# Connected Stocks via Business Groups: Evidence from an Emerging Market

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**Abstract**

We link stocks through direct and indirect common owners, showing that common ownership and belonging to a business group (indirect common owner) affect the stock price co-movement. Our analysis is based on the daily ownership of block-holders on the Tehran Stock Exchange. We show that belonging to a business group has a higher effect than having a common owner, which influenced only movement within business groups. In addition, simultaneous trades in the same direction explain co-movement in business groups.

## 1 Introduction

The literature has well established that stocks move together. Risk models are becoming increasingly popular, especially after the financial crisis of 2008. According to these models, price correlation plays a significant role in risk measurement. Companies' return co-movement was traditionally attributed to their fundamentals. (Aamong all Shiller (1989))

Although, in recent years, it has been recognized that the co-movement rises from non-fundamental sources. Barberis and Shleifer (2003) and Barberis et al. (2005) provided theoretical models for predicting a co-movement between fundamentally unrelated companies. Trying to explain factors affecting co-movement, Anton and Polk (2014) examined on the effect of common ownership[1] on co-movement[2]. This paper uses the mutual funds' ownership and suggests that co-movement increases by increasing common ownership. Also, it is shown in the paper that the co-movement increases when there is a significant net flow, either in or out-flow in the months.

Subsequently, according to Koch et al. (2016) companies show co-movement considering their owners' correlation in their liquidity needs. The author also adds that companies with higher mutual fund ownership have a more liquidity correlation than others. This paper contends that in order for companies to have co-movement, there is no need for common ownership. Plus, common ownership can explain companies' liquidity correlation.

While most of the prior investigations on factors affecting common-ownership have focused on the fund, the role of the block-holders as one the most important factors in firms' governance has remained a black box[3]. This type of owners perform particular types of behavior due to their needs and the fact that they are intermediates. Nevertheless, in Iran, the block holders' daily ownership data, including mutual fund ownership, is publicly accessible. So research through this data can show whether common ownership other than mutual fund ownership can lead to co-movement or not. Following Anton and Polk (2014), we are the first study that uses block-holder ownership to investigate the relationship between common ownership and co-movement.

Despite the presence of the business group in both emerging economies, e.g., Brazil, Chile, China, India, Indonesia, South Korea, and developed countries, e.g., Italy, Sweden, (Khanna and Yafeh (2007)), there is no evidence on whether being at the same business group can lead to the co-movement. Business groups consist of legally independent firms operating across diverse industries different from commonly held firms. Although researchers have identified co-movement among stock returns, to the best of our knowledge,

[1]The common ownership concept has been observed in financial literature in recent years. There has been a surge in the popularity of index investing in the United States, which has led to an increase in common ownership. For instance, Azar et al. (2018) claims that an increase in mutual ownership in airline companies leads to less competitive ticket pricing. However, this subject is controversial and many papers discuss whether mutual ownership affects companies' behavior. For example, Lewellen and Lowry (2021) realized that in previous investigations, other effective factors have wrongly been replaced by mutual ownership effect.

[2]The followings are some of the other sources of co-movement. Index inclusion (Barberis et al. (2005)), investors' attention to the companies (Wu and Shamsuddin (2014)), Investment banks' underwriting (Grullon et al. (2014)), correlated beliefs (David and Simonovska (2016)), shareholders' coordination (Pantzalis and Wang (2017)), and preference for companies' dividends (Hameed and Xie (2019)) are among contributing factors to co-movement that have been identified by researchers.

[3]A long literature surveyed by Holderness (2003), Edmans (2014), and Edmans and Holderness (2017) considers the potential role of blockholders in firm governance

we are the first comprehensive study about the different roles of the business groups and common ownership on co-movement.

We realize that common ownership is crucial for predicting the co-movement. Business groups play a more critical role in predicting correlation of companies' return than common ownership. We show that common ownership can predict co-movement only inside the business groups. We extend our analysis in order to validate the prominence of business groups. First, restrict the study to high level of common ownership for distinguishing effect of high level of common ownership and business groups. In this subset, like the mentioned ones, business groups have a significant impact. Second, if business group affect co-movement, there is no need to restrict our investigation to commonly hold pairs. In order to distinguish the impact of common ownership and business group, we built all possible pairs in the market. We show that for all the firms in the market, business group can increase firms' co-movement.

Finally, we show that correlated trade in business groups is the channel of co-movement. We provide evidence that the volume and direction of trades in business groups are related, and firms in the business groups with higher relation in trade have a higher level of co-movement.

# 2 Data and Methodology

## 2.1 Data and Sample

We use our unique data set, including the daily ownership table that reports all end-of-the-days block-holders of listed firms with their changes in that day. Block-holder is a shareholder who owns at least 1% of the total shares outstanding. We also gathered industries index and stock returns, trading volume, and other relevant market and accounting data from the Codal website [4] and the Tehran Securities Exchange Technology Management Co (TSETMC)[5] database.

We exclude ETFs from our listed firms because they have a different return and ownership patterns compared to other firms in our study. We restrict our empirical analysis to 2015/03-2020/03(1393/01-1398/12 Persian calendar) due to the availability of daily ownership data and the special events [6] that happened after 2020/03, which may affect our results.

[4] www.codal.ir

[5] www.tsetmc.com

[6] The Tehran Stock Exchange's main index (TEPIX) raised exponentially to quadruple value and then fell sharply due to the gigantic entrance of new individual investors that seems to be a bubble period from that period.

Business groups - groups of listed firms with interconnected ownership structures controlled by an ultimate common owner - are the principal organizational structure in many parts of the world. Business groups seem to be a central feature of corporate ownership in Iran. Most Iranian listed firms present in a complex interlinked shareholders' network that an ultimate owner governs this group through many layers of ownership(Aliabadi et al. (2021)). We do not have pre-specified Iranian business groups despite other countries like South Korea, Japan, and India that their groups are announced formally. For defining business groups, we use data provided by Aliabadi et al. (2021). They use Almeida et al. (2011) algorithm with a 40% threshold for defining groups.

Table 1 reports summary statistics of ownership data and business groups. As shown in the table, 494 firms on average have five block-holders that own 73 percent of them. There are 43 business groups on average, with seven members which own 314 (63%) firms.

Table 1: This table reports summary statistics of ownership features for all the listed firms. At this table by group, we mean business groups.

| Year | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| No. of Firms | 329 | 349 | 384 | 469 | 490 | 554 |
| No. of Blockholders | 1430 | 1564 | 1821 | 2411 | 2613 | 2921 |
| No. of Groups | 37 | 40 | 42 | 43 | 39 | 42 |
| No. of Firms in Groups | 230 | 251 | 274 | 307 | 321 | 356 |
| Ave. Number of group Members | 6 | 6 | 7 | 7 | 8 | 8 |
| Ave. ownership of each Blockholders (%) | 18 | 18 | 18 | 17 | 18 | 19 |
| Med. ownership of each Blockholders (%) | 5 | 4 | 4 | 4 | 4 | 5 |
| Ave. Number of Owners | 6 | 7 | 7 | 7 | 7 | 6 |
| Med. Number of Owners | 5 | 5 | 5 | 6 | 5 | 5 |
| Ave. Block. Ownership (%) | 77 | 77 | 76 | 76 | 75 | 72 |

## 2.2 Pair composition

If two firms have at least one common block-holder, We consider them as a pair. By this definition, there are 17522 unique pairs in entire periods, which is 9% of possible pairs ($\frac{618*617}{2} = 190653$ ). As we expected, stocks in pairs have concentrated ownership relative to the total sample, and pairs have one common owner.

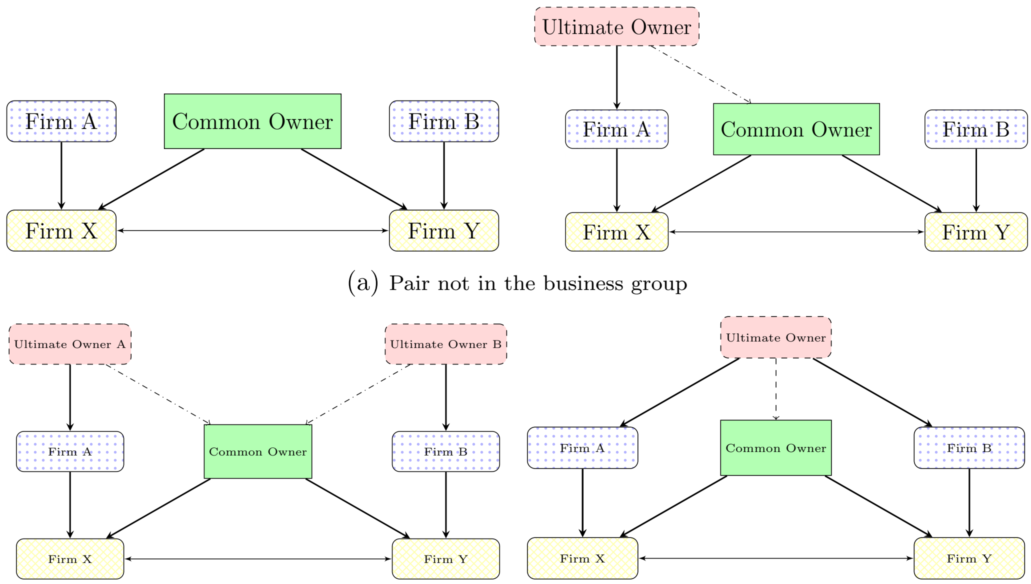
As one of our empirical studies, we study the impact of being in the same business group relative to being in two distinct groups on pair's correlation. For assigning one pair to a group, both firms should belong to one ultimate

Table 2: This table reports summary statistics of ownership features for total pairs. At this table by group, we mean business groups.

| Year | 2014 | 2015 | 2016 | 2017 | 2018 | 2019 |
|---|---|---|---|---|---|---|
| No. of Pairs | 8092 | 8017 | 8316 | 9732 | 9843 | 10776 |
| No. of Pairs not in Groups | 2807 | 2515 | 2616 | 3593 | 3380 | 3822 |
| No. of Pairs not in the same Group | 4357 | 4594 | 4709 | 4981 | 5069 | 5322 |
| No. of Pairs in the same Group | 771 | 773 | 857 | 1015 | 1209 | 1408 |
| Ave. Number of Common owner | 1 | 1 | 1 | 1 | 1 | 1 |

owner. Another possibility is that each firm belongs to a different ultimate owner or one of them, or both of them do not belong to any groups, which all of them illustrated in figure 1. By classifying pairs, on average, 15% of them belong to one business group. We report summary statistics of ownership features for all pairs in table 2.

Figure 1: Three categories for pairs base on being in business groups




(a) Pair not in the business group

(b) Pair in two distinct business group

(c) Pair in the same business group

## 2.3 Measurement of common-ownership

In table 3 we summarize common ownership measurements which are used in literature. There are two groups of measurement for common ownership.

First of all, model-based measures that capture common ownership base on a proper model. These measures have a better economic interpretation, but most of them are bi-directional or industry-level measures.(e.g, Harford et al. (2011); Azar et al. (2018); Gilje et al. (2020))

In addition to model-based measures, some ad hoc common ownership measures are used in the empirical literature. There is significant doubt on how these measures capture common ownership's impact on the management, and many of them have unappealing properties.(e.g, Anton and Polk (2014); Azar (2011); Freeman (2019); Hansen and Lott Jr (1996); He and Huang (2017); He et al. (2019); Lewellen and Lowry (2021); Newham et al. (2018))

Table 3: This table summarizes common ownership measurements in the literature.

| Group | Paper | measurment | Flaws |
|---|---|---|---|
| Model Based | Harford et al. (2011) | $\sum_{i\in I^{A,B}} \frac{\alpha_{i,B}}{\alpha_{i,A}+\alpha_{i,B}}$ | Bi-directional |
| | Azar et al. (2018) | $\sum_j \sum_k s_j s_k \frac{\sum_i \mu_{ij}\nu_{ik}}{\sum_i \mu_{ij}\nu_{ij}}$ | Industry level |
| | Gilje et al. (2020) | $\sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A})\alpha_{i,B}$ | Bi-directional |
| Ad hoc | He and Huang (2017); He et al. (2019) | $\sum_{i\in I^{A,B}} 1$ | Invariant to the level of common ownership |
| | Newham et al. (2018) | $\sum_{i\in I^{A,B}} min\{\alpha_{i,A}, \alpha_{i,B}\}$ | Ignore level of ownership |
| | Anton and Polk (2014) | $\sum_{i\in I^{A,B}} \alpha_{i,A} \frac{\bar{\nu}_A}{\bar{\nu}_A+\bar{\nu}_B} + \alpha_{i,B} \frac{\bar{\nu}_B}{\bar{\nu}_A+\bar{\nu}_B}$ | Invariant to the decomposition of ownership |
| | Freeman (2019); Hansen and Lott Jr (1996) | $\sum_{i\in I^{A,B}} \alpha_{i,A} \times \sum_{i\in I^{A,B}} \alpha_{i,B}$ | Ignore importance of the firms |

In our primary analysis, we estimate the impact of common ownership on pair's correlation. For this purpose, we need a pair-level measure with a good economic interpretation that is not bi-directional. As a result, we propose a modification for Anton's measure (Anton and Polk (2014)) that captures the extent of common ownership distribution and apply this measure in this study.

We reformulate mentioned Anton's measure in table 3. We re-weight this formula to capture the difference between ownership distribution. Our proposed measure is

$$\text{Overlap}_{Sqrt}(i,j) = [\frac{\sum_{f=1}^{F}(\sqrt{S_{i,t}^{f}P_{i,t}} + \sqrt{S_{j,t}^{f}P_{j,t}})}{\sqrt{S_{i,t}P_{i,t}} + \sqrt{S_{j,t}P_{j,t}}}]^2 \tag{1}$$

where $S_{i,t}^{f}$ is the number of shares held by owner f at time t trading at price $Pi,t$ with total shares outstanding of $S_{i,t}$, and similarly for stock j. Modified measure represent the number of equal percents held block-holder. In other words, If for a pair of stocks with n mutual owners, all owners have even shares of each firm's market cap, then the proposed index will be equal to number of holders.[7]

On each day, we measure common ownership by our proposed measure and then report an average of these daily calculations for the entire period at the end of each month. We also calculate Anton's measure in this way. Table 4 report snapshots of the distribution of common ownership measure for both methods. As we expected, the modified measure creates higher values for a high level of common ownership than Anton's measure. The average common ownership measure is five and three times larger, respectively, in business groups and industries.

Table 4: Calculation of common ownership with two measure

| variable | MFCAP | | | | | FCAP | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | mean | std | min | median | max | mean | std | min | median | max |
| All | 0.15 | 0.24 | 0.0 | 0.06 | 4.62 | 0.12 | 0.16 | 0.0 | 0.05 | 0.97 |
| Same Group | 0.47 | 0.41 | 0.0 | 0.41 | 4.04 | 0.38 | 0.25 | 0.0 | 0.37 | 0.97 |
| Not Same Group | 0.1 | 0.16 | 0.0 | 0.04 | 2.9 | 0.08 | 0.11 | 0.0 | 0.04 | 0.97 |
| Same Industry | 0.34 | 0.41 | 0.01 | 0.18 | 4.04 | 0.25 | 0.24 | 0.0 | 0.16 | 0.96 |
| Not Same Industry | 0.12 | 0.19 | 0.0 | 0.05 | 4.62 | 0.1 | 0.14 | 0.0 | 0.05 | 0.97 |

## 2.4 Stock Return comovement

We calculate the monthly correlation of each pair from stocks' daily abnormal returns. Benchmark for calculating abnormal return is the following equation which is a four-factor model plus industry return due to the importance of industries on stocks' return in the Tehran stock exchange (TSE) :

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_{mkt,i} R_{M,t} + \beta_{Ind,i} R_{Ind,t} + \\ + \beta_{HML,i} HML_t + \beta_{SMB,i} SMB_t + \beta_{UMD,i} UMD_t + \varepsilon_{i,t} \end{aligned} \tag{2}$$

where $R_{i,t}$, $R_{M,t}$ and $R_{Ind,t}$ are excess daily return of respectivly firm, market and firm's industry from bank deposit's daily rate(risk free). Other variabales difinition is base on Carhart four-factor model [Carhart (1997)].

At the end of each month, we estimate our benchmark model base on the past three-month period (from two months before the end of the preceding

[7]Each holder owns $1/n$ of each firm ,Firm's market cap is $\alpha_1$ and $\alpha_2$, So for each holder of firms we have $S^f_{i,t} P_{i,t} = \alpha_i/n$

$[\frac{\sum_{f=1}^n \sqrt{\alpha_1/n} + \sum_{f=1}^n \sqrt{\alpha_2/n}}{\sqrt{\alpha_1}+\sqrt{\alpha_2}}]^2 = [\frac{\sqrt{n}(\sqrt{\alpha_1}+\sqrt{\alpha_2})}{\sqrt{\alpha_1}+\sqrt{\alpha_2}}]^2 = n$

$[\frac{\sum_{f=1}^n (\alpha_1/n)^2 + \sum_{f=1}^n (\alpha_2/n)^2}{\alpha_1^2+\alpha_2{}^2}]^{-1} = [\frac{\alpha_1^2+\alpha_2^2}{n(\alpha_1^2+\alpha_2^2)}]^{-1} = n$

month) and measure daily residuals. After that, we calculate the monthly correlation of daily residuals during that month for the pair.

We use other benchmarks (CAPM, 4 Factor, and Benchmark[8]) for calculating a monthly correlation and report its summary in table 5. As we expected, models that include industry returns remove pairs' correlation. According to the results, it seems that our selected benchmark (4 Factor + Industry) almost captures all the pairs' comovement because it is nearly a zero mean variable. We use this correlation for our analysis.

Table 5: This table reports distribution of calculated correlation base on different models.

| | mean | std | min | median | max |
|---|---|---|---|---|---|
| CAPM + Industry | 0.016 | 0.127 | -0.950 | 0.014 | 0.818 |
| 4 Factor | 0.033 | 0.136 | -0.875 | 0.024 | 0.869 |
| 4 Factor + Industry | 0.013 | 0.124 | -0.875 | 0.010 | 0.779 |
| Benchmark | 0.008 | 0.145 | -0.933 | 0.006 | 0.860 |

## 2.5 Controls

We are interested in the effects of common ownership on pair's comovement. Our prediction of a higher correlation for a higher level of common ownership dominates by stocks' intrinsic similarity, and these similarities motivate block-holders to hold these stocks simultaneously. These related stocks will comove regardless of who owns them.

The first group of controls is pair controls. These controls include a dummy variable for whether two stocks are in the same industry, **SameIndustry** . As shown in table 6, 10% and 14% of pairs are in the same industry and business group. Furthermore, we control for cross-ownership between two stocks and define **CrossOwnership** as the maximum percent of cross-ownership between two firms in the following month.

Another group of controls are firm-specific controls. We define these variables base on Anton and Polk (2014) methodology. One of these is size control based on the normalized rank-transform of the percentile market capitalization of the two stocks, **Size1** and **Size2** (where we label the larger stock in the pair as the first stock). The other one is a book to market ratio

[8]we follow Daniel et al. (1997) to control risk characteristics: abnormal returns are calculated using a stock's daily return minus the average return of the stock's benchmark group, which is formed at every month's end based on stocks' capitalization and market-to-book ratio using the sample of all stocks

Table 6: This table reports the number of pairs in the same industry and business group.

| | Yes | No |
|---|---|---|
| SameIndustry | 1799 (10.3%) | 15732 (89.7%) |
| SameGroup | 1476 (14.0%) | 9060 (86.0%) |
| SameGroup & SameIndustry | 628 (3.5%) | 17531 (96.5%) |

based on the normalized rank-transform of the percentile book to market of the two stocks, **BookToMarket1** and **BookToMarket2**. We also control these characteristics on a pair level. Our measures of similarity, **SameSize**, and **SameBookToMarket**, are the negative of the absolute difference in percentile ranking for a particular characteristic across a pair.

We calculate our controls daily and then report the average of these variables for the entire period at the end of each month. Table 7 shows the summary statistics of specified controls in this section.

Table 7: This table shows the summary statistics of specified controls in empirical studies.

| | mean | std | min | median | max |
|---|---|---|---|---|---|
| Size1 | 0.72 | 0.22 | 0.01 | 0.77 | 1.00 |
| Size2 | 0.45 | 0.24 | 0.00 | 0.43 | 0.99 |
| SameSize | -0.28 | 0.20 | -0.97 | -0.23 | -0.00 |
| BookToMarket1 | 0.51 | 0.25 | 0.00 | 0.52 | 1.00 |
| BookToMarket2 | 0.50 | 0.23 | 0.01 | 0.50 | 1.00 |
| SameBookToMarket | -0.30 | 0.19 | -0.96 | -0.26 | -0.00 |
| CrossOwnership | 0.56 | 5.14 | 0.00 | 0.00 | 95.56 |

# 3 Empirical Evidences

## 3.1 Forecasting Co-movement

In the following month, we empirically test the impact of current measured common ownership on the next period's co-movement At the first step, we study the effects of business groups and common ownership on the co-movement. As it has shown in figure 2, a higher level of common ownership in the current period is associated with a higher level of correlation. In the following we examine the following period's co-movement on the considered variables.

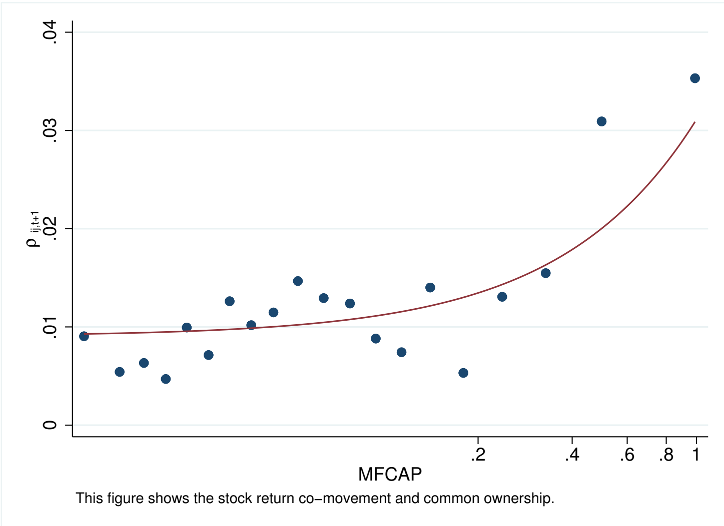



Figure 2: Future monthly correlation for different level of common ownership at this period

For this purpose, we estimate the cross-sectional regressions forecasting within-month realized correlation ($\rho_{i,j,t+1}$) of each pair of stocks abnormal return. By abnormal return, we mean daily four-factor plus industry residuals of estimated model (Specific details and reasons for using this model described in the section 2.4). We use $MFCA^{*}_{ij,t}$, $Same\ Group_{ij}$, and their interaction for our main analysis and other pair characteristics as controls:

$$\begin{aligned}\rho_{ij,t+1} = \beta_0 &+ \beta_1 * \text{MFCAP}^{*}_{ij,t} + \beta_2 * \text{SameGroup}_{ij} \\ &+ \beta_3 * \text{MFCAP}^{*}_{ij,t} \times \text{SameGroup}_{ij} \\ &+ \sum_{k=1}^{n} \alpha_k * \text{Control}_{ij,t} + \varepsilon_{ij,t+1}\end{aligned} \tag{3}$$

We estimate these regressions for each month and report the time-series average as in Fama and MacBeth (1973) to don't have any problem with cross-correlation in the residuals. We then use Newey and West (1987) to calculate standard errors of the Fama-MacBeth that take into account autocorrelation in the time series of cross-sectional estimates for four lags ($4(71/100)^{\frac{2}{9}} = 3.71 \sim 4$).

The estimated results are presented in tables 8a and **??**. In the two first columns table 8a, we estimate a simplified version of equation 3 with only common ownership measure ($MFCAP^*_{i,j}$) to investigate the relationship between common ownership and co-movement. In the first column, we estimate the model without control variables. Recall that our control variables are *Same Industry*, *Same Size*, *Same Book to Market*, and *Cross-Ownership*. The *Same Size* and the *Same Book to Market* are normalized to have a standard deviation of one and are transformed so that higher values indicate greater style similarity. We find that $MFCAP^*_{i,j}$ is significant with a coefficient of 0.00335 and a t-statistics of 5.27 in the presence of control variables.

In Columns 3 and 4 of that table, we use another simplified version of equation 3, with only Same Group. The estimated coefficient in this specification, Same Group is highly statistically significant, with a coefficient of 0.0239 and a t-statistics of 9.41. According to the results, there is a significant difference in the impact of the same business groups and the common ownership.

In the fifth specification of table 8a, we use both *Same Group* and $\mathrm{MFCAP}^*_{ij,t}$ as a forecasting variable. In this specification, only *Same Group* has a significant effect on our estimation. It suggests that common ownership affects the firms through the same business group. In the last column of table 8a, we control for pairs size type (Pairs is large or small if both firms are large or small . If one firm is large and the other is small, we call it a hybrid.), which seems important for investigating firms' co-movement. Anton and Polk (2014) restrict their analysis to large firms, but we do not restrict our investigation, and our result may be driven due to this difference. Estimation results in table 8a shows that by controlling pairs' type *Same Group* significantly increases co-movement rather than common ownership.

In Table **??**, we examine the effect of common ownership in the business groups. In the two first columns, we restrict our investigation to two subsamples. In the first one, we run our model for the pairs in the same business group and others who do not belong to the same one in the second one. It provides evidence that common ownership only matters for the pairs in the same business groups. Now for the main analysis, we include the interaction of *Same Group* and $\mathrm{MFCA}^*_{ij,t}$. We include the business group fixed effects to capture the group's characteristics for the last column. In these specifications, the economic effect of *Same Group* is not significant anymore, which cannot be reliable due to the high correlation of interaction term with *Same Group*($\rho = 0.75$). These results aver that $\mathrm{MFCA}^*_{ij,t}$ has a larger effect for the pairs in the same business group. It puts forward that the *Same Group* affects co-movement through indirect common ownership, which arises due to the same ultimate owner.

Table 8: Connected Co-movement

This table reports Fama and MacBeth (1973) estimates of monthly cross-sectional regressions forecasting the correlation of daily Fama et al. (1993)–Carhart (1997) residuals in month t + 1 for the sample of stocks defined in Table 2. The independent variables are updated quarterly and include our measure of institutional connectedness, the total ownership value held by all common funds of the two stocks scaled by the total market capitalization of the two stocks, FC APij,t, and a series of controls at time t. We measure the negative of the absolute value of the difference in size, book-to-market ratio (BE/ME), and momentum percentile ranking across the two stocks in the pair (SAMESIZEij,t, SAMEBMij,t, and SAMEMOMij,t, respectively). We also measure the number of similar SIC digits beginning with the first digit, NUMSICij,t, for the two stocks in a pair. We also include 39 other controls, which are reported in the Internet Appendix, for the sake of brevity. All independent variables, excluding dummy variables are then rank-transformed and normalized to have unit standard deviation, which we denote with *. We calculate Newey and West (1987) standard errors (four lags) of the Fama and MacBeth (1973) estimates that take into account autocorrelation in the cross-sectional slopes. We report the associated t-statistics in parentheses. We report estimates of regressions using various subsets of these variables in Panel A. Panel B shows the same set of regressions as in Panel A, but for three different subsamples (corresponding to the three decades of the sample). In Panel C, we report the results of regressing the time series of Fama and MacBeth (1973) FCAP* coefficients on a constant and a trend. In Panels B and C, only the FCAP* coefficient and the intercept estimates are shown; the remaining controls are reported in the Internet AppendixFor simplicity, we call this method the substitution welfare effect. Also, we use another way that was used in Chamount 2017. in this method, the welfare effect is computed by comparing the consumption of benchmark distribution with consumption of secondary distribution.

Panel A: Somwthing

| | Dependent Variable: Future Pairs's co-movement | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| MFCAP* | 0.00507*** | 0.00335*** | | | 0.00118 | 0.00113 |
| | (7.00) | (5.27) | | | (1.96) | (1.90) |
| Same Group | | | 0.0291*** | 0.0239*** | 0.0227*** | 0.0196*** |
| | | | (12.16) | (9.41) | (8.88) | (7.36) |
| Controls | No | Yes | No | Yes | Yes | Yes |
| PairType Control | No | No | No | No | No | Yes |
| Observations | 354209 | 354209 | 354209 | 354209 | 354209 | 354209 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Panel B: Somwthing

| | Dependent Variable: Future Pairs's co-movement | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| MFCAP* | 0.00899*** | 0.0000371 | 0.0000148 | 0.000509 |
| | (6.01) | (0.06) | (0.03) | (0.89) |
| Same Group | | | 0.00784** | 0.00521 |
| | | | (2.72) | (1.68) |
| (MFCAP*) × SameGroup | | | 0.0122*** | 0.0120*** |
| | | | (10.34) | (9.74) |
| Sub-sample | SameGroup | Others | All | All |
| Business Group FE | No | No | No | Yes |
| Observations | 43274 | 310935 | 354209 | 354209 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## 3.2 High level of common ownership

In line with the previous estimations, figure 3 provides that a higher level of common ownership affects more on the firms' co-movement. As shown in table 4, pairs in the same business group have a higher level of common ownership than others. So, the previous results could be driven by a high level of common ownership. For detailed analysis, we restrict our sample to the higher level of common ownership, which we define as the pairs with $\text{MFCAP}_{ij,t}$ in the fourth quarter in each period. Figure 4 shows the relation between future co-movement and current measurement of common ownership for that pairs. As you can see in the left panel, in line with the last explanation, common ownership only affects the pairs in the same group, and common ownership without the same group will not affect pairs' co-movement although for a high level of common ownership.

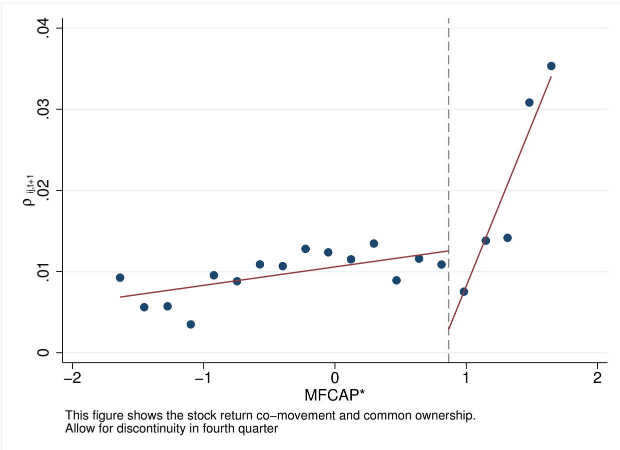



Figure 3: Future monthly correlation for different level of common ownership at this period

We estimate the equation 3 with the same methodology in section 3.1 for the sub-sample of a high level of common ownership. Table 9 reports estimations results. As expected, firms in the same business group have a high statistical and economically significant effect on forecasting future co-movements. Columns three to seven confirm our prior explanations for the importance of business groups compared to common ownership in pairs with a higher level of common ownership. Pairs in the fourth quarter may have different characteristics that affect our results. In figure 10, we summarized our control variables which shows that pairs' attributes do not look significantly different than other pairs except the presence of the pairs in the same group, which we want to examine this feature.

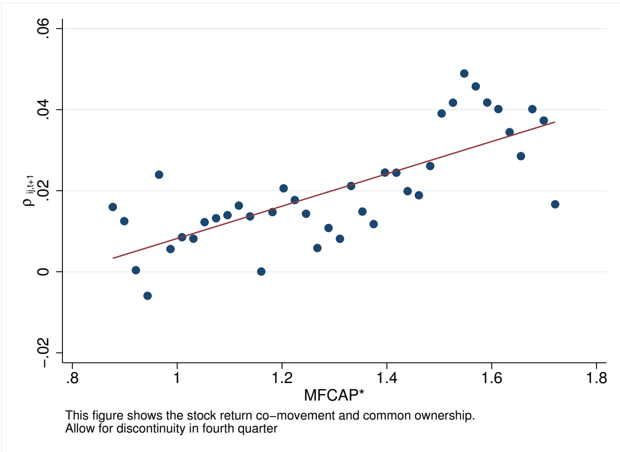



Figure 4: Monthly correlation for different level of common ownership at this period for high level of common ownership

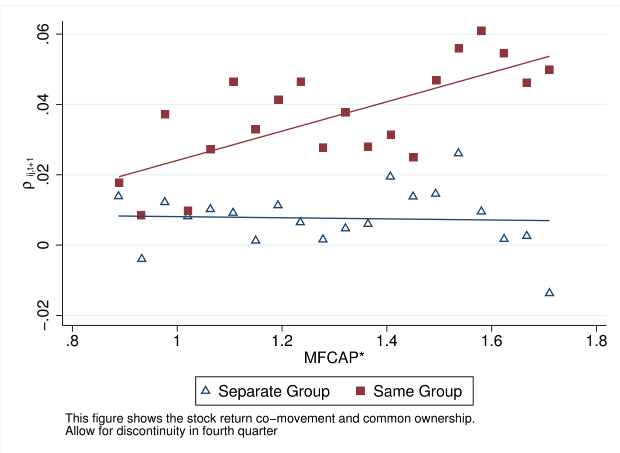



Figure 5: Monthly correlation for different level of common ownership at this period for high level of common ownership

Table 9: Estimation results for high level of common ownership

heading

| | Dependent Variable: Future Pairs's co-movement | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Same Group | 0.0312*** | | 0.0302*** | | | -0.0452* | -0.0472* |
| | (9.35) | | (9.15) | | | (-2.29) | (-2.53) |
| MFCAP* | | 0.0279*** | 0.00504 | 0.0373** | -0.00629 | -0.00704 | -0.0111* |
| | | (5.78) | (1.02) | (3.16) | (-1.18) | (-1.33) | (-2.14) |
| (MFCAP*) × SameGroup | | | | | | 0.0477*** | 0.0481*** |
| | | | | | | (3.52) | (3.75) |
| Sub-sample | All | All | All | SameGroup | Others | All | All |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Business Group FE | No | No | No | No | No | No | Yes |
| Observations | 91848 | 91848 | 91848 | 32469 | 59379 | 91848 | 91848 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Estimation results for high level of common ownership

heading

| | Mean | | | |
|---|---|---|---|---|
| | SameB/M | SameInd. | SameSize | CrossOwner. |
| Pairs | | | | |
| Others (n=323,046) | -0.30 | 0.08 | -0.28 | 0.52 |
| Forth Quarter (n=107,741) | -0.28 | 0.29 | -0.24 | 1.21 |
| Total (n=430,787) | -0.29 | 0.13 | -0.27 | 0.69 |
| Same Group | | | | |
| No (n=380,511) | -0.30 | 0.09 | -0.28 | 0.18 |
| Yes (n=50,276) | -0.25 | 0.46 | -0.26 | 4.61 |
| Total (n=430,787) | -0.29 | 0.13 | -0.27 | 0.69 |

### 3.3 All Pairs

We restrict our investigations to firms with at least one common owner in the former analyses. By this analysis, we cannot separate the effect of the business group and common ownership; both of them can affect co-movement. Furthermore, this restriction limits our result to commonly held firms, but if belonging to the same business group can increase stocks' co-movement, it would affect all the firms in the same business groups. So, we extend our investigations by constructing all the pairs in the market to separate the effect of direct common ownership and business group and solve the mentioned problems.

For this purpose, we include stocks in one pair if they have at least two months in common. By this definition, we do not restrict our investigation to commonly held stocks and set $\text{MFCA}_{ij,t}$ to zero for a pair without any common owner. Controls are defined as before, and we use equation 3 by the same methodology as used in section 3.1.

Table 11 reports results of estimations. These results suggest that pairs in the same group co-move more than stocks not in the same group. In addition, pairs with common ownership common do not co-move greater than others. In column three, we use variables of common ownership and the same business group together. Results supported our previous explanation of table 8a. The *Same Group* is critical for forecasting future co-movement, and common ownership matters for the pairs in the same business group.

Table 11: Non-connected Co-movement

heading

| | Dependent Variable: Future Pairs' co-movement | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| SameGroup | 0.0178*** | | 0.0180*** | | | 0.0122*** | 0.0105*** |
| | (9.01) | | (9.69) | | | (5.77) | (4.81) |
| MFCAP* | | 0.000393 | -0.0000580 | 0.00195* | -0.000282 | -0.000690* | -0.000156 |
| | | (1.48) | (-0.23) | (2.01) | (-1.13) | (-2.33) | (-0.51) |
| (MFCAP > $Q3$[MFCAP]) × SameGroup | | | | | | 0.0208*** | 0.0202*** |
| | | | | | | (7.38) | (7.29) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Sub-Sample | Total | Total | Total | SameGroups | Others | Total | Total |
| Business Group FE | No | No | No | No | No | No | Yes |
| Observations | 4656286 | 4656286 | 4656286 | 95686 | 4560600 | 4656286 | 4656286 |

$t$ statistics in parentheses

$^{*}$ $p < 0.05$, $^{**}$ $p < 0.01$, $^{***}$ $p < 0.001$

# 4 Evidence for correlated trading

In the previous sections, we have provided evidence consistent with the hypothesis that the presence of firms in the business groups can raise firms' co-movement. Although we don't have definitive insight into the specific channel that business groups can promote commonality, our analysis provides a useful overview. We claim that this relationship exists because the business group is an important proxy for the likelihood that trading in these stocks will be correlated. To better understand how the business group can generate co-movement in firms' returns, we now refine our basic analysis to consider other proxy measures for business group trading. We employ two proxies for business group trading that are designed to capture different trading motivations: turnover and institutional imbalance. While the first could be due to buying or selling of business groups, the latter reflects buying.

## 4.1 Turnover

First, we should show that stocks in groups have a similar daily trading behavior. Accordingly, We use the turnover measure as a daily trading measures. For each firm we run time-series regressions of the firm's daily change in turnover, $\Delta\text{TurnOver}_{i,t}$, on changes in market turnover,$\Delta\text{TurnOver}_{Market,t}$ , changes in the industry and business group portfolio's turnover,$\Delta\text{TurnOver}_{Ind,t}$ and $\Delta\text{TurnOver}_{Group,t}$ and ,as well as control variables. We compute the daily change of turnover by this definition $\Delta\text{TurnOver}_{i,t} = \ln(\frac{\text{TurnOver}_{i,t}}{\text{TurnOver}_{i,t-1}})$. We estimate the following regression for each stock across trading days in a given year separately, and cross-sectional averages of the estimated coefficients are reported, with t-statistics in parentheses :

$$\begin{aligned}\Delta\text{TurnOver}_{i,t} = \alpha + \beta_{Market,t}\Delta\text{TurnOver}_{Market,t} + \beta_{Ind,t}\Delta\text{TurnOver}_{Ind,t} \\ + \beta_{Group,t}\Delta\text{TurnOver}_{Group,t} + \delta\text{Controls} + \varepsilon_{i,t}\end{aligned}$$

We control for lead and lag changes in the two portfolios and the firm's measures and size. We estimate that model with Fama and MacBeth (1973) method and adjust its standard errors with Newey and West (1987) for seven periods. As shown in Table 12, firms' change in turnover comes from market reaction and group's change (This result is robust to the different methods of weighting for portfolios). This observation shows that firms in one group trade together each day.

We use our previous methodology to investigate these results. We calculate correlation of $\Delta$TurnOver for founded pairs and examine its relation with our variables. Table 13 reports the estimation result, which confirms that pairs in the business groups lead to correlated trade. In addition, we study effect of correlation of ΔTurnOver on co-movement for founded pairs in table 14. These results suggest that business groups yield to future co-movement through correlated trading in that month.

Table 12: cross-sectional average of the time-series coefficients for daily changes in turnover

| | Dependent Variable: $\Delta\text{TurnOver}_i$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\Delta\text{TurnOver}_{\text{Market}}$ | 0.457*** | 0.351*** | 0.182*** | 0.235*** |
| | (4.04) | (10.69) | (3.42) | (4.72) |
| $\Delta\text{TurnOver}_{\text{Industry-i}}$ | 0.220*** | 0.159*** | 0.0528 | 0.117* |
| | (4.28) | (4.10) | (1.03) | (2.37) |
| $\Delta\text{TurnOver}_{\text{Group,-i}}$ | | | 0.286*** | 0.213*** |
| | | | (6.21) | (5.15) |
| Portfo. Weight | - | - | MC | MC |
| Control | No | Yes | No | Yes |
| Observations | 746640 | 742341 | 305563 | 301329 |
| $R^2$ | 0.298 | 0.579 | 0.460 | 0.749 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Estimation results for effect of variables on co-movement ΔTurnOver

| | Dependent Variable: Future Monthly Correlation of Delta turnover | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Same Group | 0.0358*** | 0.0180*** | | | 0.0173*** | | | 0.0150*** | 0.0168*** |
| | (9.91) | (6.19) | | | (5.53) | | | (4.89) | (5.40) |
| MFCAP* | | | 0.00726*** | 0.00219** | 0.000543 | 0.00115 | 0.000372 | 0.000363 | -0.000413 |
| | | | (6.05) | (2.84) | (0.69) | (0.57) | (0.41) | (0.40) | (-0.37) |
| (MFCAP*) × SameGroup | | | | | | | | 0.00260 | 0.00296 |
| | | | | | | | | (1.03) | (1.19) |
| Controls | No | Yes | No | Yes | Yes | Yes | Yes | Yes | Yes |
| Sub-sample | All | All | All | All | All | SameGroup | Others | All | All |
| Business Group FE | No | No | No | No | No | No | No | No | Yes |
| Observations | 339697 | 294864 | 339697 | 294864 | 294864 | 37076 | 257788 | 294864 | 294864 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Furthermore, we have to directly show that firms with a higher level of group turnover have a higher level of co-movement. So, we extract the annual average level of firms and monthly turnover for each month. We assume that the residual of the model belongs to the business groups. We expect firms

Table 14: Estimation results for effect of correlation in $\Delta$TurnOver on co-movement

| | Dependent Variable: Future Pairs's co-movement | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| $\rho(\Delta \text{TurnOver})_{t+1}$ | 0.0474*** | 0.0451*** | 0.0447*** | 0.0846*** | 0.0385*** |
| | (9.35) | (9.20) | (9.18) | (10.70) | (8.38) |
| $\rho_t$ | 0.0483*** | 0.0471*** | 0.0463*** | 0.119*** | 0.0345*** |
| | (13.10) | (12.83) | (12.66) | (18.94) | (9.26) |
| Control | No | Yes | Yes | Yes | Yes |
| Sub-sample | Total | Total | Total | SameGroup | Others |
| Business Group FE | No | No | No | No | No |
| Observations | 305048 | 305048 | 305048 | 38275 | 266773 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

in the groups to have a lower dispersion in their residuals than firms out of the groups. We calculate firms' residuals by the mentioned hypothesis. Its summary stats is in table 15. As we expected, residuals in business groups have a lower dispersion than others.

We calculate the standard error of firms' monthly turnover residuals in each business group. Groups' standard errors description is shown in table 16 and time series in in figure 6. On average, the affiliated firms' standard error is lower than unaffiliated ones. For finding the relation between the standard error of monthly turnover residuals, we define a dummy variable for groups in the low level of standard error, which is lower than the median. For analysis, we restrict our investigations to a subsample of *Same Group* and others and estimate our desired variable. For further study, we use the interaction of *Same Group* with our dummy variable for the full sample, which confirmed our prior results. As shown in table 17, pairs in the business groups of low dispersion have a higher level of co-movement than other firms.

Table 15: Frims' Monthly residuals' summary statistics

| | Firm × Month | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Grouped | | | | | | | | |
| Ungrouped | 8050 | -0.001 | 0.822 | -4.789 | -0.509 | -0.016 | 0.504 | 4.407 |
| Grouped | 18199 | 0.001 | 0.777 | -4.832 | -0.481 | -0.033 | 0.469 | 4.955 |

Table 16: Gtoups' Monthly residuals' standard erros' summary statistics

| Grouped | Group × Month | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Ungrouped | 72 | 0.776 | 0.108 | 0.516 | 0.694 | 0.774 | 0.840 | 1.140 |
| Grouped | 2393 | 0.604 | 0.300 | 0.001 | 0.413 | 0.580 | 0.763 | 2.797 |

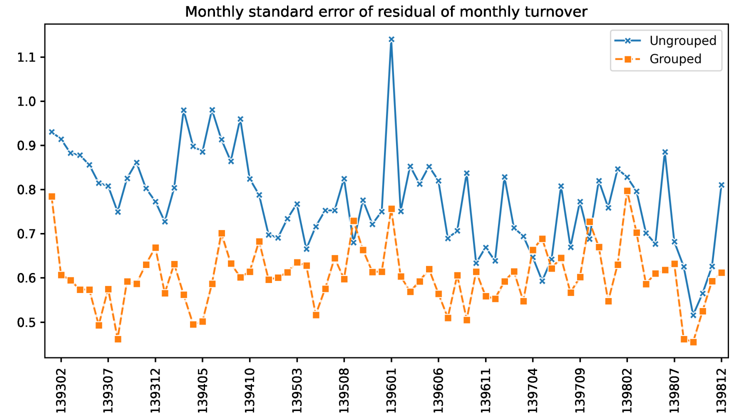



Figure 6: Average of standard errors in residuals for groups

Table 17: Estimation results for the relation between low residual std groups and co-movement

| | Dependent Variable: Future Pairs's co-movement | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Same Group | 0.0208*** | 0.0210*** | | | 0.0137*** | 0.0113** |
| | (7.91) | (7.77) | | | (3.73) | (3.19) |
| LowResidualStd | | 0.000929 | 0.0171*** | -0.000982 | -0.00107 | 0.00279 |
| | | (0.84) | (3.88) | (-0.93) | (-1.04) | (1.39) |
| LowResidualStd × SameGroup | | | | | 0.0181*** | 0.0183*** |
| | | | | | (3.65) | (3.91) |
| Sub-sample | Total | Total | SameGroup | Others | Total | Total |
| Business Group FE | No | No | No | No | No | Yes |
| Observations | 354209 | 354209 | 43274 | 310935 | 354209 | 354209 |

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

## 4.2 Institutional Imbalance

We should show that stocks in groups that trade together are traded in the same direction. So, for each firm, we calculate daily institutional imbalances, which is the net buying value of institutional investors relative to total traded value on that day (InsImb $= \frac{\text{Buy}_{\text{value}} - \text{Sell}_{\text{value}}}{\text{Buy}_{\text{value}} + \text{Sell}_{\text{value}}}$ [Seasholes and Wu (2007)]). We expect that institutional imbalances have a lower variation in groups due to the correlated tradings that the ultimate owner ordered to do. So, we calculate monthly institutional imbalances for firms at the first step. As we expected, firms in the business groups have a lower level of standard error in imbalances (Table18). Then, we calculate the monthly standard deviation of the group's imbalances and compare them to unaffiliated ones. The standard error is 12.2% and significantly (with a p-value of 0) lower than ungrouped firms.

Table 18: Frims' Monthly Imbalances' summary statistics

| Grouped | Group × Month | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Ungrouped | 20197 | 0.010 | 0.630 | -1.0 | -0.474 | 0.016 | 0.479 | 1.0 |
| Grouped | 12021 | -0.041 | 0.581 | -1.0 | -0.462 | -0.009 | 0.341 | 1.0 |

Table 19: Gtoups' Monthly Imbalances' standard erros' summary statistics

| Grouped | Group × Month | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Ungrouped | 72 | 0.624 | 0.054 | 0.48 | 0.601 | 0.631 | 0.655 | 0.735 |
| Grouped | 2057 | 0.502 | 0.251 | 0.00 | 0.337 | 0.503 | 0.647 | 1.414 |

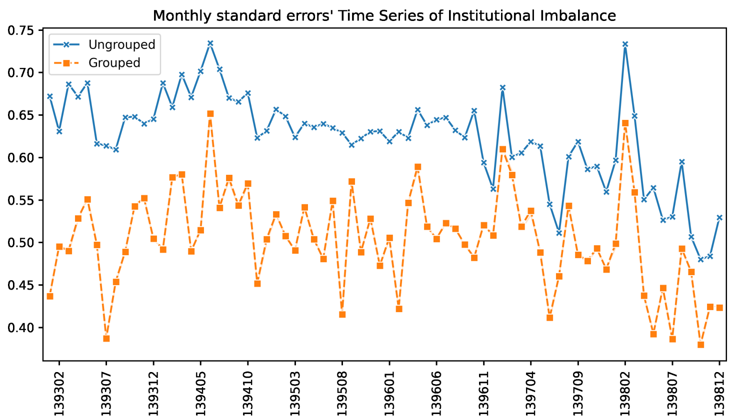



Figure 7: Average of standard errors in imbalance for groups

According to the main hypothesis, we need to compare pairs in groups with low standard error and other pairs. For this purpose, we define **Low Imbalance std** dummy for groups whose average standard errors are lower than half of the sample. So, this dummy is equal to one if at least one pair's firms belong to the low imbalance std business group. We expect pairs in the same business groups with a low standard imbalance error to comove more than others. Table 20 reports estimation results and confirms that pairs in the low imbalance std comove greater than others.

Table 20: Estimation results for the relation between low imbalance std groups and co-movement

| | Dependent Variable: Future Pairs's co-movement | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Same Group | 0.0208*** | 0.0205*** | | | 0.00614 | 0.00630* |
| | (7.91) | (7.61) | | | (1.80) | (2.04) |
| Low Imbalance std | | -0.00129 | 0.0282*** | -0.00724*** | -0.00597*** | -0.00267 |
| | | (-1.03) | (6.06) | (-5.74) | (-4.61) | (-1.85) |
| Low Imbalance std × SameGroup | | | | | 0.0362*** | 0.0325*** |
| | | | | | (8.78) | (7.48) |
| Sub-sample | Total | Total | SameGroup | Others | Total | Total |
| Business Group FE | No | No | No | No | No | Yes |
| Observations | 354209 | 354209 | 43274 | 310935 | 354209 | 354209 |

$t$ statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

# 5 Conclusion

We show that stocks are connected through mutual ultimate owners they have in common. In particular, pairs of stocks linked through ultimate owners covary more than commonly hold firms. We distinguished the effect of the high level of common ownership and the same ultimate owner and confirmed that the same ultimate owner affects more than direct common ownership. When we talk about the presence of two stocks in the same business group, we talk about a high level of invisible common ownership between two stocks that we cannot measure that by mutual stockholders.

# References


Aliabadi, E., Heidari, M., and Ebrahimnejad, A. (2021). Internal capital markets in business groups: Evidence from an emerging market.

Almeida, H., Park, S. Y., Subrahmanyam, M. G., and Wolfenzon, D. (2011). The structure and formation of business groups: Evidence from korean chaebols. *Journal of Financial Economics*, 99(2):447–475.

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

Azar, J. (2011). A new look at oligopoly: Implicit collusion through portfolio diversification.

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

Barberis, N. and Shleifer, A. (2003). Style investing. *Journal of financial Economics*, 68(2):161–199.

Barberis, N., Shleifer, A., and Wurgler, J. (2005). Comovement. *Journal of financial economics*, 75(2):283–317.

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

Daniel, K., Grinblatt, M., Titman, S., and Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of finance*, 52(3):1035–1058.

David, J. M. and Simonovska, I. (2016). Correlated beliefs, returns, and stock market volatility. *Journal of International Economics*, 99:S58–S77.

Edmans, A. (2014). Blockholders and corporate governance. *Annu. Rev. Financ. Econ.*, 6(1):23–50.

Edmans, A. and Holderness, C. G. (2017). Blockholders: A survey of theory and evidence. *The handbook of the economics of corporate governance*, 1:541–636.

Fama, E. F., French, K. R., Booth, D. G., and Sinquefield, R. (1993). Differences in the risks and returns of nyse and nasd stocks. *Financial Analysts Journal*, 49(1):37–41.

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

Freeman, K. (2019). The effects of common ownership on customer-supplier relationships. *Kelley School of Business Research Paper*, (16-84).

Gilje, E. P., Gormley, T. A., and Levit, D. (2020). Who's paying attention? measuring common ownership and its impact on managerial incentives. *Journal of Financial Economics*, 137(1):152–178.

Grullon, G., Underwood, S., and Weston, J. P. (2014). Comovement and investment banking networks. *Journal of Financial Economics*, 113(1):73–89.

Hameed, A. and Xie, J. (2019). Preference for dividends and return comovement. *Journal of Financial Economics*, 132(1):103–125.

Hansen, R. G. and Lott Jr, J. R. (1996). Externalities and corporate objectives in a world with diversified shareholder/consumers. *Journal of Financial and Quantitative Analysis*, pages 43–68.

Harford, J., Jenter, D., and Li, K. (2011). Institutional cross-holdings and their effect on acquisition decisions. *Journal of Financial Economics*, 99(1):27–39.

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

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

Holderness, C. G. (2003). A survey of blockholders and corporate control. *Economic policy review*, 9(1).

Khanna, T. and Yafeh, Y. (2007). Business groups in emerging markets: Paragons or parasites? *Journal of Economic literature*, 45(2):331–372.

Koch, A., Ruenzi, S., and Starks, L. (2016). Commonality in Liquidity: A Demand-Side Explanation. *The Review of Financial Studies*, 29(8):1943–1974.

Lewellen, K. and Lowry, M. (2021). Does common ownership really increase firm coordination? *Journal of Financial Economics.*

Newey, W. K. and West, K. D. (1987). Hypothesis testing with efficient method of moments estimation. *International Economic Review*, pages 777–787.

Newham, M., Seldeslachts, J., and Banal-Estanol, A. (2018). Common ownership and market entry: Evidence from pharmaceutical industry.

Pantzalis, C. and Wang, B. (2017). Shareholder coordination, information diffusion and stock returns. *Financial Review*, 52(4):563–595.

Seasholes, M. S. and Wu, G. (2007). Predictable behavior, profits, and attention. *Journal of Empirical Finance*, 14(5):590–610.

Shiller, R. J. (1989). Comovements in stock prices and comovements in dividends. *The Journal of Finance*, 44(3):719–729.

Wu, Q. and Shamsuddin, A. (2014). Investor attention, information diffusion and industry returns. *Pacific-Basin Finance Journal*, 30:30–43.