Connected Stocks: Evidence from Iran

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Abstract

We connect stocks by their common blockholders. We introduce a measure that captures the extent to which distribution of joint holders. A vital feature of the measure is allowing the joint ownership distributions to affect the measure. After that, We show that the degree of shared ownership that crosses a threshold forecasts return correlation, controlling for exposure to systematic return factors and other pair characteristics. We study this effect in business groups and find that being in the same business group significantly affects comovement. Further investigations explain that comovement increases when a bank is a business group's ultimate owner.

Keywords: Asset management; Institutional investors; Return comovement; Common ownership; Indexing

JEL Classifications: G10; G11; G23

1 Introduction

- Table 10 :
  - Common ownership increases co-movement
  - The effect is stronger for pairs that are in the same business groups
- Table 11:
  - For all the pairs, same business groups have an greater effect on co-movement.
  - Common ownership increases co-movement for the pairs in the same business group

2 Data and Methodology

2.1 Data and Sample

We gathered industries index and stock returns, trading volume, and other relevant market and accounting data from the Codal website [1] and the Tehran Securities Exchange Technology Management Co (TSETMC)[2] database. We also 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 exclude ETFs from our listed firms because it has a different return and ownership patterns compared to other firms in our study. We restrict

[1] www.codal.ir

[2] www.tsetmc.com

our empirical analysis to 2015/03-2020/03(1394/01-1398/12 Persian calendar) due to the availability of daily ownership data and the special events [3] 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 members which own 314 (63%) firms.

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 9336 unique pairs in entire periods, which is 18% of possible pairs (597*596/2 = 177906). As we expected, stocks in pairs have concentrated ownership relative to the total sample, and pairs

[3]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.

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	2020	2021
No. of Firms	360	369	393	543	570	608	642	645
No. of Blockholders	745	774	901	1284	1373	1446	1454	1295
No. of Groups	38	41	42	46	44	44	43	43
No. of Firms not in Groups	114	116	119	216	230	256	269	272
No. of Firms in Groups	246	264	281	350	350	376	373	373
Mean Number of Members	6	6	7	8	8	9	9	9
Med. of Number of Members	5	5	4	6	6	6	6	6
Mean Of each Blockholder's ownership	21	21	22	21	21	23	23	21
Med. of Owners' Percent	7	7	7	8	7	9	9	7
Mean Number of Blockholders	5	5	5	5	5	5	5	5
Med. Number of Owners	4	5	4	4	4	4	4	4
Mean Block. Ownership	76	77	77	75	75	72	68	68
Med. Block. Ownership	82	82	82	80	80	78	73	72

have one common owner.

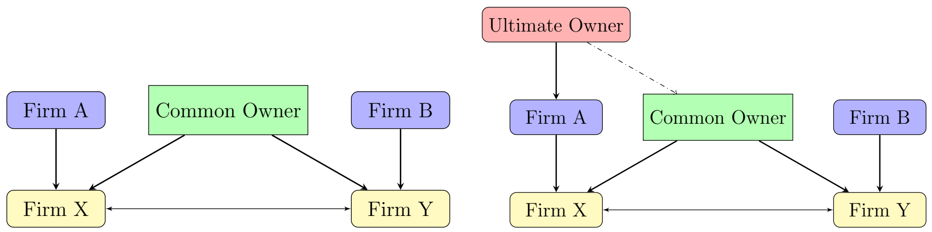
As one of our empirical studies, we study the impact of being in the same business group relative to being in two distinct groups on pair's correlation. (Further explanations about business groups are in section 2.6) For assigning one pair to a group, both firms should belong to one ultimate owner. Another 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, and 74% of them are not in the same business groups each year. We report summary statistics of ownership features for all pairs in table 2.

Figure 2 shows the time series of unique pairs' number in each month. The pattern shows that the portion of pairs that are in one business group

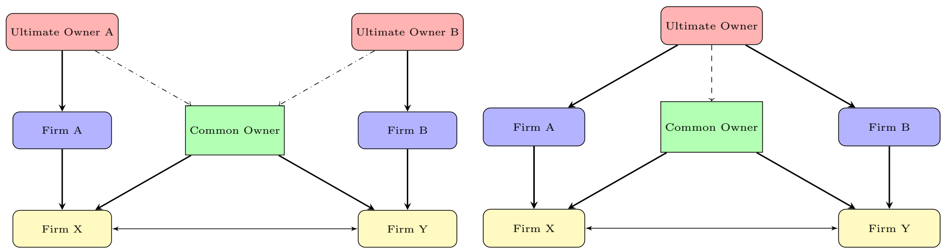
Table 2: This table reports summary statistics of ownership features for total pairs. At this table by group, we mean business groups.

Year	2015	2016	2017	2018	2019	2020	Mean
No. of Pairs	8188	9934	11925	12998	12055	8195	10549
No. of Groups	40	41	43	43	38	38	41
No. of Pairs not in Groups	3491	3879	5213	5876	6175	4466	4850
No. of Pairs in the same Group	675	795	1016	1120	1062	807	913
No. of Pairs not in the same Group	3853	4845	5221	5339	4440	2817	4419
Mean Number of Common owner	1.21	1.19	1.19	1.16	1.17	1.16	1.18
Med. Number of Common owner	1	1	1	1	1	1	1.00
Mean Number of Pairs in one Group	24	26	27	29	28	21	25.83
Med. Number of Pairs in one Group	10	11	9	6	7	6	8.17
Mean Percent of each Blockholder	16.53	17.12	16.82	16.87	16.73	16.61	16.78
Med. Percent of each Blockholder	9.92	9.95	9.78	9.65	10.03	10.57	9.98
Mean Number of Owners	5.82	5.79	5.7	5.78	5.91	6.08	5.85
Med. Number of Owners	5.91	5.88	5.77	5.84	5.95	6.09	5.91
Mean Block. Ownership	71.68	72.82	71.38	72.09	71.79	72.55	72.05
Med. Block. Ownership	73.37	74.57	72.89	73.61	73.14	73.79	73.56

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



(a) Pair not in the business group

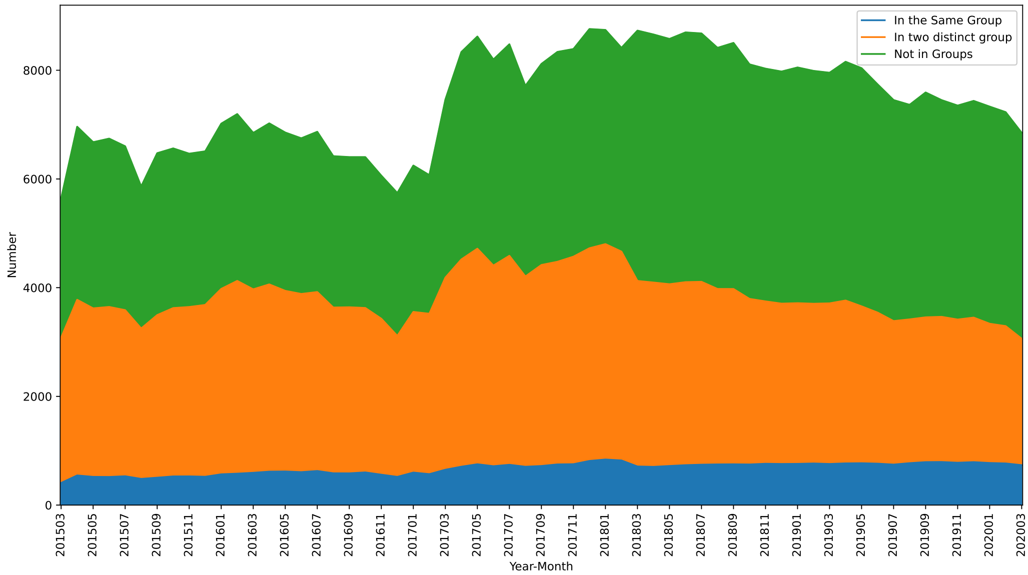


(b) Pair in two distinct business group

(c) Pair in the same business group

is roughly stable. The number of pairs in each period is between 322 to 5101 pairs which, on average, there are 4325 pairs.

Figure 2: The number of unique pairs in each month



2.3 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) :

$$\begin{aligned} R_{i,t} = \alpha_i + \beta_{mkt,i} R_{M,t} + \beta_{Ind,i} R_{Ind,t} + \\ + \beta_{HML,i} HML_t + \beta_{SMB,i} SMB_t + \beta_{UMD,i} UMD_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

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 for calculating a monthly correlation and report its summary in table 3. 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 these correlations for our analysis.

Table 3: This table reports distribution of calculated correlation base on different models.

$\rho_{ij,t}$	mean	std	min	25%	50%	75%	max
CAPM + Industry	0.007	0.328	-1	-0.194	0.006	0.208	1
4 Factor	0.038	0.338	-1	-0.172	0.035	0.248	1
4 Factor + Industry	0.006	0.326	-1	-0.194	0.005	0.206	1
4 Factor + Industry (With Lag)	0.006	0.325	-1	-0.194	0.006	0.206	1

2.4 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 4, 10% and 6% 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 4: This table reports the number of pairs in the same industry and business group.

Type of Pairs	Yes	No
SameIndustry	1760	16739
	(10%)	(90%)
SameGroup	1118	17381
	(6%)	(94%)
SameGroup & SameIndustry	492	18007
	(3%)	(97%)

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 5 shows the summary statistics of specified controls in this section.

Table 5: This table shows the summary statistics of specified controls in empirical studies.

	mean	std	min	25%	50%	75%	max
SameIndustry	0.10	0.29	0.00	0.00	0.00	0.00	1.00
SameGroup	0.06	0.23	0.00	0.00	0.00	0.00	1.00
Size1	0.72	0.21	0.01	0.58	0.78	0.91	1.00
Size2	0.43	0.25	0.00	0.23	0.42	0.62	0.99
SameSize	-0.29	0.21	-0.97	-0.42	-0.24	-0.12	0.00
BookToMarket1	0.53	0.26	0.00	0.34	0.54	0.73	1.00
BookToMarket2	0.52	0.24	0.00	0.34	0.52	0.71	1.00
SameBookToMarket	-0.30	0.19	-0.99	-0.42	-0.26	-0.15	0.00
CrossOwnership	0.01	0.05	0.00	0.00	0.00	0.00	0.96

2.5 Measurement of cross-ownership

In table 6 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))

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

Table 6: 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)	$\sum_{i\in I^{A,B}} min\{\alpha_{i,A}, \alpha_{i,B}\}$	?
	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)	$\sum_{i\in I^{A,B}} \alpha_{i,A} \times \sum_{i\in I^{A,B}} \alpha_{i,B}$	? ?

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.

2.5.1 Modified Anton's measure

We reformulate mentioned Anton's measure in table 6. This factor measure common ownership as the total value of stock held by the F common-holders of the two stocks, scaled by the total market capitalization of the two stocks

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

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. As shown in equation 2, this measure neglects different distribution of common owners and represents the percent of joint-held market capitalization from the total market capitalization of the two stocks.

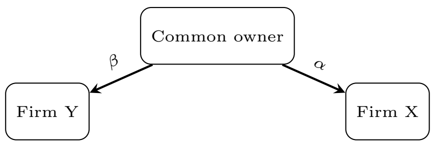
We reweight this formula to capture the difference between ownership distribution. Our proposed measures are shown in equation 3 and 4 where all variables as the same Anton's measure. Both modified measures represent the number of equal percents held block-holder. In other words, If for a pair of stocks with n mutual owners, all owners have even shares of each firm's market cap, then the proposed indexes will be equal to number of holders.[4]

$$\text{Overlap}_{Sqrt}(i,j) = [\frac{\sum_{f=1}^{F}(\sqrt{S_{i,t}^{f}P_{i,t}} + \sqrt{S_{j,t}^{f}P_{j,t}})}{\sqrt{S_{i,t}Pi,t} + \sqrt{S_{j,t}Pj,t}}]^2 \tag{3}$$

$$\text{Overlap}_{Quadratic}(i,j) = [\frac{\sum_{f=1}^{F}[(S_{i,t}^{f}P_{i,t})^2 + (S_{j,t}^{f}P_{j,t})^2]}{(S_{i,t}Pi,t)^2 + (S_{j,t}Pj,t)^2}]^{-1} \tag{4}$$

There are some numeric examples for better comparison. Two firms (X and Y) have one common owner who has α and β from each market capitalization, respectively. (illustrated in figure 3) for better illustration, assume that the sum of holder's ownership equal to 100 percent ($\alpha + \beta = 100$), and two firms' market cap is equal.

Figure 3: Numeric example 1



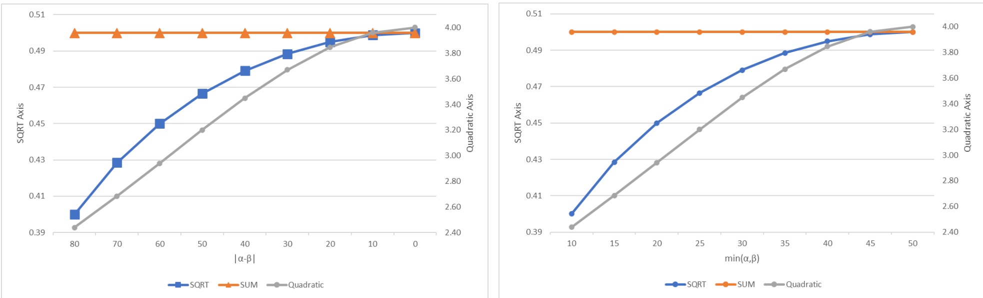
We calculate common ownership measures base on equations 2 (Sum), 3 (SQRT), and 4 (Quadratic) for different ownership distributions. Figure 4 reports calculations results. As we expected, Anton's measure is constant at a fixed level of aggregate common ownership, but SQRT and Quadratic vary from concentrated to dispersed ownership. Concentrated ownership (50-50) has a greater common ownership measure than dispersed (10-90).

[4] 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 $S_{i,t}^{f}P_{i,t} = \alpha_i/n$

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

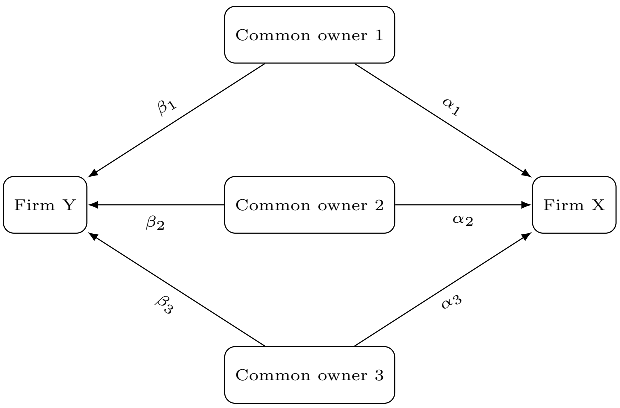
$[\frac{\sum_{f=1}^{n}(\alpha_1/n)^2+\sum_{f=1}^{n}(\alpha_2/n)^2}{\alpha_1^2+\alpha_2{}^2}]^{-1} = [\frac{\alpha_1^2+\alpha_2^2}{n(\alpha_1^2+\alpha_2^2)}]^{-1} = n$

Figure 4: Comparison of three measure for common ownership



Now assume that there are three common owners for the two mentioned firms. First holder's ownership from firm X and Y are respectively α_1 and β_1. It is similar for other holders. (illustrated in figure 5). As before, the firm's market cap is equal. We calculate measures for concentrated or disparate ownership and ownerships that are less than the aggregate of the firm's market cap. Table 7 reports calculation results. For ownerships that consist of total market cap, results are consistent with the first example. Although, when aggregate ownership decreases, the Quadratic measure denotes unrealistic numbers. We conclude that our Quadratic measure is not a good measure for common ownership.

Figure 5: Numeric example 2



A fundamental assumption in previous examples is equality of firms' mar-

Table 7: text

Ownership	Type I	Type II	Type III	Type IV	Type V	Type VI	Type VII
α_1	1/3	20	10	20	10	5	1
β_1	1/3	10	10	20	10	5	1
α_2	1/3	10	80	20	10	5	1
β_2	1/3	20	80	20	10	5	1
α_3	1/3	70	10	20	10	5	1
β_3	1/3	70	10	20	10	5	1
SQRT	3	2.56	2.33	1.8	0.9	0.45	0.09
SUM	1	1	1	0.6	0.3	0.15	0.03
Quadratic	3	1.85	1.52	8.33	33.33	133.33	3333.33

ket cap. In the last example, we relax this assumption. Table 8 reports calculated measures for fixed aggregate ownership on different relative market cap ratios. We extend our analysis to higher market cap ratios and report our results in figure 6 and 7. In this setting, the SQRT measure has a better variation relative to Anton's measure.

Figure 6: SQRT measure for fixed aggregate ownership on different relative market cap ratios

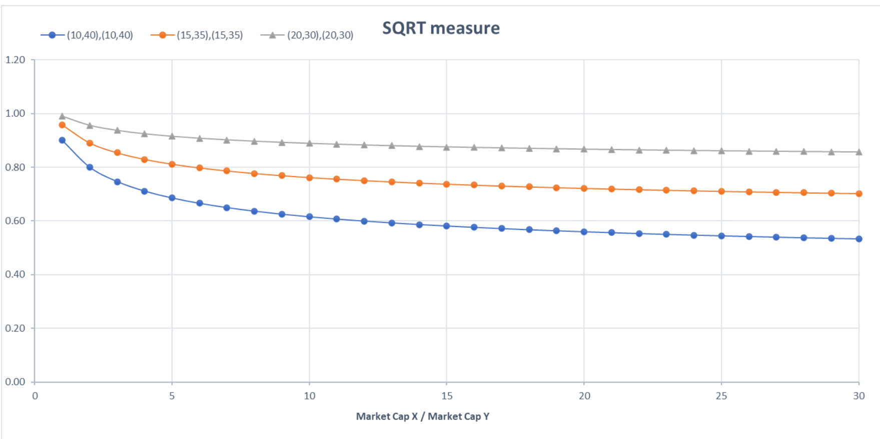


Figure 7: Sum measure for fixed aggregate ownership on different relative market cap ratios

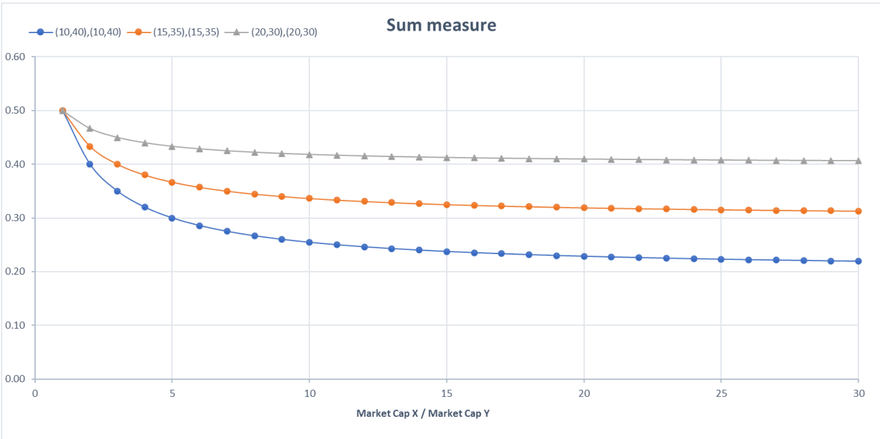


Table 8: text

	$(\alpha_1,\beta_1),(\alpha_2,\beta_2)$					
	(10,40),(10,40)		(15,35),(15,35)		(20,30),(20,30)	
$\frac{\text{MarketCap}_x}{\text{MarketCap}_y}$	SQRT	SUM	SQRT	SUM	SQRT	SUM
1	0.90	0.50	0.96	0.50	0.99	0.50
2	0.80	0.40	0.89	0.43	0.96	0.47
3	0.75	0.35	0.85	0.40	0.94	0.45
4	0.71	0.32	0.83	0.38	0.92	0.44
5	0.69	0.30	0.81	0.37	0.91	0.43
6	0.67	0.29	0.80	0.36	0.91	0.43
7	0.65	0.28	0.79	0.35	0.90	0.43
8	0.64	0.27	0.78	0.34	0.90	0.42
9	0.63	0.26	0.77	0.34	0.89	0.42
10	0.62	0.25	0.76	0.34	0.89	0.42

In conclusion, We use the SQRT measure for our main study. This measure has an acceptable variation within different distributions and relative market caps. Also, it has a fair value at a lower level of aggregate common ownership.

On each day, we measure common ownership by SQRT 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 9 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 9: text

	variable	count$_{(\text{month} \times \text{id})}$	mean	std	min	25%	median	75%	max
Total	FCA	454343	0.144	0.235	0.003	0.025	0.058	0.151	3.967
	FCAP	454343	0.123	0.164	0.003	0.024	0.054	0.144	0.992
Same Group	FCA	44109	0.491	0.418	0.005	0.170	0.435	0.691	3.967
	FCAP	44109	0.396	0.259	0.004	0.145	0.405	0.608	0.985
Not Same Group	FCA	410234	0.107	0.168	0.003	0.023	0.050	0.119	3.734
	FCAP	410234	0.094	0.117	0.003	0.022	0.048	0.117	0.992
Same Industry	FCA	56549	0.345	0.409	0.007	0.055	0.189	0.512	3.967
	FCAP	56549	0.258	0.242	0.006	0.051	0.165	0.431	0.992
Not Same Industry	FCA	397794	0.116	0.181	0.003	0.024	0.051	0.124	2.619
	FCAP	397794	0.104	0.140	0.003	0.023	0.048	0.122	0.985

2.6 Overview of Business Groups in Tehran Stock Exchange

There is no difference between emerging markets (such as Chile, India, Indonesia, South Korea, Pakistan, and many more) and developed ones (like Italy and Sweden); business groups present everywhere. However, group-affiliated firms are relatively large and economically important in emerging markets. These groups principally consist of legally independent firms grouped by persistent formal (e.g., equity) and informal (e.g., family) links.(Khanna and Yafeh (2007)) There is a complex ownership network in TSE as an emerging market. This complicated ownership creates a vast number of business groups in which an ultimate owner controls them through a multi-layer of ownership. (Farajpour et al. (2019))

The reason for many of these business groups back to the 1979 revolution. After the revolution, due to social sentiment, critical sectors of the economy nationalized, and their ownership transferred to the government or other pseudo-government foundations. Also, some other groups of firms in heavy industries were established and controlled by the Industrial Development and Renovation Organization (IDRO) during the 1960s and 1970s. (IDRO was a state-owned holding company for investing in capital-intensive industries)

The business groups are formed from mentioned ancestors due to two related forces; A multi-phased privatization by the state and the development of the domestic stock market. In the first wave of privatization, more than 300 companies were fully or partially privatized. In the second one, approximately $150 billion ownership of State-Owned Enterprises (SOEs) and assets were transferred. Pension funds, military institutions, cultural and religious foundations, and revolutionary foundations (pseudo-government groups) primary customers in the second wave of privatization. These waves of privatization transferred control of hundreds of SOEs to semi-governmental groups and were the main driver of the formation of business groups in Iran. In addition, the developing stock market from the early 2000s enhances this effect. The government tried to develop the stock market as a tool for better privatization. (Aliabadi et al. (2021))

In conclusion, the multiple waves of privatization with the development of the stock market changed ownership structure in pre-revolutionary holding companies and post-revolutionary foundations. They created large business groups that govern primary industries. As a result, we expect that pairs in the business groups belong to the same sector, and figure 8 confirms that. As you can see, only 8% of our pairs belong to the same industry, but 43% of pairs in the same group are in the same industry. Pairs in the business groups are the same size and book to market as other pairs. However, as said before, the common ownership level in these pairs is much greater, and cross-ownership is higher in business group pairs. Figure 9 reports an average of control variables in these two types of groups.

Figure 8

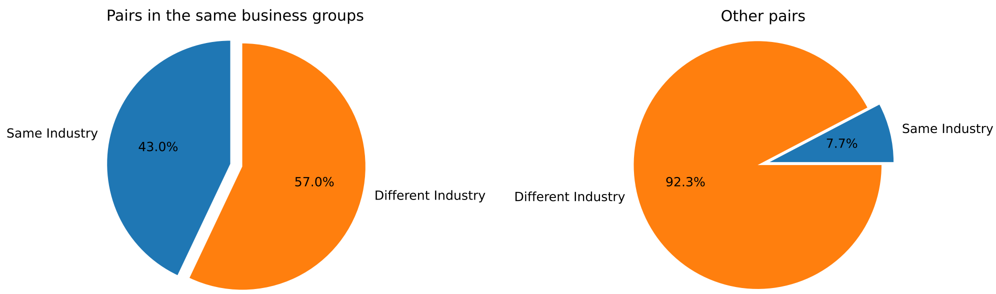
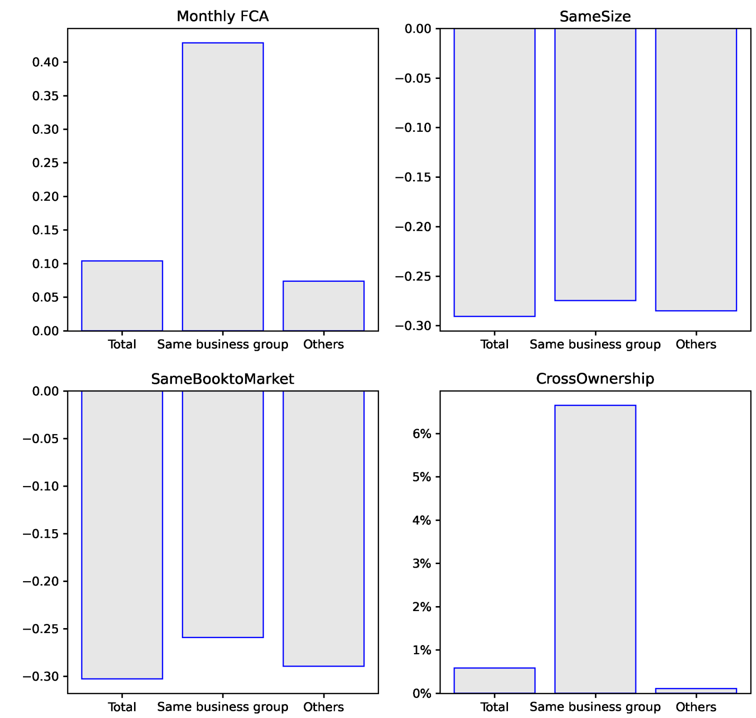


Figure 9


Monthly FCA
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
Total
Same business group
Others
SameSize
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
−0.30
Total
Same business group
Others
SameBooktoMarket
0.00
−0.05
−0.10
−0.15
−0.20
−0.25
−0.30
Total
Same business group
Others
CrossOwnership
6%
5%
4%
3%
2%
1%
0%
Total
Same business group
Others

3 Results

3.1 Forecasting Co-movement

Our specific interest is how the common ownership affects a pair of stocks return co-movement. As it has shown in figure 10, a higher level of common ownership in the current period is associated with a higher level of correlation in the following month. We empirically test the impact of current measured common ownership on the next period's co-movement.

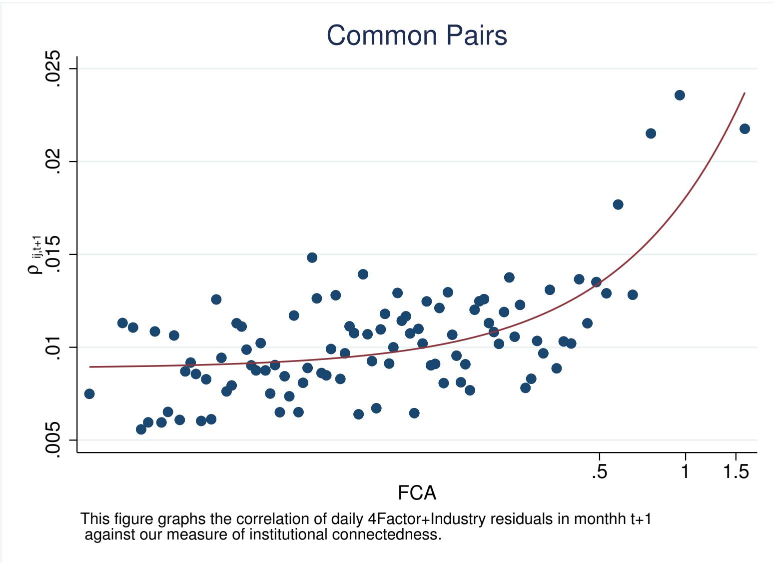


Figure 10: Future monthly correlation for different level of common ownership at this period

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 2.3). We use $FCA^*_{ij,t}$, $SameGroup_{ij}$, and their interaction for our main analysis and other pair characteristics as controls:

$$\begin{aligned}\rho_{ij,t+1} = \beta_0 &+ \beta_1 * \text{FCA}^*_{ij,t} + \beta_2 * \text{SameGroup}_{ij} \\ &+ \beta_3 * \text{FCA}^*_{ij,t} \times \text{SameGroup}_{ij} \\ &+ \sum_{k=1}^{n} \alpha_k * \text{Control}_{ij,t} + \varepsilon_{ij,t+1}\end{aligned} \tag{5}$$

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 $(4(60/100)^{\frac{2}{9}} = 3.57 \sim 4)$.

Table 10 shows that results from forecasting cross-sectional variation in pair's co-movement. In the first two columns, we estimate a simplified version of equation 5 with only the *Same Group* as an independent variable. 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 the *Same Group* has a high statically significant effect, with a coefficient of 0.0235 and a t-statistic of 7.98, in the presence of control variables. In columns three and four, we estimate our simplified model with only common ownership, $\text{FCA}^*_{ij,t}$, as a forecasting variable. We find that $\text{FCA}^*_{ij,t}$ significantly improves our forecast, with a coefficient of 0.0035 and a t-statistic of 1.91, which is significant at ten percent level, however, the impact of the *Same Group* is seven times bigger than this.

In the fifth specification of table 10, we use both *Same Group* and $\text{FCA}^*_{ij,t}$

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. Furthermore, in the sixth and seventh columns of table 10, 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 maim analysis, we include the interaction of *Same Group* and $\text{FCA}^*_{ij,t}$. We include the business group fixed effects to capture the group's characteristics for the last column. These results aver that $\text{FCA}^*_{ij,t}$ has a larger effect for the pairs in the same business group. However, *Same Group* do not have a significant effect on our estimation. It puts forward that the *Same Group* affects co-movement through indirect common ownership, which arises due to the same ultimate owner. On the other hand, as shown in figure 9, pairs in the same business group have a higher level of common ownership than others. This evidence, in line with figure 10, implies that a higher level of common ownership has a major effect on the pair's co-movement.

We extend our investigation to separate the effect of business groups and a high level of common ownership by constructing all the pairs in the market. For this purpose, we include stocks in one pair if they have two months in common. By this definition, we do not restrict our investigation to commonly hold stocks and set $\text{FCA}^*_{ij,t}$ to zero for two stocks that do not have any common owner. We define a dummy variable that equals one if pairs' common ownership, $\text{FCA}^*_{ij,t}$, is in the fourth quarter of that period and use it as our variable of interest. Other controls are defined as before,

Table 10: Connected Co-movement

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Same Group	0.0235***	0.0241***			0.0227***			0.00507	0.00164
	(7.98)	(8.63)			(7.55)			(1.27)	(0.37)
FCA*			0.00349**	0.00309*	0.0000468	0.0162***	-0.00192	-0.00222	-0.000280
			(2.14)	(1.91)	(0.03)	(5.37)	(-1.19)	(-1.39)	(-0.17)
(FCA*) × SameGroup								0.0196***	0.0164***
								(6.27)	(5.04)
Observations	200737	200737	200737	200737	200737	32208	168529	200737	200737
Sub-sample	All	All	All	All	All	SameGroup	Others	All	All
Group Effect	No	No	No	No	No	No	No	No	Yes
Controls	No	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00189	0.00565	0.00124	0.00520	0.00662	0.0297	0.00605	0.00784	0.0488

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

and we use the same methodology as used for estimating equation 5:

$$\begin{aligned}\rho_{ij,t+1} = \beta_0 + \beta_1 * (\text{FCA}^*_{ij,t} > Q3[\text{FCA}^*_{ij,t}]) + \beta_2 * \text{SameGroup}_{ij} \\ + \beta_3 * (\text{FCA}^*_{ij,t} > Q3[\text{FCA}^*_{ij,t}]) \times \text{SameGroup}_{ij} \\ + \sum_{k=1}^{n} \alpha_k * \text{Control}_{ij,t} + \varepsilon_{ij,t+1}\end{aligned} \tag{6}$$

In table 11, we show that pairs in the same group co-move with each other more than stocks that are not in the same group. In addition, as we expected, pairs by the high level of common ownership co-move greater than others (columns 1 and 2). In the third specification, we used both variables and supported our previous results from table 10 that *Same Group* and FCA* are both critical for forecasting future co-movement.

In columns four and five of the table 11, we estimate our variable of interest for the subsample of pairs in the same business group. These specifications help us to separate common ownership and the group effect. The results confirm that common ownership will increase the co-movement of the stocks' abnormal return for the pairs in the same group. Furthermore, we estimate model 6 for the full sample. The last column of table 11 reports the result of this estimation. Contrary to previous results of table 10, the interaction of *Same Group* and the high level of common ownership is not significantly improved our forecasts. According to figure 9 and table 9, pairs in the same group have higher measures of common ownership which make the interaction correlated with *Same Group* ($\rho =$). 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.It seems that

Table 11: Non-connected Co-movement

	Future Monthly Correlation of 4F+Industry Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
(FCA $> Q3$[FCA])		0.00543***	0.00549***	0.00695*		0.00539***
		(4.12)	(4.17)	(2.10)		(4.04)
SameGroup	0.0122***		0.0124***			0.00901*
	(5.81)		(5.97)			(2.62)
(FCA $> Q3$[FCA]) $\times$ SameGroup						0.00392
						(1.20)
FCA*					0.00174*	
					(2.43)	
Observations	5148109	5148109	5148109	76240	76240	5148109
Sub Sample	Total	Total	Total	SameGroups	SameGroups	Total
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000455	0.000457	0.000501	0.0133	0.0135	0.000512

t statistics in parentheses

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

Figure 11: Random Pairs from Same Business Group

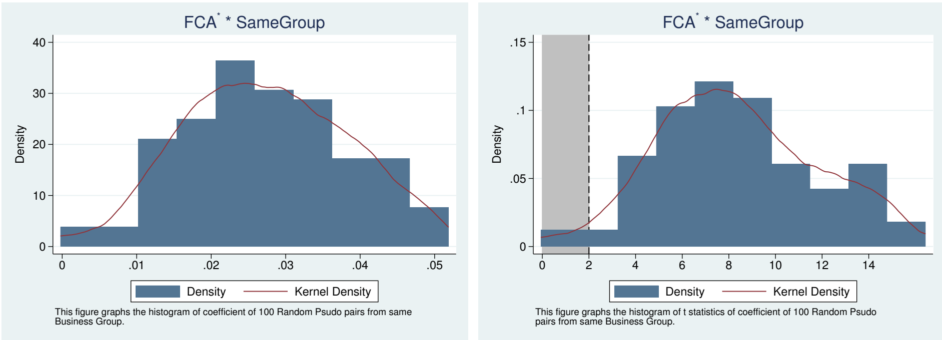


Figure 12: Random Pairs from Same Size

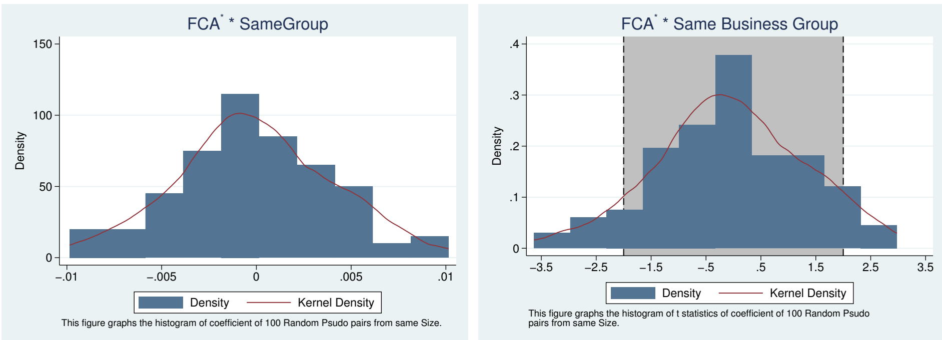
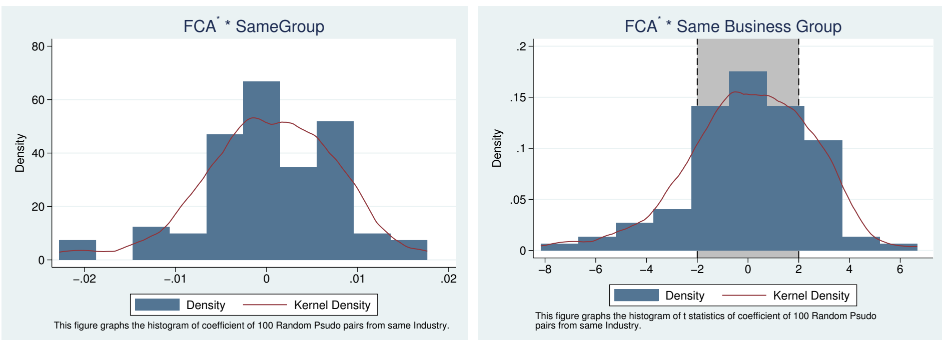
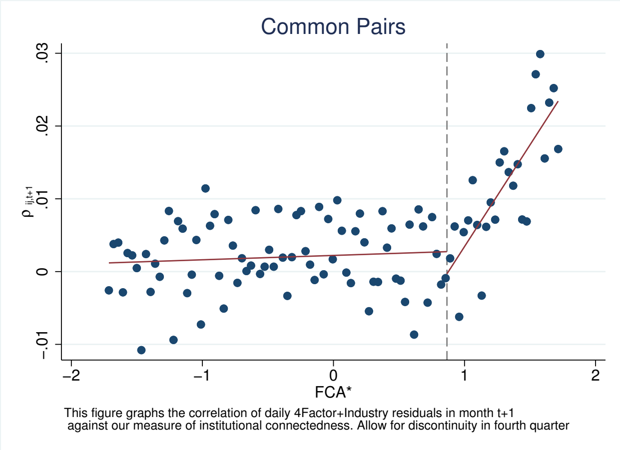
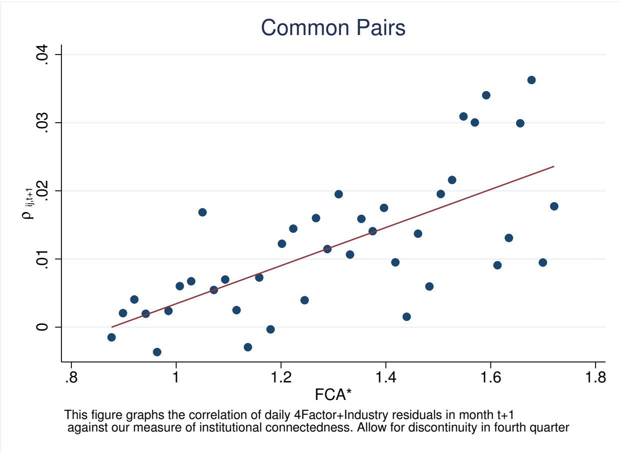


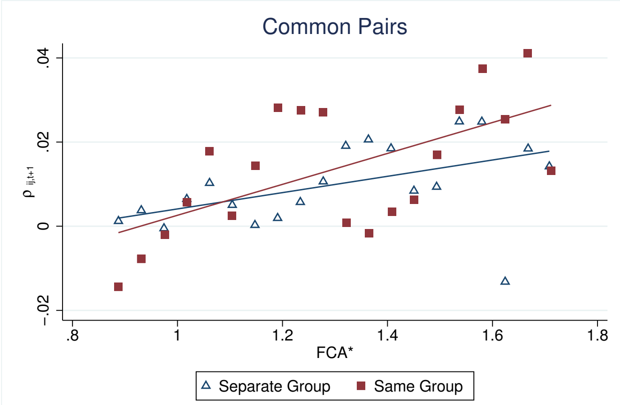
Figure 13: Random Pairs from Same Industry



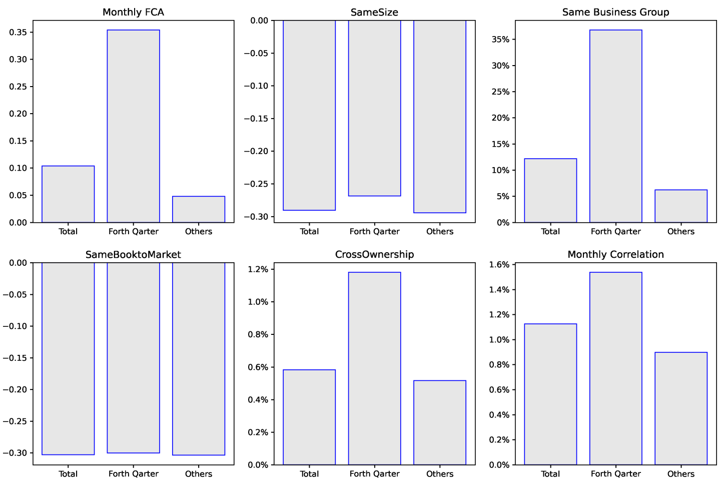
3.2 High level of common ownership

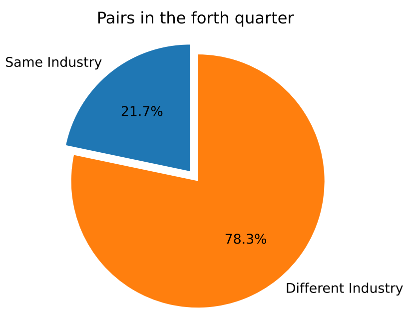






This figure graphs the correlation of daily 4Factor+Industry residuals in month t+1 against our measure of institutional connectedness. Allow for discontinuity in fourth quarter





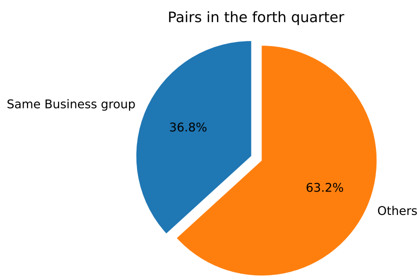


Table 12:

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
FCA*	0.0302***	0.0283***	0.0241***	0.0215***	0.0208***	0.0156**
	(5.38)	(5.27)	(4.59)	(3.74)	(3.68)	(2.76)
Same Group				0.00382	0.00337	0.00285
				(1.52)	(1.32)	(0.95)
ρ_t		0.0545***	0.0544***	0.0544***	0.0539***	0.0533***
		(9.47)	(9.49)	(9.49)	(9.51)	(9.69)
SameIndustry			0.00862***	0.00806**	0.00564**	0.00699**
			(3.56)	(3.27)	(2.72)	(2.92)
SameSize					0.00609	0.00773
					(1.10)	(1.45)
SameBookToMarket					0.0213***	0.0208***
					(4.60)	(4.35)
CrossOwnership					0.0335	0.0239
					(1.83)	(1.29)
Observations	97528	97528	97528	97528	97528	97528
Group FE	No	No	No	No	No	Yes
R^2	0.00143	0.00552	0.00645	0.00722	0.00954	0.0324

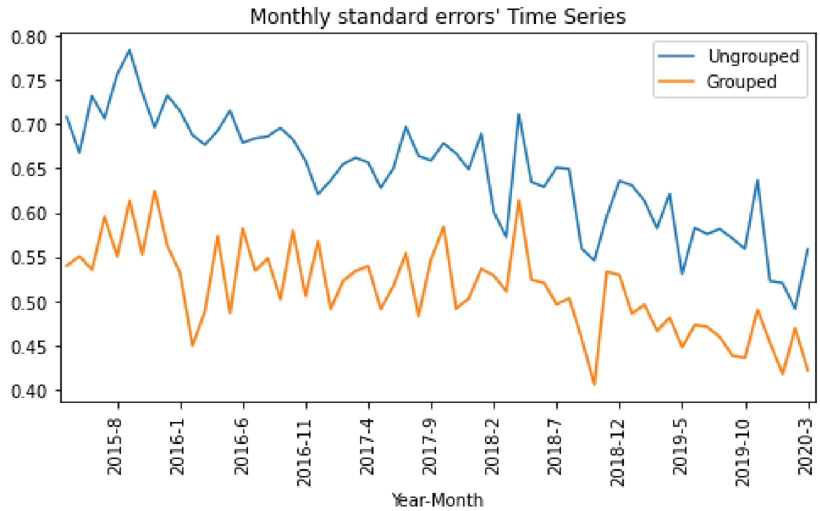
t statistics in parentheses

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

3.3 Evidence for correlated trading

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 ($\text{InsImb} = \frac{\text{Buy}_{\text{value}} - \text{Sell}_{\text{value}}}{\text{Buy}_{\text{value}} + \text{Sell}_{\text{value}}}$). 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 the monthly standard deviation of the group's imbalances and compare them to unaffiliated ones. As we expected grouped standard error is 13.1% and significantly (with t-stat of 12.57) lower than ungrouped firms.

	count	mean	std	min	median	max
Ungrouped	60	0.645	0.063	0.492	0.653	0.784
Grouped	60	0.514	0.050	0.406	0.514	0.625



According to the main hypothesis, we need to compare comovement between 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.

	Future Monthly Corr. of 4F+Ind. Residuals						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FCA*	0.00296***	0.00277***	0.00275***		0.00611**	0.00244**	0.00284**
	(3.77)	(3.57)	(3.55)		(3.21)	(3.14)	(3.40)
Same Group	0.00978***	0.00981***	0.00858**	0.0110***		0.00861**	0.00826**
	(4.29)	(4.35)	(3.37)	(4.73)		(3.38)	(3.05)
Low Imbalance std		-0.00364**	-0.00388**	-0.00446**	-0.00725*	-0.00393**	0.000437
		(-2.81)	(-2.83)	(-3.24)	(-2.47)	(-2.87)	(0.21)
Low Imbalance std × SameGroup			0.00301	0.00365		-0.00904	-0.00990*
			(0.81)	(0.98)		(-1.84)	(-2.02)
Low Imbalance std × SameGroup × FCA*						0.0104***	0.00941***
						(3.87)	(3.53)
Observations	388492	388492	388492	388492	37114	388492	388492
Group Effect	No	No	No	No	No	No	Yes
Sub-sample	Total	Total	Total	Total	Same Groups	Total	Total
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00229	0.00255	0.00274	0.00246	0.0199	0.00290	0.00906

t statistics in parentheses

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

Furthermore, we should show that stocks in groups have a similar daily trading behavior. Accordingly, for each firm we run time-series regressions of the firm's daily change in trading measure, $\Delta\text{Measure}_{i,t}$, on changes in market measure,$\Delta\text{Measure}_{Market,t}$, changes in the industry and business group portfolio's measure,$\Delta\text{Measure}_{Ind,t}$ and $\Delta\text{Measure}_{Group,t}$ and ,as well as control variables.

We compute the daily change of measure by this definition $\Delta\text{Measure}_{i,t} = \ln(\frac{\text{Measure}_{i,t}}{\text{Measure}_{i,t-1}})$. We estimate the following regression for each stock across trading days and cross-sectional averages of the estimated coefficients are reported, with t-statistics in parentheses :

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

We use the turnover and Amihud measure as a daily trading measures separately. For turnover measure, we use size of the firm as a control variable and for Amihud, we include lead, lag, and contemporaneous market returns, contemporaneous firm return squared, and lead and lag changes in the two portfolio illiquidity measures.

Table 13: cross-sectional average of the time-series coefficients for daily changes in turnover

	Dependent Variable: $\Delta\text{TurnOver}_i$					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\text{TurnOver}_{\text{Market}}$	0.405***	0.396***	0.360***	0.425***	0.388***	0.448***
	(12.25)	(10.74)	(7.62)	(12.08)	(8.23)	(12.20)
$\Delta\text{TurnOver}_{\text{Group}}$			0.222***	0.229***	0.253**	0.268***
			(3.46)	(4.09)	(3.28)	(3.82)
$\Delta\text{TurnOver}_{\text{Industry}}$	0.120**	0.0205	-0.0156	-0.0237	-0.0833	-0.0999
	(3.25)	(0.24)	(-0.23)	(-0.42)	(-1.04)	(-1.46)
Observations	293264	292179	184699	183442	184699	183442
Weight	-	-	MC × CR	MC × CR	MC	MC
Control	No	Yes	No	Yes	No	Yes
R^2	0.129	0.168	0.246	0.286	0.247	0.286

t statistics in parentheses

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

Table 14: Pairwise correlation in turnover

	Dependent Variable: Future Monthly Correlation of Delta turnover						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same Group	0.0134**	-0.00613*			-0.0102***	-0.00763	-0.00600
	(3.13)	(-2.20)			(-3.81)	(-1.75)	(-1.36)
FCA*			0.00784***	0.00308**	0.00389***	0.00410***	0.00304*
			(4.71)	(3.39)	(4.29)	(4.07)	(2.23)
(FCA*) × SameGroup						-0.00244	-0.00104
						(-0.82)	(-0.33)
Observations	378502	370726	378502	370726	370726	370726	370726
Group Effect	No	No	No	No	No	No	Yes
Controls	No	Yes	No	Yes	Yes	Yes	Yes
R^2	0.000603	0.00766	0.00110	0.00774	0.00806	0.00827	0.0236

t statistics in parentheses

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

4 Conclusion

Appendix A Further group analysis

Stock returns of group affiliated firms exhibit robustly positive comovement even after controlling for both market and industry effects. Group betas ($\beta_{Businussgroup}$) are highly significant across all models.

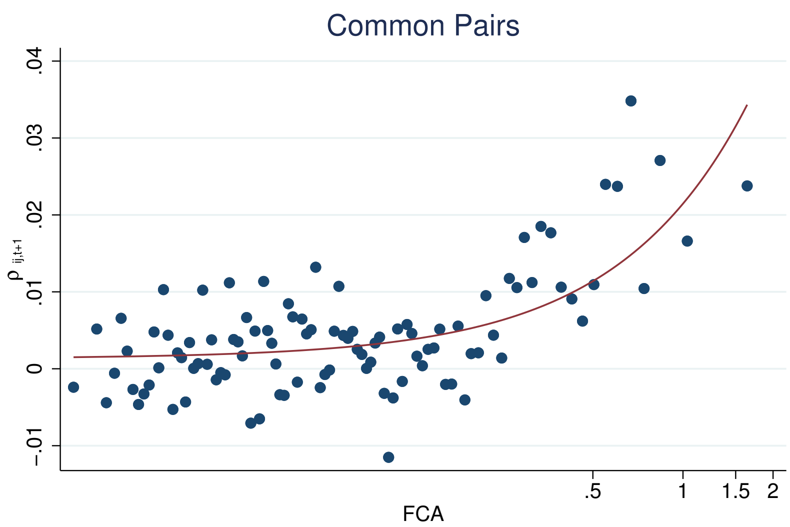
Table 15: Cross-sectional average of the time-series coefficients

	Return$_i - r_f = R_i$				
	(1)	(2)	(3)	(4)	(5)
R_M	0.801***	0.643***	0.701***	0.257***	0.280***
	(29.99)	(10.68)	(11.05)	(8.84)	(9.02)
$R_{Industry}$		-2.085	-1.878	-0.150	-0.148
		(-0.92)	(-0.93)	(-0.48)	(-0.50)
$R_{Businessgroup}$				0.493***	0.493***
				(11.36)	(11.34)
SMB			0.104***		0.0770***
			(3.52)		(5.24)
UMD			0.0282		0.0218
			(1.23)		(1.94)
HML			0.102***		0.0395***
			(6.05)		(6.39)
Constant	0.0442	0.0145	-0.0297	0.0499***	0.0198
	(1.92)	(0.53)	(-0.83)	(3.87)	(1.25)
Observations	207552	207552	207552	207552	207552
R^2	0.123	0.196	0.213	0.672	0.679

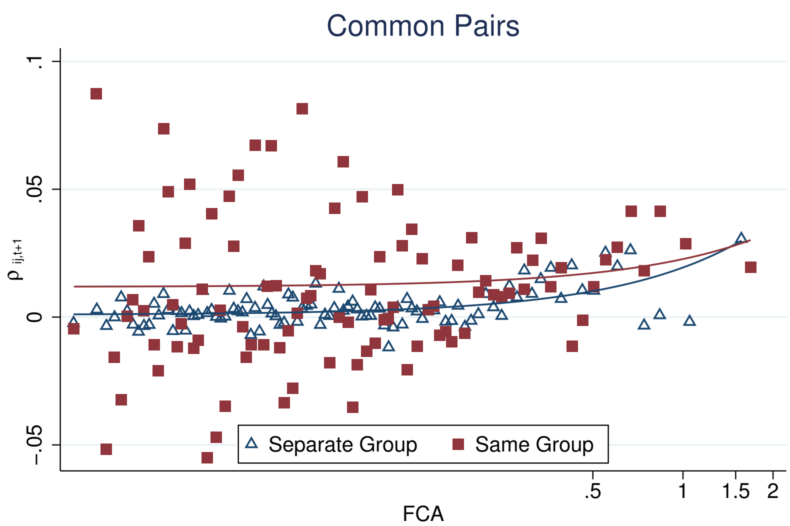
t statistics in parentheses

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

Appendix B Logaritmic Transformation



This figure graphs the correlation of daily 4Factor+Industry residuals in monthh t+1 against our measure of institutional connectedness.



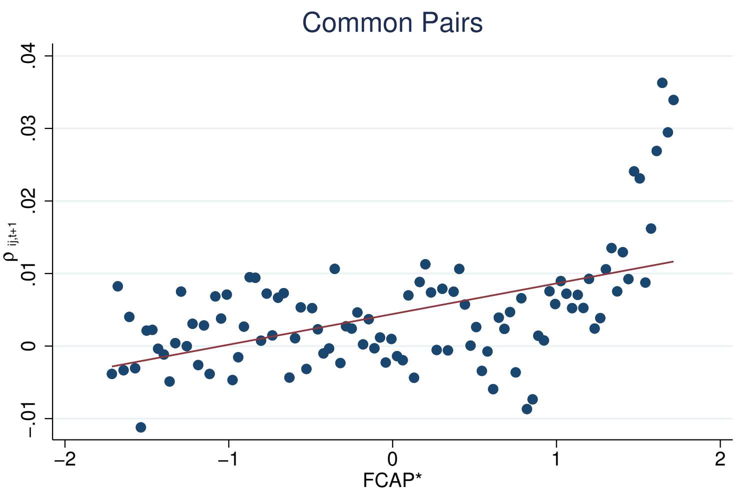
This figure graphs the correlation of daily 4Factor+Industry residuals in monthh t+1 against our measure of institutional connectedness.

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
$\ln(FCA)$	0.00316***	0.00252***	0.00108	0.000550	0.000748	0.000574
	(4.76)	(4.80)	(1.68)	(0.80)	(1.19)	(0.91)
$(\ln(FCA)) \times$ SameGroup				0.00446*	0.00451*	0.00528**
				(2.44)	(2.45)	(3.33)
ρ_t		0.129***	0.129***	0.129***	0.129***	0.129***
		(4.94)	(4.93)	(4.92)	(4.92)	(4.92)
SameGroup			0.0152***	0.0217***	0.0235***	0.0237***
			(6.06)	(5.14)	(4.90)	(5.03)
SameIndustry					-0.00497*	-0.00602**
					(-2.30)	(-3.00)
SameSize						0.00903***
						(4.31)
SameBookToMarket						0.00132
						(0.59)
CrossOwnership						0.0202
						(1.79)
Constant	0.0137***	0.0111***	0.00586**	0.00433	0.00532**	0.00785***
	(6.02)	(6.45)	(2.77)	(1.86)	(2.68)	(4.14)
Observations	436735	434850	434850	434850	434850	434850
Group FE	No	No	No	No	No	Yes
R^2	0.000344	0.0355	0.0358	0.0360	0.0362	0.0366

t statistics in parentheses

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

Appendix C Anton Polk's measure



This figure graphs the correlation of daily 4Factor+Industry residuals in month t+1 against normalized rank transformed of our measure of institutional connectedness.

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FCAP*	0.00349***	0.00275***	0.00129	0.000761	0.000928	0.000671	0.00108
	(4.69)	(4.75)	(1.98)	(1.09)	(1.46)	(1.05)	(1.70)
(FCAP*) × SameGroup				0.00662*	0.00670*	0.00808**	0.00795**
				(2.20)	(2.21)	(3.12)	(3.15)
SameGroup			0.0154***	0.00919**	0.0110***	0.00871**	0.00753*
			(6.66)	(3.13)	(3.74)	(2.76)	(2.27)
ρ_t		0.129***	0.129***	0.129***	0.129***	0.129***	0.129***
		(4.94)	(4.93)	(4.92)	(4.92)	(4.92)	(4.91)
SameIndustry					-0.00480*	-0.00587**	-0.00568**
					(-2.16)	(-2.82)	(-2.67)
SameSize						0.00892***	0.00894***
						(4.18)	(4.01)
SameBookToMarket						0.00137	0.00220
						(0.61)	(0.94)
CrossOwnership						0.0223*	0.0215*
						(2.22)	(2.02)
Observations	436735	434850	434850	434850	434850	434850	434850
Group FE	No	No	No	No	No	No	Yes
R^2	0.000316	0.0355	0.0358	0.0360	0.0362	0.0366	0.0432

t statistics in parentheses

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

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