Connected Stocks: Evidence from Tehran Stock Exchange

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- **Can the common ownership cause stock return comovement ?**
  - We connect stocks through the common ownership by blockholders (ownership $> 1\%$)
  - We focus on excess return comovement for a pair of the stocks
  - We use common ownership to forecast cross-sectional variation in the realized correlation of four-factor $+$ industry residuals

Why does it matter?

- Covariance
  - Covariance is a key component of risk in many financial applications.
    (Portfolio selection, Risk management, Hedging and Asset pricing)
  - Covariance is a significant input in risk measurement models
    (Such as Value-at-Risk)
- Return predictability
  - If it's valid, we can build a profitable buy-sell strategy

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Common-ownership measurements

Model based measures

- $\mathrm{HJL}_I^A(A,B) = \sum_{i \in I^{A,B}} \frac{\alpha_{i,B}}{\alpha_{i,A}+\alpha_{i,B}}$
  Harford et al. (2011)
- $\mathrm{MHHI} = \sum_j \sum_k s_j s_k \frac{\sum_i \mu_{ij}\nu_{ik}}{\sum_i \mu_{ij}\nu_{ij}}$
  Azar et al. (2018)
- $\mathrm{Top5}_j = \frac{1}{n-1} \sum_i^5 \sum_{j \neq k} \nu_{ik}$
  Antón et al. (2020)
- $\kappa_{ij} = \cos(\nu_i, \nu_j) . \sqrt{\frac{IHHI_j}{IHHI_i}}$
  Backus et al. (2020)
- $\mathrm{GGL}^A(A,B) = \sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A}) \alpha_{i,B}$
  Gilje et al. (2020) , Lewellen and Lewellen (2021)
- $\mathrm{MHHI}_{\mathrm{Delta}} =$
  $\sum_{j=1}^{J} \sum_{k \neq j}^{K} \frac{\sum_{i=1}^{N} w_j * w_k * \mu_{i,j} * \mu_{i,k}}{\sum_{i=1}^{N} \mu_{i,j} * \mu_{i,k}}$
  Lewellen and Lowry (2021)

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Ad-hoc measures

- $\text{Overlap}_{AP}(A,B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \frac{\bar{\nu}_A}{\bar{\nu}_A+\bar{\nu}_B} + \alpha_{i,B} \frac{\bar{\nu}_B}{\bar{\nu}_A+\bar{\nu}_B}$
  Anton and Polk (2014)
- $\text{Overlap}_{Count}(A,B) = \sum_{i \in I^{A,B}} 1$
  He and Huang (2017),He et al. (2019)
- $\text{Overlap}_{Min}(A,B) = \sum_{i \in I^{A,B}} min\{\alpha_{i,A}, \alpha_{i,B}\}$
  Newham et al. (2018)
- $\text{Overlap}_{HL}(A,B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \times \sum_{i \in I^{A,B}} \alpha_{i,B}$
  Hansen and Lott Jr (1996) , Freeman (2019)

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Selected measure

We need a pair-level measure, which is bi-directional, so we use the AP measure.

Measues' detail

Main effect

Comovement effect

Papers

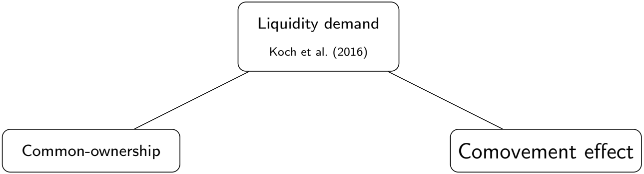
Main effect

Common-ownership

Comovement effect

Papers

Main effect



Papers

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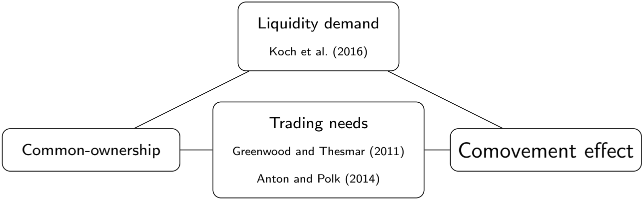

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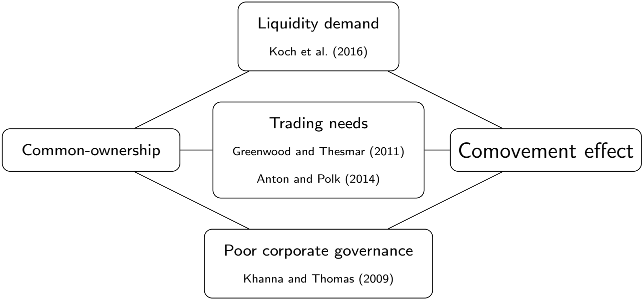

Papers

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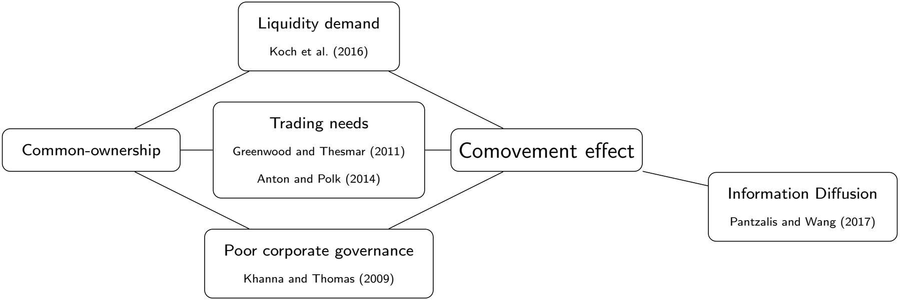

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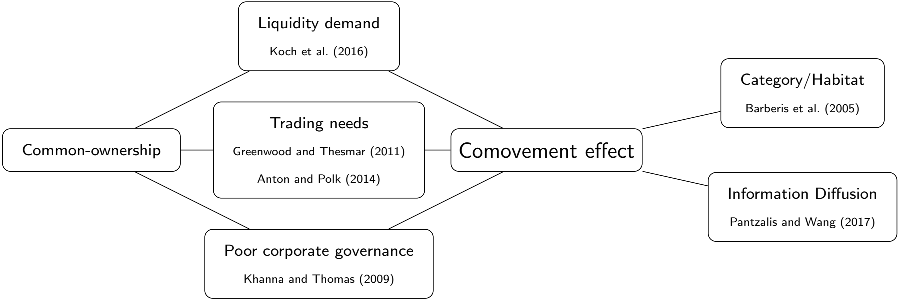

Papers

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Measuring Common-ownership

Anton and Polk (2014)

$$\boxed{FCAP_{ij,t} = \frac{\sum_{f=1}^{F}(S_{i,t}^{f}P_{i,t} + S_{j,t}^{f}P_{j,t})}{S_{i,t}Pi,t + S_{j,t}Pj,t}}$$

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SQRT

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

Quadratic

$$\boxed{[\frac{\sum_{f=1}^{F}[(S_{i,t}^{f}P_{i,t})^2 + (S_{j,t}^{f}P_{j,t})^2]}{(S_{i,t}Pi,t)^2 + (S_{j,t}Pj,t)^2}]^{-1}}$$

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Quadratic

$$\boxed{[\frac{\sum_{f=1}^{F}[(S_{i,t}^{f}P_{i,t})^{2} + (S_{j,t}^{f}P_{j,t})^{2}]}{(S_{i,t}Pi,t)^{2} + (S_{j,t}Pj,t)^{2}}]^{-1}}$$

Intuition

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 n. Proof

Measuring Common Ownership

Example

$$\text{Firm Y} \xleftarrow{\beta} \text{Common owner} \xrightarrow{\alpha} \text{Firm X}$$

Measuring Common Ownership

Example

$$\text{Firm Y} \xleftarrow{\beta} \text{Common owner} \xrightarrow{\alpha} \text{Firm X}$$

For better observation, assume that

- $\alpha + \beta = 100$
- both firm have equal market cap

Measuring Common Ownership

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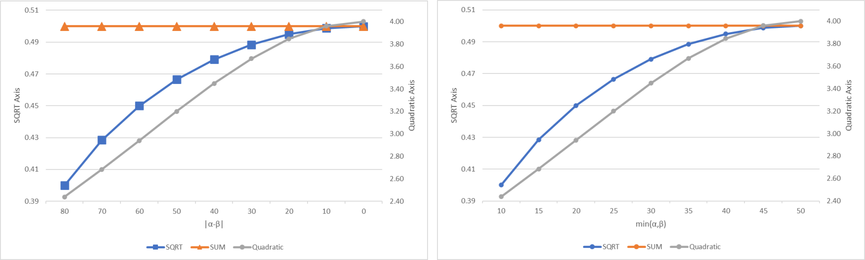

Comparison of three methods for calculating common ownership

Measuring Common Ownership

Example of three common owner

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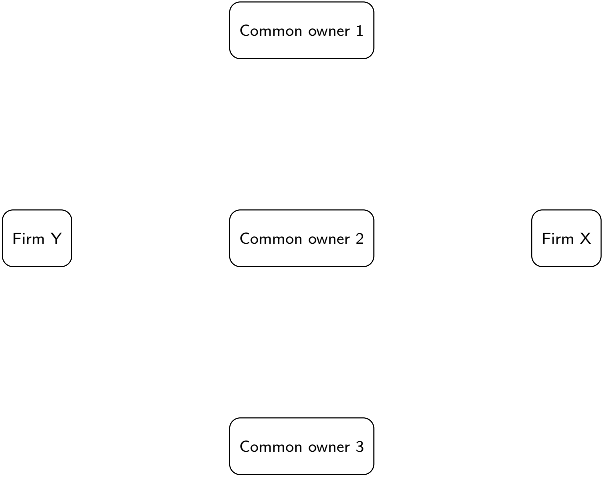

Measuring Common Ownership

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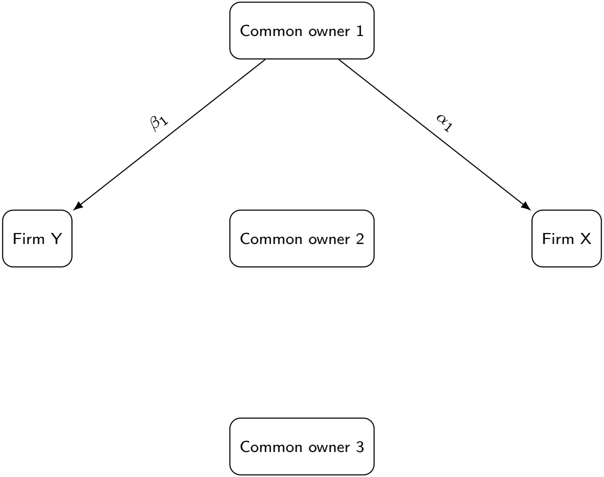

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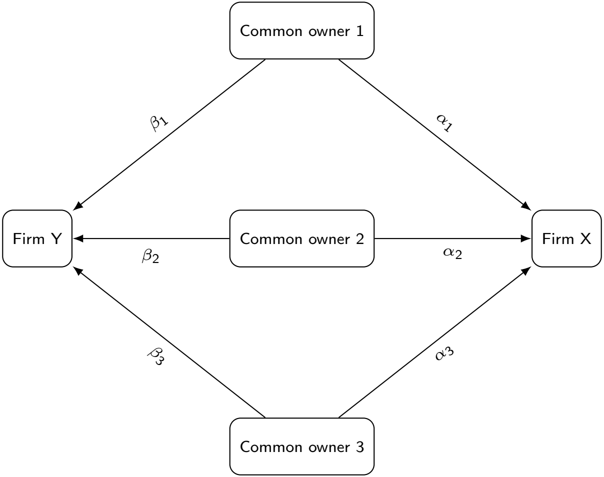


Measuring Common Ownership

Example of three common owner

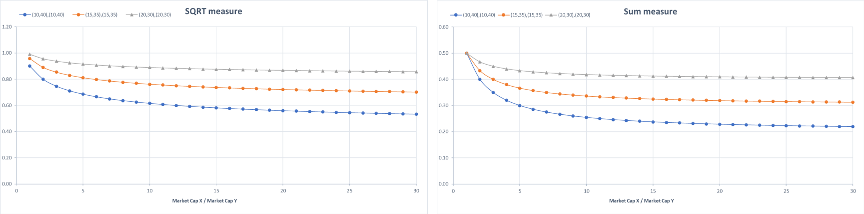
Ownership	Type I	Type II	Type III	Type IV	Type V	Type VI	Type VII
α_1	1/3	20	10	20	10	5	1
β_1	1/3	10	10	20	10	5	1
α_2	1/3	10	80	20	10	5	1
β_2	1/3	20	80	20	10	5	1
α_3	1/3	70	10	20	10	5	1
β_3	1/3	70	10	20	10	5	1
SQRT	3	2.56	2.33	1.8	0.9	0.45	0.09
SUM	1	1	1	0.6	0.3	0.15	0.03
Quadratic	3	1.85	1.52	8.33	33.33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

- For better comparison we relax previous assumptions:
  - Two Firms with different market caps.

	$(\alpha_1,\beta_1),(\alpha_2,\beta_2)$					
	(10,40),(10,40)		(15,35),(15,35)		(20,30),(20,30)	
$\frac{MarketCap_x}{MarketCap_y}$	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

Measuring Common Ownership

Comparison



Comparison of two methods for calculating common ownership

Conclusion

We use the SQRT measure because it has an acceptable variation and has fair values at a lower level of aggregate common ownership.

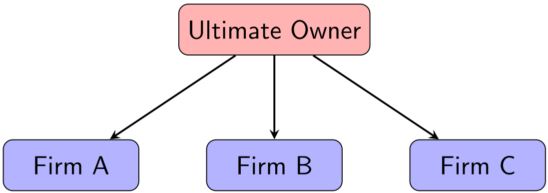
Pair Composition and Business Group

Business Group

Ultimate Owner

Pair Composition and Business Group

Business Group



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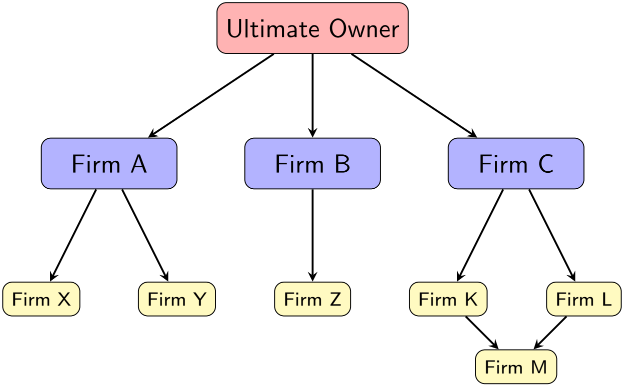
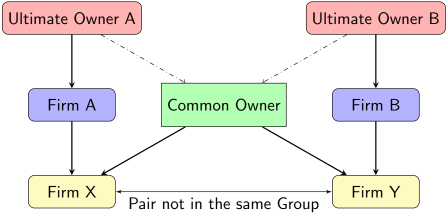
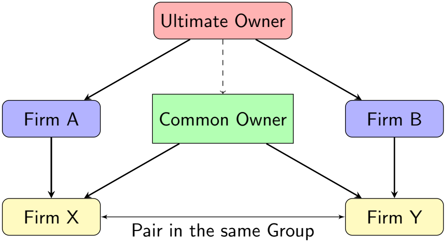


Pair Composition and Business Group

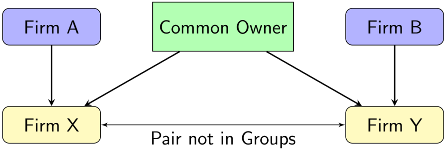
Pair in the Business Group

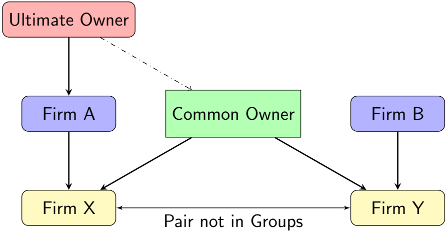




Pair Composition and Business Group

Pair not in any of Business Groups





Data Summary

- We use blockholders' data from 2015/03/25 (1394/01/06) to 2020/03/18 (1398/12/28)
  - Includes of 1203 Days and 60 Months
  - Consists of 600 firm inculding 548 firm with common owners

Year	2015	2016	2017	2018	2019	2020	Meann
No. of Firms	355	383	520	551	579	602	498
No. of Blockholders	724	887	1274	1383	1409	1390	1178
No. of Groups	41	42	46	45	40	40	42
No. of Firms not in Groups	113	128	207	224	247	270	198
No. of Firms in Groups	242	265	332	339	332	332	307
Mean Number of Members	6	6	7	8	8	8	7
Med. of Number of Members	4	4	6	5	6	6	5
Mean Of each Blockholder's ownership	21.30	22.00	20.80	20.50	21.90	23.00	21.58
Med. of Owners' Percent	7.94	7.55	6.95	6.34	8.31	9	8
Mean Number of Blockholders	5	5	5	5	5	4	5
Med. Number of Owners	4	4	4	4	4	3	4
Mean Block. Ownership	71.6	71.2	68	67.7	65.4	62.00	67.65
Med. Block. Ownership	79.9	80.1	77	77.1	72.9	69.70	76.12

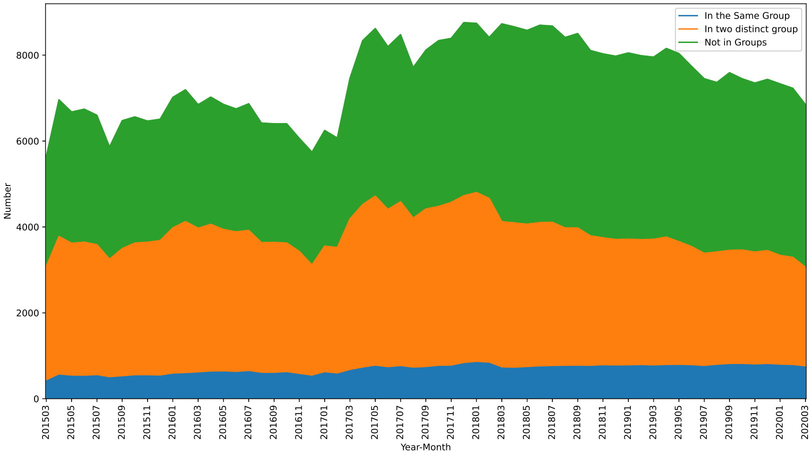
Pair Composition

- Pairs consist of two firms with at least one common owner
  - 18692 unique pairs which is 10% of possible pairs ($\frac{548*547}{2} = 149878$)

	mean	min	median	max
Number of unique paris	7448	5642	7451	8759

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

Number of Pairs



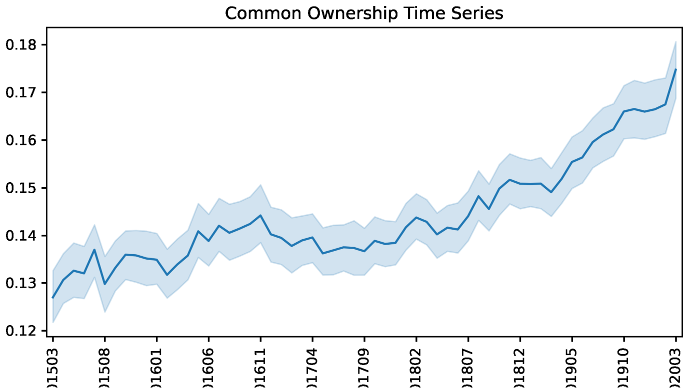
FCA vs. FCAP Summary

	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

Results

- By the proposed measurement, common ownership increases
- Common ownership is greater in pairs that are in the same business group and insutry

FCA's time series



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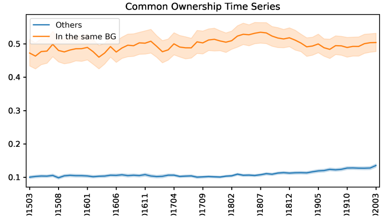
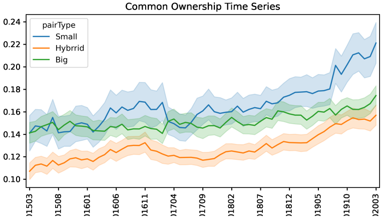
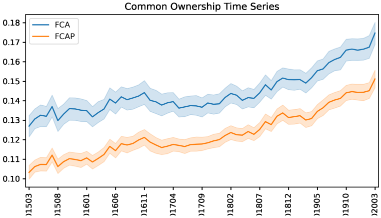
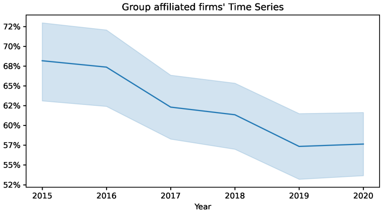
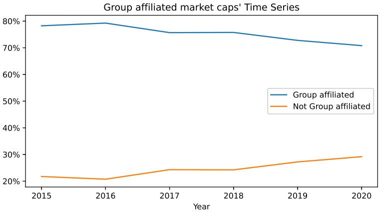






Group affiliated firm's time series





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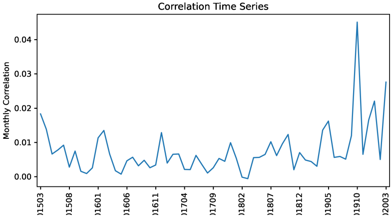
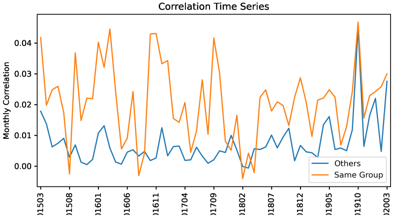
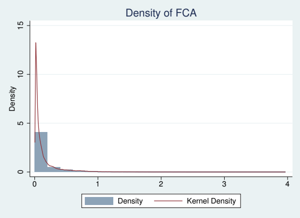
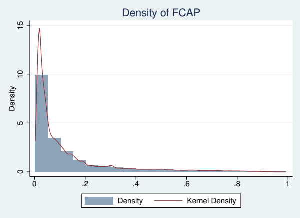




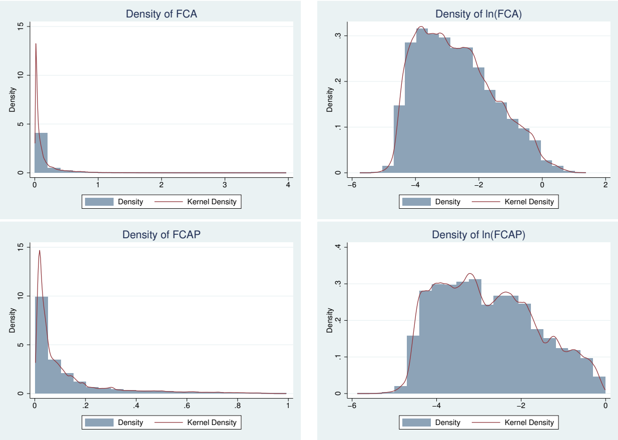
FCA vs. FCAP Distributions
Monthly



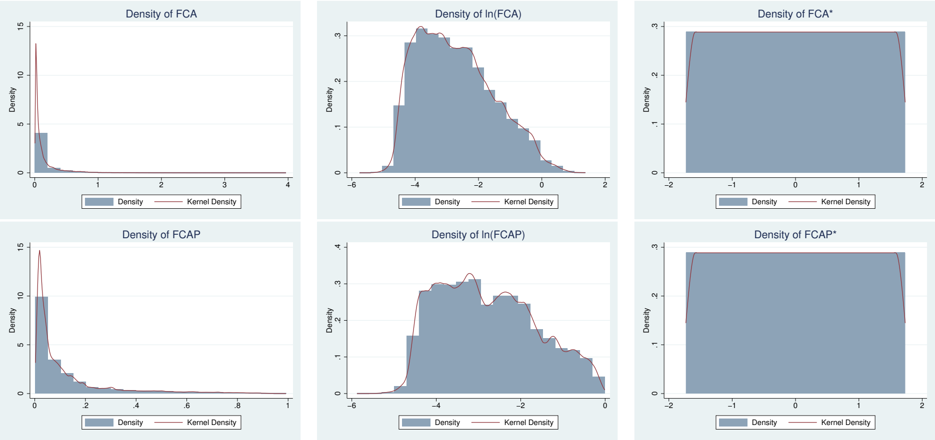


FCA vs. FCAP Distributions

Monthly



FCA vs. FCAP Distributions
Monthly



1. Frist Step:
   Estimate each of these models on periods of three month:
   - CAPM + Industry (2 Factor):

$$R_{i,t} = \alpha_i + \beta_{mkt,i} R_{M,t} + \beta_{Ind,i} R_{Ind,t} + \boxed{\varepsilon_{i,t}}$$

   - 4 Factor :

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

   - 4 Factor + Industry (5 Factor) :

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

2. Second Step:
   Calculate monthly correlation of each stock pair's daily abnormal returns (residuals)

Correlation Calculation Results

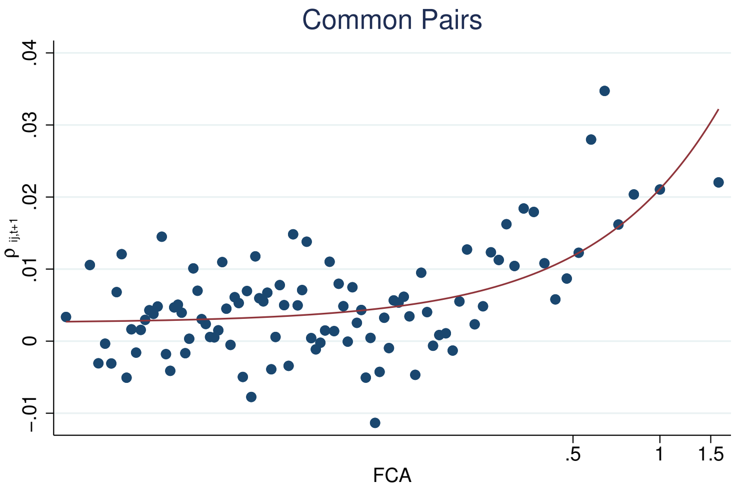
Factors	mean	std	min	max
SMB	0.19	1.47	-5.64	19.52
HML	-0.12	1.39	-4.90	23.20
Winner − Loser	0.69	1.06	-2.61	8.58
Market	0.24	1.23	-4.71	4.89

$\rho_{ij,t}$	mean	std	min	25%	50%	75%	max
CAPM + Industry	0.01	0.33	-1	-0.194	0.006	0.208	1
4 Factor	0.04	0.34	-1	-0.172	0.035	0.249	1
4 Factor + Industry	0.01	0.33	-1	-0.194	0.005	0.206	1
4 Factor + Industry (With Lag)	0.01	0.32	-1	-0.194	0.006	0.206	1

Conclusion

We use the 4 Factor + Industry model to control for exposure to systematic risk because it almost captures all correlations between two firms in each pair.

Future Correlation via *FCA*



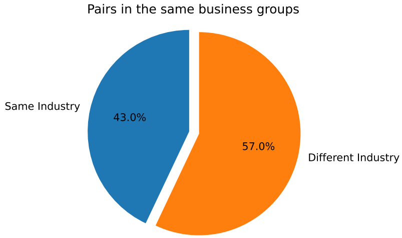
This figure graphs the correlation of daily 4Factor+Industry residuals in monthh t+1 against our measure of institutional connectedness.

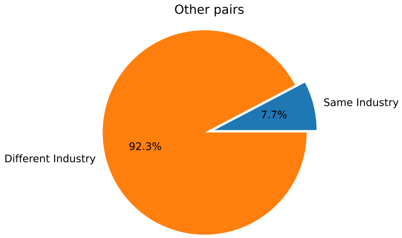
Controls

- ρ_t : Current period correlation
- **SameGroup** : Dummy variable for whether the two stocks belong to the same business group.
- **SameIndustry** : Dummy variable for whether the two stocks belong to the same Industry.
- **SameSize** : The negative of absolute difference in percentile ranking of size across a pair
- **SameBookToMarket** :The negative of absolute difference in percentile ranking of the book to market ratio across a pair
- **CrossOwnership**: The maximum percent of cross-ownership between two firms

Industry & Business group

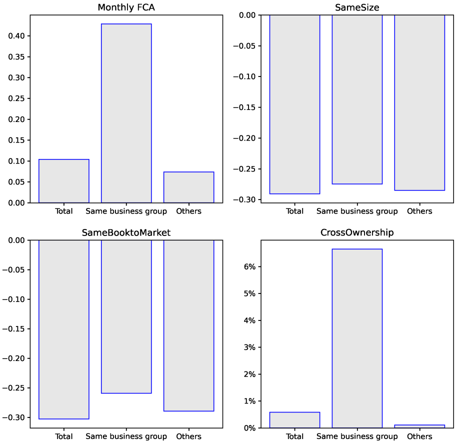
Type of Pairs	Yes	No
SameIndustry	1760	16739
	(10%)	(90%)
SameGroup	1118	17381
	(6%)	(94%)
SameGroup & SameIndustry	492	18007
	(3%)	(97%)





Business group

Pairs' characteristic



Summary of Controls

Variables' distribution

	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
MonthlyCrossOwnership	0.01	0.05	0.00	0.00	0.00	0.00	0.96

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Fama-MacBeth Estimation

- Fama-MacBeth regression analysis is implemented using a two-step procedure.
  - The first step is to run periodic cross-sectional regression for dependent variables using data of each period.
  - The second step is to analyze the time series of each regression coefficient to determine whether the average coefficient differs from zero.

Fama-MacBeth (1973)

- Two Step Regression
  - First Step

$$
\begin{aligned}
Y_{i1} &= \delta_{0,1} + \delta^{1}_{1,1} X^{1}_{i,1} + \cdots + \delta^{k}_{k,1} X^{k}_{i,1} + \varepsilon_{i,1} \\
&\vdots \\
Y_{iT} &= \delta_{0,1} + \delta^{1}_{1,T} X^{1}_{i,T} + \cdots + \delta^{k}_{k,T} X^{k}_{i,T} + \varepsilon_{i,T}
\end{aligned}
$$

  - Second Step

$$
\begin{bmatrix} \bar{Y}_1 \\ \vdots \\ \bar{Y}_T \end{bmatrix}_{T\times 1} = \begin{bmatrix} 1 & \delta^0_1 & \delta^1_1 & \dots & \delta^k_1 \\ \vdots & \vdots & \vdots & \dots & \vdots \\ 1 & \delta^0_T & \delta^1_T & \dots & \delta^k_T \end{bmatrix}_{T\times(k+2)} \times \begin{bmatrix} \lambda \\ \lambda_0 \\ \lambda_1 \\ \vdots \\ \lambda_k \end{bmatrix}_{(k+2)\times 1}
$$

- Fama-MacBeth technique was developed to account for correlation between observations on different firms in the same period

Calculating standard errors

- In most cases, the standard errors are adjusted following Newey and West (1987).
  - Newey and West (1987) adjustment to the results of the regression produces a new standard error for the estimated mean that is adjusted for autocorrelation and heteroscedasticity.
  - Only input is the number of lags to use when performing the adjustment

    $$Lag = 4(T/100)^{\frac{2}{9}}$$

    where T is the number of periods in the time series

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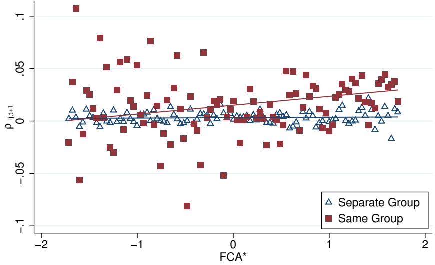
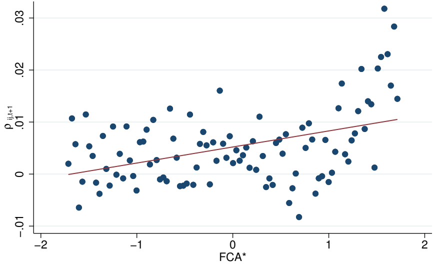
Future Correlation via *FCA*

Normalized Rank-Transformed



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



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

Estimation model

- Use Fama-MacBeth to estimate this model

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

- Estimate the model on a monthly frequency
- Adjust standard errors by Newey and West adjustment with 4 lags $(4(60/100)^{\frac{2}{9}} = 3.57 \sim 4)$

Model Estimation

Normalized Rank-Transformed

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
FCA*	0.00320***	0.00235***			0.00154	0.00105	0.00103	0.000548	0.000948
	(4.05)	(3.90)			(1.73)	(1.51)	(1.12)	(0.80)	(1.37)
Same Group			0.0194***	0.0183***	0.0176***	0.0172***	0.0111***	0.00952**	0.00829*
			(9.72)	(6.03)	(7.15)	(5.09)	(3.53)	(2.73)	(2.25)
(FCA*) × SameGroup							0.00679*	0.00744**	0.00734**
							(2.41)	(3.32)	(3.30)
Observations	436735	434850	436735	434850	436735	434850	436735	434850	434850
Group Effect	No	No	No	No	No	No	No	No	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes	Yes
R^2	0.000306	0.0360	0.000496	0.0363	0.000719	0.0364	0.000909	0.0366	0.0432

t statistics in parentheses

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

Business group & Common-ownership

regression

	(1)	(2)	(3)	(4)	(5)	(6)
	Future Monthly Correlation of 4F+Industry Residuals					
($FCA > Median$[FCA])		-0.00168	-0.00337**	0.00855**		-0.00513***
		(-1.45)	(-2.89)	(2.76)		(-4.32)
SameGroup	0.0122***		0.0135***			0.00574*
	(5.81)		(6.48)			(2.02)
($FCA > Median$[FCA]) × SameGroup						0.0181***
						(5.91)
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	0.000439	0.000485	0.0136	0.0135	0.000513

t statistics in parentheses

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

Business group & Common-ownership

regression

	Future Monthly Correlation of 4F+Industry Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
Common Ownership		-0.00350**	-0.00445***	0.00651*		-0.00527***
		(-3.30)	(-4.22)	(2.48)		(-4.72)
SameGroup	0.0122***		0.0140***			0.00607*
	(5.81)		(7.01)			(2.09)
Common Ownership $\times$ SameGroup						0.0157***
						(5.51)
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	0.000456	0.000504	0.0135	0.0135	0.000528

t statistics in parentheses

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

Business group return

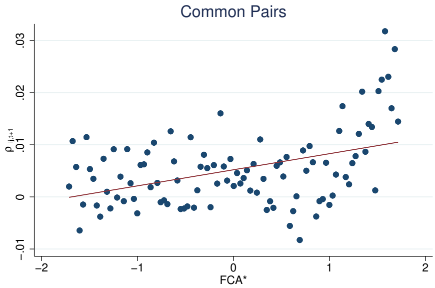
	$Return_i - r_f = R_i$				
	(1)	(2)	(3)	(4)	(5)
R_M	0.216***	0.181***	0.124***	0.173***	0.118***
	(12.43)	(11.10)	(9.91)	(11.07)	(9.98)
$R_{Industry}$		0.119***	0.119***	0.130***	0.130***
		(6.41)	(6.41)	(7.62)	(7.62)
$R_{Businessgroup}$				0.0549***	0.0549***
				(14.81)	(14.81)
SMB			0.0194**		0.0193**
			(2.95)		(3.11)
UMD			0.00751		0.00681
			(1.31)		(1.27)
HML			0.0105*		0.0105*
			(1.98)		(2.22)
Constant	0.0155	-0.00383	-0.00387	-0.000620	-0.00107
	(0.66)	(-0.18)	(-0.39)	(-0.03)	(-0.11)
Observations	207552	207552	207552	207552	207552
R^2	0.000	0.054	0.054	0.133	0.133

t statistics in parentheses

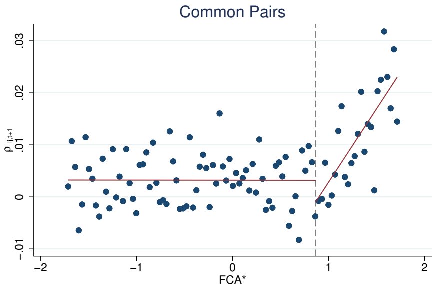
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Future Correlation via *FCA*

Discontinuity



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



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

Estimation model

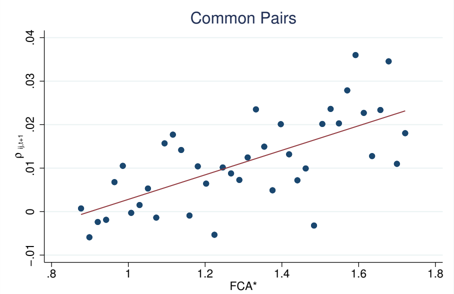
- Use Fama-MacBeth to estimate this model

$$\begin{aligned}\rho_{ij,t+1} = {} & \beta_0 + \beta_1 * \text{FCA}^*_{ij,t} + \beta_2 * (\text{FCA}^*_{ij,t} > Q3[\text{FCA}^*_{ij,t}]) \times \text{FCA}^*_{ij,t} \\ & + \beta_3 * (\text{FCA}^*_{ij,t} > Q3[\text{FCA}^*_{ij,t}]) \times \text{FCA}^*_{ij,t}\text{SameGroup}_{ij} \\ & + \sum_{k=1}^{n} \alpha_k * \text{Control}_{ij,t} + \varepsilon_{ij,t+1}\end{aligned} \tag{2}$$

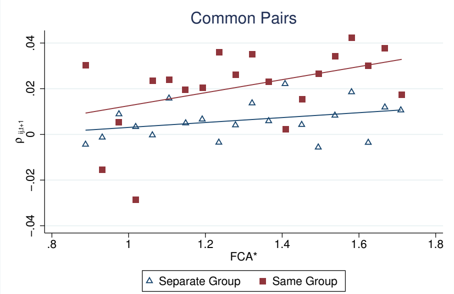
- Estimate that model on a monthly frequency

4 Factor + Industry Future Correlation via FCA^*

Discontinuity & Business Groups



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



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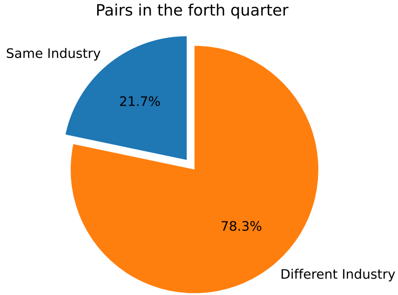
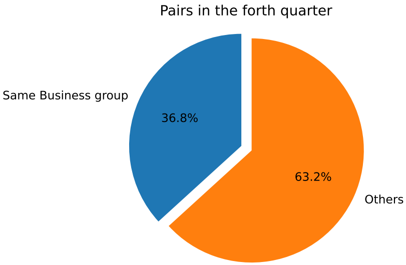
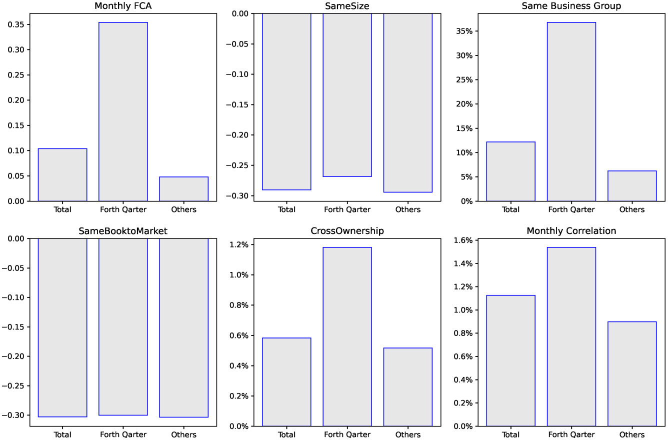
Quarter summary





Quarter summary



Fama-MacBeth Estimation

Discontinuity (sub-sample)

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
FCA*	0.0284***	0.0237***	0.0207***	0.0103	0.00914	0.00686
	(5.92)	(5.74)	(4.81)	(1.98)	(1.73)	(1.30)
Same Group				0.0154***	0.0153**	0.0136**
				(3.63)	(3.23)	(2.87)
ρ_t		0.148***	0.148***	0.147***	0.147***	0.146***
		(6.59)	(6.60)	(6.55)	(6.54)	(6.56)
SameIndustry			0.00645**	0.00289	0.00118	0.00317
			(2.76)	(0.94)	(0.43)	(1.00)
SameSize					0.00672	0.00651
					(1.32)	(1.25)
SameBookToMarket					0.0165***	0.0139*
					(3.57)	(2.62)
CrossOwnership					0.0114	0.0107
					(0.53)	(0.50)
Observations	110827	110387	110387	110387	110387	110387
Group FE	No	No	No	No	No	Yes
R^2	0.00119	0.0389	0.0397	0.0408	0.0429	0.0660

t statistics in parentheses

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

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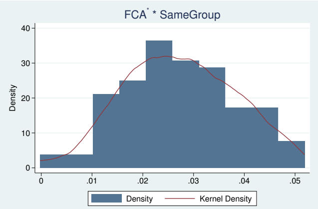
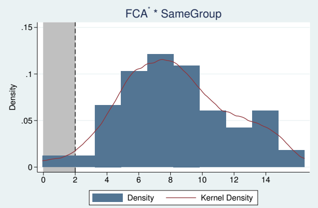
Random Pairs from Same Business Group

β_3 in model 1

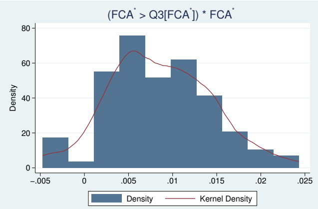


This figure graphs the histogram of coefficient of 100 Random Psudo pairs from same Business Group.



This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Business Group.

β_2 in model 2



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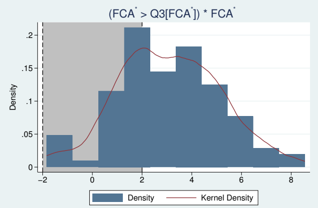
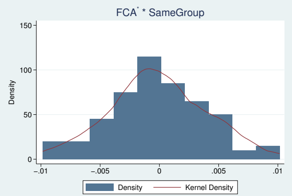


This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Business Group.

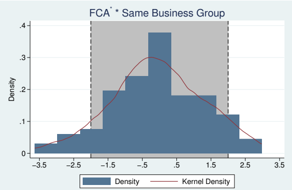
Random Pairs from Same Size

β_3 in model 1

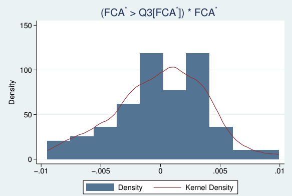
β_2 in model 2



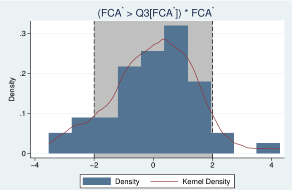
This figure graphs the histogram of coefficient of 100 Random Psudo pairs from same Size.



This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Size.



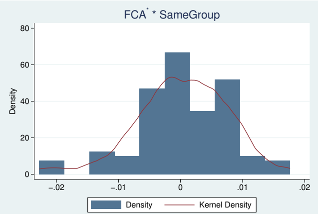
This figure graphs the histogram of coefficient of 100 Random Psudo pairs from same Size.



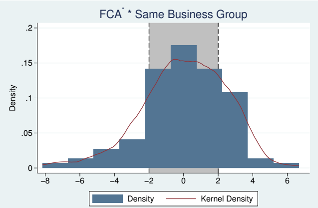
This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Size.

Random Pairs from Same Industry

β_3 in model 1

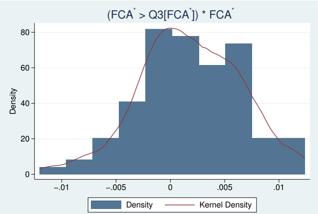


This figure graphs the histogram of coefficient of 100 Random Psudo pairs from same Industry.

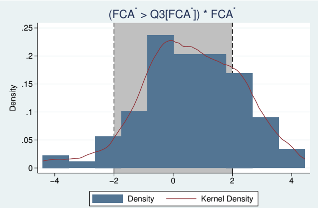


This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Industry.

β_2 in model 2



This figure graphs the histogram of coefficient of 100 Random Psudo pairs from same Industry.



This figure graphs the histogram of t statistics of coefficient of 100 Random Psudo pairs from same Industry.

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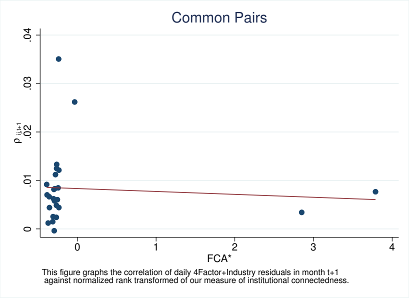
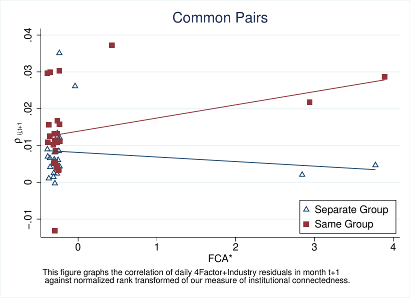
- Generate pairs that they don't have common-owner
- Pseudo pairs' $FCA_{ij,t}$ equal to zero
-





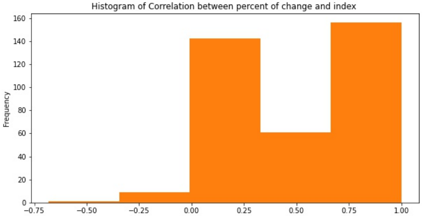
- Trading index for business groups:
  - For business group of k:

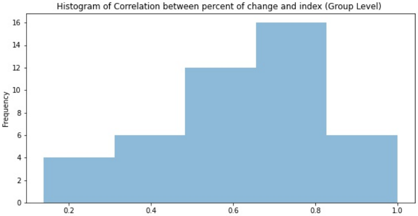
$$BGTI_{kt} = \sum w_{ikt} \frac{\Delta BlockOwnership_{i,t}}{BlockOwnership_{i,t-1}}$$

  - which w_{ikt} is $\frac{\text{MarketCap}_{it} \times \text{CR}_k}{\sum \text{MarketCap}_{jt} \times \text{CR}_k}$
- Calculate correlation of $\frac{\Delta BlockOwnership_{i,t}}{BlockOwnership_{i,t-1}}$ with $BGTI_{kt}$ for each firm in group

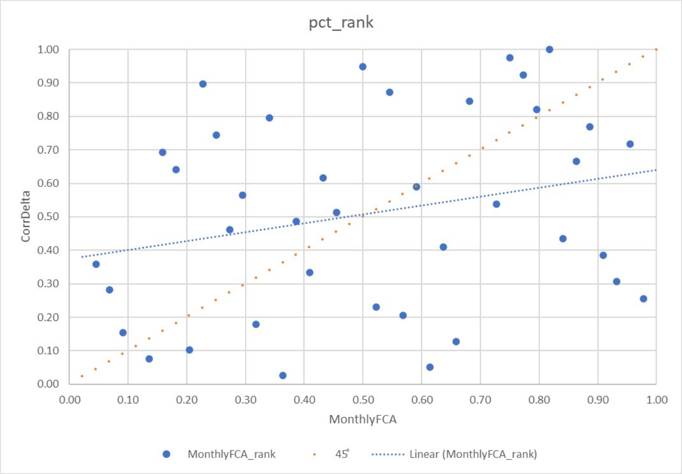
Average correlation between Index and symbols

$\rho(\frac{\Delta BlockOwnership_{it}}{BlockOwnership_{it}}, BGTI_{kt})$



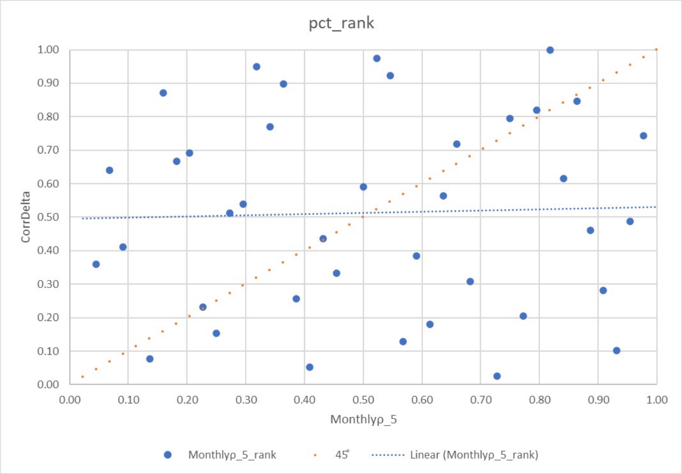


Trading Index correlation & FCA
Group Level



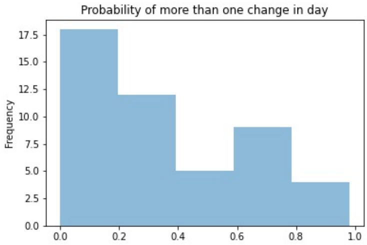
Trading Index correlation & return correlation

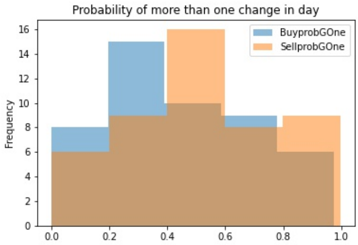
Group Level



Simultaneous Trade

Group Level





Ins Imbalance

$$\text{InsImbalance}_i = \frac{\text{InsBuy} - \text{InsSell}}{\text{InsBuy} + \text{InsSell}}$$

	Future Monthly Corr. of 4F+Ind. Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
FCA*	0.00105	0.00105	0.000959		0.000925	0.00143
	(1.51)	(1.51)	(1.37)		(1.32)	(1.97)
Same Group	0.0172***	0.0174***	0.0104*	0.0114**	0.0104*	0.00890*
	(5.09)	(4.96)	(2.55)	(2.93)	(2.54)	(2.14)
Low Imbalance		0.000588	-0.00129	-0.00141	-0.00130	-0.000485
		(0.67)	(-1.26)	(-1.36)	(-1.27)	(-0.16)
Low Imbalance × SameGroup			0.0253***	0.0255***	0.0218**	0.0220**
			(5.24)	(5.29)	(3.21)	(3.21)
Low Imbalance × SameGroup × FCA*					0.00268	0.00232
					(0.63)	(0.52)
Observations	434850	434850	434850	434850	434850	434850
Group Effect	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0364	0.0366	0.0369	0.0367	0.0370	0.0436

t statistics in parentheses

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

TrunOver

$$\Delta \text{TurnOver} = \ln\left(\frac{\text{TurnOver}_{i,t}}{\text{TurnOver}_{i,t-1}}\right) = \ln\left(\frac{\text{volume}_{i,t}}{\text{MarketCap}_{i,t}}\right) - \ln\left(\frac{\text{volume}_{i,t-1}}{\text{MarketCap}_{i,t-1}}\right)$$

	Dependent Variable: $\Delta \text{TurnOver}_i$			
	(1)	(2)	(3)	(4)
$\Delta \text{TurnOver}_{\text{Market}}$	0.448***	0.387***	0.445***	0.353***
	(5.61)	(7.80)	(11.13)	(10.18)
$\Delta \text{TurnOver}_{\text{Group}}$		0.231**	0.234*	0.245***
		(2.67)	(2.07)	(8.22)
$\Delta \text{TurnOver}_{\text{Industry}}$	0.0993	-0.0558	-0.0970	0.0365
	(1.55)	(-0.61)	(-0.84)	(0.68)
$\ln(\text{size})_{i,t}$	-0.00571	-0.0136***	-0.0210**	-0.0119**
	(-0.03)	(-5.21)	(-3.06)	(-3.24)
Constant	-0.303	0.380***	0.610**	0.334**
	(-0.05)	(5.03)	(2.86)	(3.11)
Observations	293264	184699	184699	184699
Group Weight	-	MC × CR	MC	Equal
R^2	0.111	0.213	0.215	0.124

t statistics in parentheses

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

Amihud

$$\Delta\text{Amihud} = \ln\left(\frac{\text{Amihud}_{i,t}}{\text{Amihud}_{i,t-1}}\right) = \ln\left(\frac{|\text{Return}_{i,t}|}{\text{volume}_{i,t}}\right) - \ln\left(\frac{|\text{Return}_{i,t-1}|}{\text{volume}_{i,t-1}}\right)$$

	Dependent Variable: ΔAmihud_i					
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\text{Amihud}_{\text{Market}}$	0.324***	0.549*	0.373***	0.343***	0.391***	0.361***
	(6.46)	(2.23)	(13.09)	(12.01)	(13.09)	(12.14)
$\Delta\text{Amihud}_{\text{Group}}$			0.165**	0.153*	0.143*	0.129*
			(2.60)	(2.57)	(2.07)	(1.98)
$\Delta\text{Amihud}_{\text{Industry}}$	0.0567	0.121	-0.00390	-0.00670	-0.00322	-0.00430
	(1.21)	(1.36)	(-0.06)	(-0.10)	(-0.04)	(-0.06)
Observations	293264	291933	184699	183301	184699	183301
Weight	-	-	MC × CR	MC × CR	MC	MC
Control	No	Yes	No	Yes	No	Yes
R^2	0.0976	0.132	0.194	0.220	0.199	0.224

t statistics in parentheses

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

Trading

- Antón et al. (2018):

$$CQ_{ijt} = \sum_{d=1}^{D_t} \omega_{dt} corr(NQ_{idt}, NQ_{jdt})$$

$$\omega_{dt} = \frac{\min(TQ_{idt}, TQ_{jdt})}{\sum_{d=1}^{D} \min(TQ_{idt}, TQ_{jdt})}$$

- Ivashina and Sun (2011):

$$\frac{1}{N} \sum_{i=1}^{N} \frac{\sum_{j=1}^{M_i} D_{ji} CAR_i}{M_i}$$

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Conclusion

- We derive a measure that captures the extent of common ownership distribution.
- The common ownership comovement effect with a extra explanation:
    - Common ownership that crosses a threshold affect on comovement
    - Be in the same business group has a major effect on comovement

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- If two stocks in pair have n mutual owner, which total market cap divides them equally, the mentioned indexes equal n.
  - 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 $S^f_{i,t} P_{i,t} = \alpha_i$
  - SQRT

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

  - Quadratic

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

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Main Effect

- Common-ownership and comovement effect
  [Anton and Polk (2014)]
  Stocks sharing many common investors tend to comove more strongly with each other in the future than otherwise similar stocks.
- Common-ownership and liquidity demand
  [Koch et al. (2016), Pastor and Stambaugh (2003), Acharya and Pedersen (2005)]
  Commonality in stock liquidity is likely driven by correlated trading among a given stock's investors. Commonality in liquidity is important because it can influence expected returns
- Trading needs and comovement
  [Greenwood and Thesmar (2011)]
  If the investors of mutual funds have correlated trading needs, the stocks that are held by mutual funds can comove even without any portfolio overlap of the funds themselves
- Stock price synchronicity and poor corporate governance
  [Boubaker et al. (2014), Khanna and Thomas (2009), Morck et al. (2000)]
  Stock price synchronicity has been attributed to poor corporate governance and a lack of firm-level transparency. On the other hand, better law protection encourages informed trading, which facilitates the incorporation of firm-specific information into stock prices, leading to lower synchronicity

Grapgh

- Three types of network
  1. Equity network
  2. Director network
  3. Owner network
- Dependent variables

  Using deterended weekly return for calculation
  1. Pairwise returns synchronicity $= \frac{\sum_t (n^{up}_{i,j,t} n^{down}_{i,j,t})}{T_{i,j}}$
  2. Correlation $= \frac{Cov(i,j)}{\sqrt{Var(i).Var(j)}}$
- Tobit estimation of

$$f^{d}_{i,j} = \alpha I_{i,j} + \beta(1 * N_{i,j}) + \gamma Ind_{i,j} + \varepsilon_{i,j}$$

being in the same director network has a significant effect

- Stock price synchronicity:

$$SYNCH = \log\left(\frac{R^2_{i,t}}{1 - R^2_{i,t}}\right)$$

where $R^2_{i,t}$ is the R-squared value from

$$RET_{i,w} = \alpha + \beta_1 MKRET_{w-1} + \beta_2 MKRET_w + \beta_3 INDRET_{i,w-1} + \beta_4 INDRET_{i,w} + \varepsilon_{i,w}$$

- OLS estimation of

$$SYNCH_{i,t} = \beta_0 + \beta_1 Excess_{i,t} + \beta_2 UCF_{i,t} + \sum_k \beta_k Control^k_{i,t} + IndustryDummies + YearDummies + \varepsilon_{i,t}$$

- Stock price synchronicity increases with excess control
- Firms with substantial excess control are more likely to experience stock price crashes

Connected Stocks

JF-2014-Anton Polk

- Common active mutual fund owners
- Measuring Common Ownership
  - $FCAP_{ij,t} = \frac{\sum_{f=1}^{F}(S_{i,t}^{f}P_{i,t}+S_{j,t}^{f}P_{j,t})}{S_{i,t}Pi,t+S_{j,t}Pj,t}$
  - Using normalized rank-transformed as $FCAP_{ij,t}^{*}$
- $\rho_{ij,t}$: within-month realized correlation of each stock pair's daily four-factor returns
-

$$\rho_{ij,t+1} = a + b_f \times FCAPF_{ij,t}^{*} + \sum_{k=1}^{n} CONTROL_{ij,t,k} + \varepsilon_{ij,t+1}$$

Estimate these regressions monthly and report the time-series average as in Fama-MacBeth

Commonownership measurements

Model-based measures

- $\text{HJL}_I^A(A,B) = \sum_{i \in I^{A,B}} \frac{\alpha_{i,B}}{\alpha_{i,A}+\alpha_{i,B}}$ Harford et al. (2011)
  - Bi-directional
  - Pair-level measure of common ownership
  - Its potential impact on managerial incentives
  - Measure not necessarily increases when the relative ownership increases
  - Accounts only for an investor's relative holdings
- $\text{MHHI} = \sum_j \sum_k s_j s_k \frac{\sum_i \mu_{ij}\nu_{ik}}{\sum_i \mu_{ij}\nu_{ij}}$ Azar et al. (2018)
  - Capture a specific type of externality
  - Measured at the industry level
  - Assumes that investors are fully informed about the externalities
- $\text{GGL}^A(A,B) = \sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A}) \alpha_{i,B}$ Gilje et al. (2020)
  - Bi-directional
  - Less information
  - Not sensitive to the scope
  - Measure increases when the relative ownership of firm A increases

Commonownership measurements

Ad hoc common ownership measures

- $Overlap_{Count}(A, B) = \sum_{i \in I^{A,B}} 1$
  He and Huang (2017),He et al. (2019)
- $Overlap_{Min}(A, B) = \sum_{i \in I^{A,B}} min\{\alpha_{i,A}, \alpha_{i,B}\}$
  Newham et al. (2018)
- $Overlap_{AP}(A, B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \frac{\bar{\nu}_A}{\bar{\nu}_A + \bar{\nu}_B} + \alpha_{i,B} \frac{\bar{\nu}_B}{\bar{\nu}_A + \bar{\nu}_B}$
  Anton and Polk (2014)
- $Overlap_{HL}(A, B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \times \sum_{i \in I^{A,B}} \alpha_{i,B}$
  Hansen and Lott Jr (1996) , Freeman (2019)
- Unappealing properties
  - Unclear is whether any of these measures represents an economically meaningful measure of common ownership's impact on managerial incentives.
  - Both Overlap$_{Count}$ and Overlap$_{AP}$ are invariant to the decomposition of ownership between the two firms, which leads to some unappealing properties.

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