(2.050)	(3.228)	(3.515)	(3.200)	(3.429)
Pair_ind_concentration	-1.031***	-1.326***	-0.602***	-0.901***	-0.622***	-0.953***
	(-4.149)	(-4.207)	(-2.942)	(-3.664)	(-3.207)	(-3.896)
Pair_MV	0.449***	0.685***	0.515**	0.589**	0.467**	0.503**
	(2.693)	(3.315)	(2.244)	(2.170)	(2.191)	(2.091)
Pair_analyst_coverage	0.000	0.000***	0.000	0.000**	0.000	0.000**
	(0.928)	(2.662)	(0.878)	(2.037)	(1.116)	(2.142)
Ind_volatility	0.307	-0.303	-0.265	-0.169	0.131	0.467
	(0.500)	(-0.475)	(-0.590)	(-0.280)	(0.271)	(0.674)
Ind_size	0.143**	0.092	-0.055	-0.100	-0.056	-0.099
	(2.123)	(1.030)	(-0.944)	(-1.133)	(-1.202)	(-1.629)
Constant	-0.147	0.324	0.660**	0.961**	0.615***	0.899***
	(-0.462)	(0.783)	(2.373)	(2.267)	(2.778)	(3.087)
Observations	1,883	1,883	1,435	1,435	1,413	1,413
Adjusted R-squared	0.678	0.755	0.739	0.777	0.727	0.751
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N	N
Cluster by Firm	Y	Y	Y	Y	Y	Y
Bootstrapping (times)	500	500	500	500	500	500

Table 7: Tobit Regression of Comovement on Common Ownership

This table shows the effects of PairGGL on two primary measures of pairwise comovement, f_log and C_log. F_log is the logistic transformation of comovement f in stock returns of firm pair, whereas C, and C_log is the logistic transformation of correlation C in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by year and industry.

Panel A:	**f**		**c**	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.002***	0.001***	0.005***	0.002***
	(194.260)	(92.59)	(190.691)	(85.48)
Pair_product_similarity		0.556***		0.132***
		(108.80)		(111.04)
Pair_ind_concentration		-0.136***		-0.320***
		(-511.51)		(-480.85)
Pair_MV		0.000***		0.000***
		(21.49)		(45.33)
Pair_analyst_coverage		0.143***		0.345***
		(436.36)		(393.93)
Ind_volatility		-0.031***		0.072***
		(-34.42)		(35.71)
Ind_size		-0.007***		-0.023***
		(-203.59)		(-257.37)
Constant	0.558***	0.609***	0.131***	0.281***
	(17,293.294)	(2942.16)	(1,688.262)	(503.49)
Observations	3,064,481	2,602,451	3,064,481	2,602,451
Pseudo R2	-0.0107	-0.1277	-0.0295	-0.3714
P-value	0	0	0	0
Chi-square test	37737		36363	
Bootstrapping (times)	100	100	100	100

Table 7: continued

Panel B:	fd		cd	
	(1)	(2)	(3)	(4)
PairGGL_5pct	0.000***	0.000***	0.002***	0.001***
	(14.247)	(3.86)	(40.489)	(18.49)
Pair_product_similarity		0.230***		0.450***
		(97.67)		(109.43)
Pair_ind_concentration		0.019***		-0.063***
		(14.70)		(-27.52)
Pair_MV		0.000***		0.000***
		(-34.53)		(-28.33)
Pair_analyst_coverage		0.051***		0.191***
		(46.25)		(86.32)
Ind_volatility		0.605***		1.490***
		(147.22)		(179.63)
Ind_size		-0.018***		-0.046***
		(-127.52)		(-150.17)
Constant	0.574***	0.618***	0.205***	0.346***
	(3,425.093)	(719.46)	(684.993)	(190.44)
Observations	3,064,481	2,602,451	3,064,481	2,602,451
Pseudo R2	0.000550	0.2110	0.000394	0.0206
P-value	0	0	0	0
Chi-square test	203		1639	
Bootstrapping (times)	100	100	100	100

Table 8: OLS Regression of Comovement on Common Ownership and Production Similarity 1

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Table 2 and 3. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by industry.

	f_log	**c_log**	**fd_log**	**cd_log**
	(1)	(2)	(3)	(4)
PairGGL	0.004***	0.005***	0.005***	0.008***
	(8.299)	(7.187)	(3.768)	(4.954)
PairGGL X Pair_product_similarity	-0.010**	-0.010	-0.022*	-0.027**
	(-2.477)	(-1.367)	(-1.800)	(-1.988)
Pair_product_similarity	0.310***	0.325***	1.148***	1.006***
	(4.635)	(3.016)	(3.709)	(4.602)
Pair_ind_concentration	-0.555***	-0.666***	0.145	-0.199
	(-7.733)	(-7.037)	(1.191)	(-1.458)
Pair_MV	0.000	0.000**	-0.000***	-0.000**
	(0.726)	(2.196)	(-5.700)	(-2.236)
Pair_analyst_coverage	0.556***	0.705***	0.327***	0.624***
	(13.684)	(9.273)	(5.742)	(7.221)
Ind_volatility	0.142	0.198	1.702*	1.498*
	(1.283)	(1.260)	(1.949)	(1.659)
Ind_size	-0.008	-0.013	0.065	0.070
	(-0.321)	(-0.298)	(0.878)	(0.975)
Constant	0.307**	0.376*	-0.204	-0.029
	(2.287)	(1.657)	(-0.554)	(-0.088)
Observations	2,602,250	2,602,250	2,602,250	2,602,250
Adjusted R-squared	0.413	0.448	0.088	0.117
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by SIC3	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Table 8. continued

Panel B: High product similarity	**f_log** (1)	**c_log** (2)	**fd_log** (3)	**cd_log** (4)
PairGGL	0.002***	0.003***	0.002**	0.004***
	(5.890)	(4.696)	(2.074)	(3.426)
Pair_product_similarity	0.227***	0.268**	0.905***	0.815***
	(3.831)	(2.311)	(3.125)	(4.222)
Pair_ind_concentration	-0.657***	-0.791***	0.319***	-0.136
	(-12.968)	(-11.456)	(2.740)	(-1.104)
Pair_MV	0.000	0.000**	-0.000***	-0.000***
	(0.795)	(2.141)	(-5.820)	(-3.348)
Pair_analyst_coverage	0.545***	0.720***	0.408***	0.700***
	(13.005)	(10.675)	(5.973)	(7.280)
Ind_volatility	0.148	0.254	1.903	1.850
	(1.236)	(1.456)	(1.476)	(1.413)
Ind_size	-0.013	-0.019	0.123	0.088
	(-0.388)	(-0.335)	(1.285)	(1.263)
Constant	0.366**	0.443	-0.479	-0.077
	(2.001)	(1.426)	(-0.868)	(-0.203)
Observations	1,099,124	1,099,124	1,099,124	1,099,124
Adjusted R-squared	0.463	0.495	0.099	0.127
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Industry	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Table 9: OLS Regression of Comovement on Common Ownership and Production Similarity 2

This table shows the effect of common ownership on pairwise comovement in relation to their product similarity using the same sample as in Table 2 and 3. Panel A shows the effects for the subsample with low product similarity, while Panel B shows the effects for the subsample with high product similarity, divided by the medium product similarity of the sample. The dependent variables are two measures of comovement and two measures of correlations with and without trend. F_log and Fd_log are the logistic transformations of comovement f and fd in stock returns of firm pair, where as C_log and Cd_log is the logistic transformation of correlation C and Cd in their stock returns. Pair GGL is the measures of common ownership, computed by aggregating the effects of all common institutional owners between two firms with at least 5% ownership in each firm. Pair_product_similarity is the similarity in products between two firms provided by Hoberg and Philips (2016). Pair_ind_concentration is the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms. Pair_MV is the average market capitalization between two firms. Pair_analyst_coverage is the number of common analysts between two firms. Ind_volatility is the industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry. Ind_size is the industry size where the two firms operate in, computed by the log number of firms in that industry. The model controls for year and industry fixed effects. The standard errors are clustered by industry.

Panel A:	**f_log**	**c_log**	**fd_log**	**cd_log**
Low product similarity	(1)	(2)	(3)	(4)
PairGGL	0.004***	0.006***	0.004***	0.007***
	(12.857)	(12.377)	(5.701)	(7.474)
Pair_product_similarity	0.396***	0.490***	1.756***	1.486***
	(3.252)	(3.595)	(3.339)	(4.070)
Pair_ind_concentration	-0.494***	-0.588***	0.098	-0.200
	(-7.336)	(-6.737)	(0.600)	(-1.325)
Pair_MV	0.000	0.000*	-0.000***	-0.000
	(0.359)	(1.663)	(-3.063)	(-1.543)
Pair_analyst_coverage	0.543***	0.643***	0.253***	0.523***
	(11.877)	(7.326)	(4.285)	(6.076)
Ind_volatility	0.100	0.102	1.539**	1.102
	(1.066)	(0.698)	(2.147)	(1.585)
Ind_size	-0.005	-0.007	0.060	0.094
	(-0.341)	(-0.323)	(1.019)	(1.490)
Constant	0.273***	0.324***	-0.223	-0.208
	(3.722)	(2.716)	(-0.783)	(-0.680)
Observations	1,503,106	1,503,106	1,503,106	1,503,106
Adjusted R-squared	0.339	0.373	0.074	0.101
Industry FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Cluster by Industry	Y	Y	Y	Y
Bootstrapping (times)	100	100	100	100

Appendices

1. Measures of comovement: R2 and decomposition of variance analysis

A vast of literature measures comovement in returns using R-squared from regressions of individual stock returns on market returns (Roll, 1988). An aggregate R-squared measure represents the proportion of the variation in firm returns explained by total market variation, whereas (1 – R2) is inferred to represent the share of firm-specific variation (Jin & Myers, 2006). To investigate whether pairwise comovement contributes a proportion to market-level return variation, I first compute the total market and industry variation which is estimated widely using R-squared measure obtained from the following market model for each fiscal year:

$$Ret_{it} = \alpha + \beta_1 MktRet_t + \beta_2 MktRet_{t-1} + \beta_3 IndRet_t + \beta_4 IndRet_{t-1} + \varepsilon_{it} \quad (14)$$

I regress daily returns Ret_{it} in a fiscal year t for commonly owned firm i on value-weighted market returns $MktRet$ and industry returns $IndRet$ for firms in the same 3-digit SIC industry (with firm i's daily returns excluded) in both year t and t-1. Lagged industry and market returns are added to control for potential non-synchronous trading biases associated with the daily return data (Scholes & Williams, 1977). Eventually, I average the annual R-squared for all commonly owned firms to observe the market-level effects, which equals 0.1537. On average, 15.37% of the variation in returns of commonly owned firms can be explained by market and industry variation, and nearly 85% are left undescribed by these effects. Thus, this paper attempt to answer whether ownership overlapped by institutional investors can explain for this undefined 85% by being associated with pairwise comovement among commonly owned firms. The results show that common ownership network measures do contribute to market-level variation, accounting for a portion of the overall variation. The firm-specific residuals are reduced when the measure of common ownership is included, improving the overall fit of the regression equation. The benchmark R^2 of the regression (when only the market index is included as a dependent variable) is 0.117 and adding the industry index for each firm increases the R^2 to 0.150. Almost 15% of total variation in stock price returns is attributable to market and industry effects.

Next, common ownership network index is added to the regression in turn. Along with the market and industry indexes, produces an R^2 of 0.170. That is, adding the common ownership network index increase the extent of return variation explained by the regression. Since the R^2 value is larger than for the market model regressions, the results suggest that common ownership network is important factor in explaining variation in returns.

Table A.1. Variable Definitions

This table shows the definition for all variables.

Variable	Definition	Data source
PairGGL	The measure of common ownership effect on firm managerial incentives, computed by aggregating the effects of all common institutional owners between two firms who hold at least 5% ownership in each firm (blockholders).	Refinitiv's 13F
f	The measure of return comovement which is equal to one (zero) if the two firms always move in the same (opposite) directions.	CRSP
C	The measure of correlation in return between pairs of firms.	CRSP
fd	The detrended measure of return comovement using simple linear regression following Khanna and Thomas (2009) to remove the value of its average trend over the year.	CRSP
Cd	The detrended measure of return correlation using simple linear regression following Khanna and Thomas (2009) to remove the value of its average trend over the year.	CRSP
f_log	The logistic transformation of f	CRSP
C_log	The logistic transformation of fd	CRSP
fd_log	The logistic transformation of C	CRSP
Cd_log	The logistic transformation of Cd	CRSP
Pair_product_similarity	the similarity in products between two firms provided by Hoberg and Philips (2016)	Hoberg and Phillips (2016)
Pair_ind_concentration (Pair_ind_HHI)	the level of industry concentration measured by averaging the Herfindahl-Hirschman Index between two firms.	WRDS
Pair_MV	The average market capitalization between two firms	CRSP
Pair_analyst_coverage	The number of common analysts between two firms	IBES Academic
Ind_volatility	The industry volatility where two firms operate in, computed by the standard deviation of returns for each 3-digit SIC industry.	CRSP
Ind_size	The industry size where the two firms operate in, computed by the log number of firms in that industry	CRSP