Connected Stocks via Business Groups: Evidence from an Emerging Market

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Abstract

We link stocks through direct and indirect common owners, and we show that having common ownership and belonging to a business group (indirect common owner) affect the co-movement. Our analysis is based on the daily ownership of blockholders on the Tehran Stock Exchange. The study found that belonging to a business group had more impact than being a common owner, and a common owner influenced only movement within business groups. In addition, co-movement in business groups is explained by simultaneous trades in the same direction.

1 Introduction

The phenomenon of "co-movement" has been observed by researchers and analysts. There is an increase in interest in risk models, notably 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. (For example 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. The following 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.

Furthermore, Anton and Polk (2014) examined on the effect of common ownership on co-movement[1]. This paper suggests that co-movement increases by increasing common ownership. Also, as the mutual fund ownership data was accessible to the author, 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.

In addition, 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.

According to the restriction of data in the US that only fund ownership data is available, investigations in this area are limited to the fund ownership impact on co-movement. 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.

[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.

Additionally, there are business groups with a share of almost 85% of the Iran stock market. Business groups are essential phenomena that can be seen in developed and developing countries. This paper analyzes co-movement in business groups. Two papers are found in the literature debate this subject, considering co-movement in business groups.

Although the co-movement in business groups is accepted, the co-movement channels remained undiscovered. Both Cho and Mooney (2015) and Kim et al. (2015) studied the South Korean market and suggested two different sources for the co-movement in business groups. The first paper attributed co-movement to the companies' fundamentals. However, the second paper presents that the investors' category/habitat behavior is responsible for co-movement.

In this paper, we consider the co-movement of the companies in business groups. Best of our knowledge, it is the first study that compares direct and indirect common ownership. A modified measurement is introduced in this paper to calculate the common ownership of the companies.

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 [2] and the Tehran Securities Exchange Technology Management Co (TSETMC)[3] database.

We exclude ETFs from our listed firms because it has 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 [4] that happened after 2020/03, which may affect our results.

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

[2] www.codal.ir

[3] www.tsetmc.com

[4] 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.

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.

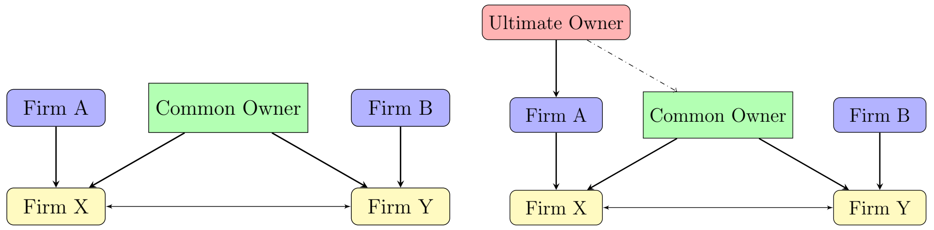
Year	2014	2015	2016	2017	2018	2019
No. of Firms	365	376	446	552	587	618
No. of Blockholders	1606	1676	2099	2978	3374	3416
No. of Groups	38	41	43	44	40	43
No. of Firms in Groups	249	268	300	336	346	375
Ave. Number of group Members	7	7	7	8	9	9
Ave. ownership of each Blockholders	18	19	18	17	18	19
Med. ownership of each Blockholders	5	4	4	4	4	5
Ave. Number of Owners	7	6	6	7	7	7
Ave. Block. Ownership	77	77	75	76	75	72

2.2 Pair composition

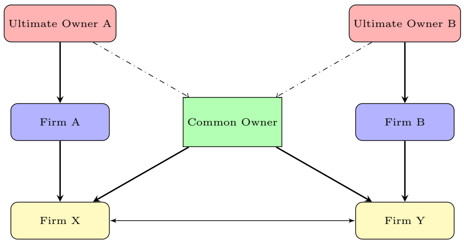
If two firms have at least one common block-holder, We consider them as a pair. By this definition, there are 17522 unique pairs in entire periods, which is 9% of possible pairs ($\frac{618*617}{2} = 190653$). As we expected, stocks in pairs have concentrated ownership relative to the total sample, and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

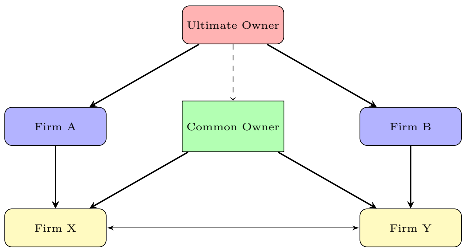
Figure 1: Three categories for pairs base on being in business groups



(a) Pair not in the business group



(b) Pair in two distinct business group



(c) Pair in the same business group

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	7471	7233	7515	8985	9479	9565
No. of Pairs not in Groups	2579	2268	2228	3379	3247	3417
No. of Pairs not in the same Group	4045	4149	4361	4548	4870	4756
No. of Pairs in the same Group	716	695	803	926	1192	1204
Ave. Number of Common owner	1	1	1	1	1	1

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

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

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.[5]

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

	MonthlyFCA					MonthlyFCAPf				
	mean	std	min	median	max	mean	std	min	median	max
All	0.158	0.272	0.003	0.06	12.65	0.127	0.168	0.003	0.055	1.0
Same Group	0.491	0.447	0.005	0.412	6.174	0.379	0.256	0.004	0.372	1.0
Not Same Group	0.104	0.175	0.004	0.044	3.84	0.087	0.117	0.004	0.041	0.998
Same Industry	0.358	0.44	0.005	0.189	5.656	0.255	0.242	0.004	0.162	0.999
Not Same Industry	0.128	0.222	0.003	0.053	12.65	0.108	0.144	0.003	0.049	1.0

[5] Each holder owns $1/n$ of each firm ,Firm's market cap is α_1 and α_2, So for each holder of firms we have $S_{i,t}^{f}P_{i,t} = \alpha_i/n$

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

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

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 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[6]) 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	0.129	-0.950	0.013	0.830
4 Factor	0.032	0.137	-0.875	0.024	0.869
4 Factor + Industry	0.012	0.125	-0.875	0.010	0.779
Benchmark	0.008	0.146	-0.927	0.006	0.848

[6]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

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**; a dummy variable for whether two stocks are in the same business group, **SameGroup**. 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.

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

	Yes	No
SameIndustry	1673 (10.2%)	14688 (89.8%)
SameGroup	1390 (14.0%)	8534 (86.0%)
SameGroup & SameIndustry	597 (3.5%)	16361 (96.5%)

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 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	0.73	0.21	0.02	0.77	1.00
Size2	0.45	0.24	0.00	0.44	0.99
SameSize	-0.28	0.20	-0.97	-0.23	-0.00
BookToMarket1	0.50	0.25	0.00	0.51	1.00
BookToMarket2	0.50	0.23	0.01	0.50	1.00
SameBookToMarket	-0.30	0.19	-0.99	-0.26	-0.00
CrossOwnership	0.56	5.17	0.00	0.00	95.79

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.

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

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:

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

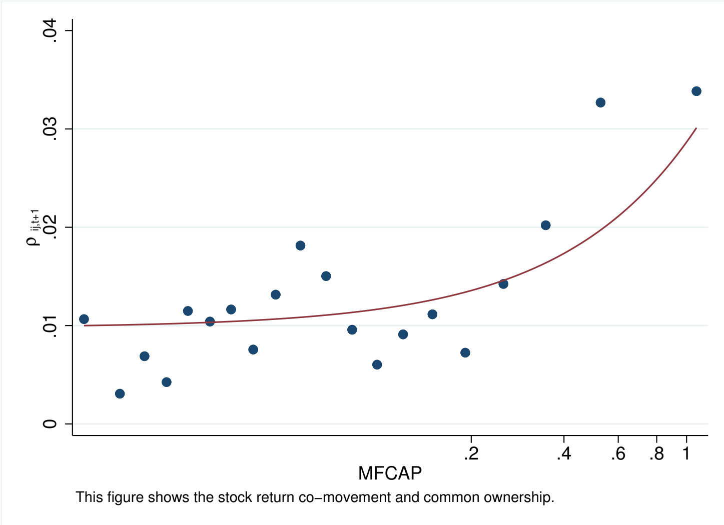


Figure 2: Future monthly correlation for different level of common ownership at this period

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 8 and 9. In the two first columns table 8, we estimate a simplified version of equation 3 with only common ownership measure($MFCAP^*_{i,j}$). 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 0.00324 and a t-statistics of 4.8 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 0.0312 and a t-statistics of 5.39. There is a significant difference in the impact of same business groups and the common ownership, according to the results.

In the fifth specification of table 8, 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 pair in the same business group affects more than a higher level of common ownership Anton and Polk (2014) study large firms but we do not restrict our investigation. In the last column of table 8, we control for pairs type (Pairs is large or small if both firms are large or small . If one firm is large and other is small, we call it hybrid.) Estimation results in table 8 shows that for all the pairs *Same Group* significantly increases co-movement.

In Table 9, we examine effect of common ownership in the business groups. In two first columns, we restrict our investigation to two sub-samples. 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 $\text{MFCA}^*_{ij,t}$. We include the business group fixed effects to capture the group's characteristics for the last column. These results aver that $\text{MFCA}^*_{ij,t}$ 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

	Dependent Variable: Future Pairs's co-movement					
	(1)	(2)	(3)	(4)	(5)	(6)
MFCAP*	0.00501***	0.00324***			0.000682	0.000348
	(7.27)	(4.80)			(1.01)	(0.46)
Same Group			0.0346***	0.0312***	0.0304***	0.0275***
			(8.96)	(5.39)	(5.13)	(4.44)
Controls	No	Yes	No	Yes	Yes	Yes
PairType Control	No	No	No	No	No	Yes
Observations	297874	297874	297874	297874	297874	297874

t statistics in parentheses

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

Table 9: Connected Co-movement

	Dependent Variable: Future Pairs's co-movement			
	(1)	(2)	(3)	(4)
MFCAP*	0.0123***	-0.000448	-0.000463	0.00111
	(4.10)	(-0.70)	(-0.75)	(1.06)
Same Group			0.0318	0.0338
			(1.40)	(1.24)
(MFCAP*) $\times$ SameGroup			0.000209	-0.00476
			(0.02)	(-0.27)
Sub-sample	SameGroup	Others	All	All
Business Group FE	No	No	No	Yes
Observations	36061	261813	297874	297874

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 drive from 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.

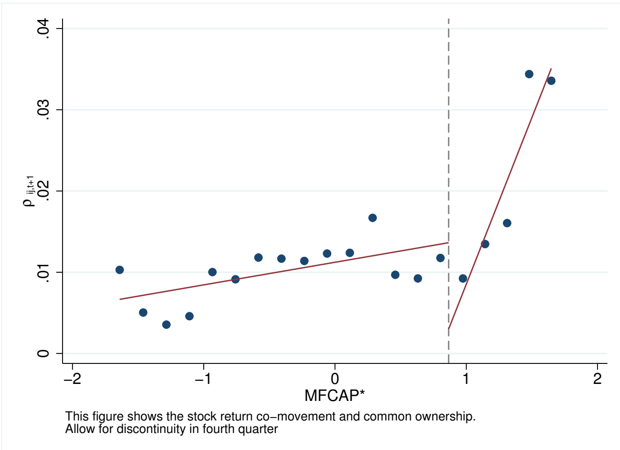


Figure 3: Future monthly correlation for different level of common ownership at this period

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 10 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 six and seven prove our prior explanations for the importance of business groups compared to common ownership in pairs with a higher level of common ownership.

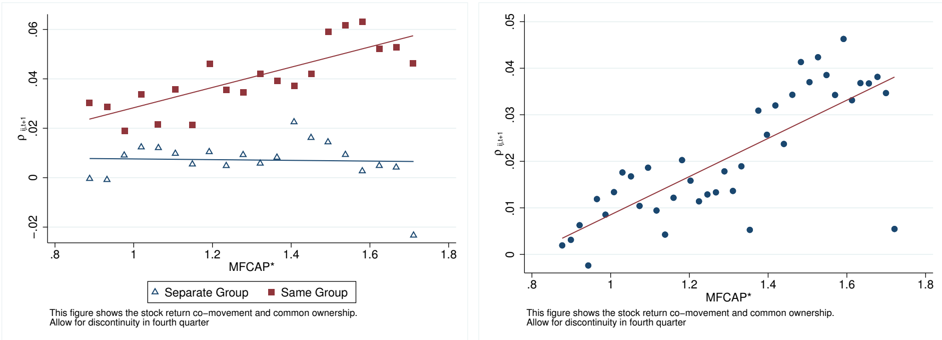


Figure 4: Future monthly correlation for different level of common ownership at this period for high level of common ownership

Table 10: Estimation results for high level of common ownership

	Dependent Variable: Future Pairs's co-movement			
	(1)	(2)	(3)	(4)
Same Group	0.0341***		-0.0410	-0.0407*
	(8.32)		(-1.94)	(-2.09)
MFCAP*		0.0338***	-0.0423	-0.0338
		(4.75)	(-1.29)	(-1.47)
(MFCAP*) $\times$ SameGroup			0.0518***	0.0526***
			(3.62)	(3.87)
Controls	Yes	Yes	Yes	Yes
Business Group FE	No	No	No	Yes
Observations	76527	76527	76527	76527

t statistics in parentheses

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

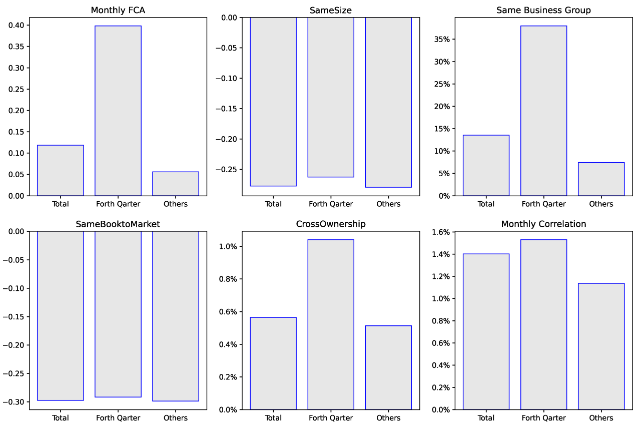


Figure 5: Pairs' characteristics for the pairs with high level of common ownership

3.3 All Pairs

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

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 the same methodology as used for estimating equation 3. We estimate equation 3.

Table 11 reports results of estimations for two models. These results suggest that pairs in the same group co-move more than stocks that are not in the same group. In addition, pairs with common ownership common does not co-move greater than others. In columns 3 , we use variables of common ownership and the same business group together. Results supported our previous explanation of table 8 that the *Same Group* is critical for forecasting future co-movement, and common ownership does not matter for pairs. In the pairs with common ownership, pairs in the same group have a higher level of co-movement than the pairs no in the same group.

Table 11: Non-connected Co-movement

	Dependent Variable: Future Pairs' co-movement						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SameGroup	0.0156***		0.0158***			0.0138***	0.0131***
	(9.84)		(10.22)			(8.27)	(7.68)
MFCAP*		-0.0000723	-0.000277	0.00169	-0.000322*	-0.000390**	-0.000427*
		(-0.44)	(-1.80)	(1.42)	(-2.19)	(-2.70)	(-2.29)
(MFCAP*) × SameGroup						0.00313**	0.00364**
						(2.80)	(3.34)
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	6018646	6018646	6018646	114526	5904120	6018646	6018646

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 gain a clearer understanding of how the business group is able to generate co-movement in firms' return, we now refine our basic analysis to consider other proxy measures for business group trading. We employ one proxy for business group trading that is designed to capture trading motivations: turnover which could be due to buying or selling of business groups.

4.1 Turnover

First of all, 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 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 portfolio and market's measures and size of the firm. 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 method of weighting for portfolios) This observation shows that firms in one group trade together in each day.

Furthermore, we have to show that firms with higher level of group turnover, have a higher level of co-movement. So, For each month, we extract annual average level of firms' turnover and monthly turnover. We assume that the residual of the model belongs to the business groups. We expect that firms in the groups have a lower dispersion in their residuals than firms out of the groups. We calculate firms' residuals. Its summary stats is in table 13. As we expected, residuals in business groups have a lower dispersion than others. We calculate standard error of monthly turn over residuals of firms in the business groups for each business group. Groups' standard errors description is shown in table 14. On average group's standard error is lower than ungrouped ones. For finding relation between standard error of monthly turnover residuals, we define a dummy variable for groups in the low level

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

	Dependent Variable: ΔTurnOver_*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

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

	Dependent Variable: Future Monthly Correlation of Delta turnover						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same Group	0.0385***	0.0225***			0.0217***	0.0259*	0.00626
	(10.19)	(4.95)			(4.71)	(2.30)	(0.60)
MFCAP*			0.00623***	0.00128	-0.000254	-0.000331	-0.00691
			(4.20)	(1.04)	(-0.22)	(-0.29)	(-1.10)
(MFCAP*) × SameGroup						-0.00244	0.0101
						(-0.37)	(1.58)
Controls	No	Yes	No	Yes	Yes	Yes	Yes
Business Group FE	No	No	No	No	No	No	Yes
Observations	288164	278286	288164	278286	278286	278286	278286

t statistics in parentheses

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

	Dependent Variable: Future Pairs's co-movement				
	(1)	(2)	(3)	(4)	(5)
$\rho(\Delta\text{TurnOver})_{t+1}$	0.0498***	0.0494***	0.0481***	0.0822***	0.0410***
	(7.96)	(6.71)	(7.24)	(10.23)	(7.03)
ρ_t	0.0455***	0.0415***	0.0399***	0.118***	0.0280***
	(10.05)	(6.41)	(5.60)	(17.54)	(3.62)
Control	No	Yes	Yes	Yes	Yes
Sub-sample	Total	Total	Total	SameGroup	Others
Business Group FE	No	No	No	No	No
Observations	288146	288146	288146	35026	253120

t statistics in parentheses

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

of standard error which is lower than median. As shown in table 15, pairs in the business groups of low dispersion have a higher level of co-movement than other firms.

Table 13: Frims' Monthly residuals' summary statistics

Grouped	Firm × Month	mean	std	min	25%	50%	75%	max
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 14: Frims' 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

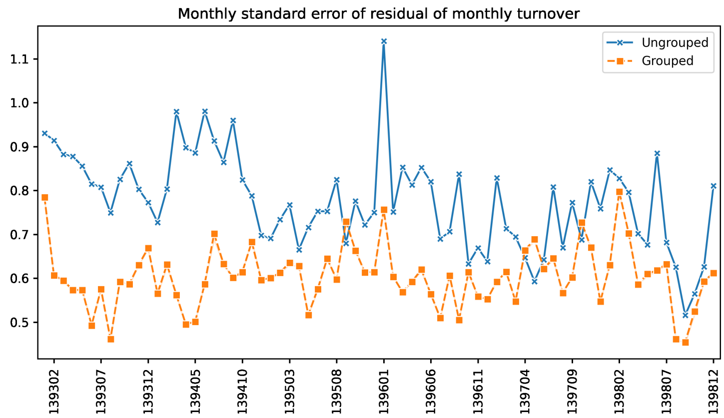


Table 15: text

	Dependent Variable: Future Pairs's co-movement			
	(1)	(2)	(3)	(4)
Same Group	0.0277***	0.0280***	0.0204***	-0.0301
	(4.88)	(5.32)	(3.50)	(-0.71)
LowResidualStd		-0.00160	-0.00369	-0.0313
		(-0.70)	(-1.56)	(-0.98)
LowResidualStd × SameGroup			0.0182***	0.0190***
			(3.60)	(4.06)
Group Size Effect	No	Yes	Yes	No
Business Group FE	No	No	No	Yes
Observations	297874	297874	297874	297874

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 that are 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.

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