How are stocks connected?

The evidence from emerging market.

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Table of Contents

- **Stock return co-movement is caused by direct or indirect common ownership?**
  - common ownership:
    - We connect stocks through the common ownership by blockholders (ownership $> 1\%$) for direct common ownership
    - We connect stocks through the ultimate owner for indirect common ownership
  - We focus on excess return co-movement for a pair of the stocks
  - We use common ownership to forecast cross-sectional variation in the realized correlation of four-factor + industry residuals
  - We demonstrate that correlated trading can be a channel of co-movement

Why does it matter?

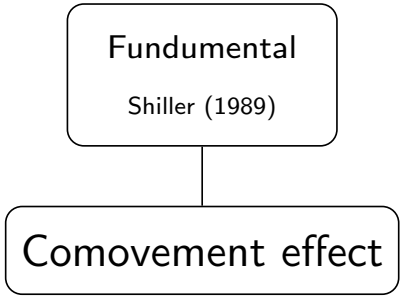
- Covariance
  - Covariance is a key component of risk in many financial applications.
    (Portfolio selection, Risk management, Hedging and Asset pricing)
  - Covariance is a significant input in risk measurement models
    (Such as Value-at-Risk)
- Return predictability
  - If it's valid, we can build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

Table of Contents

Main effect

Comovement effect

Main effect



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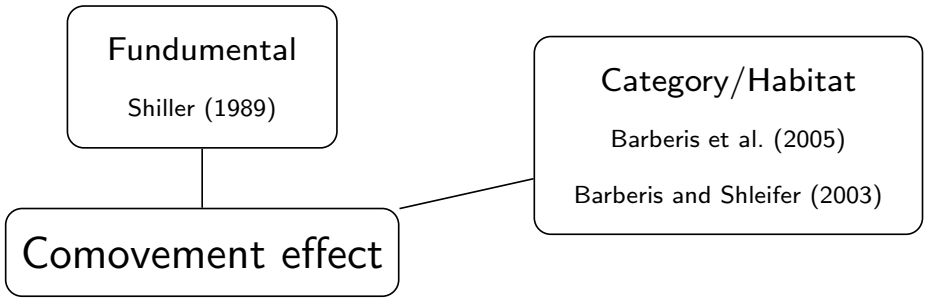

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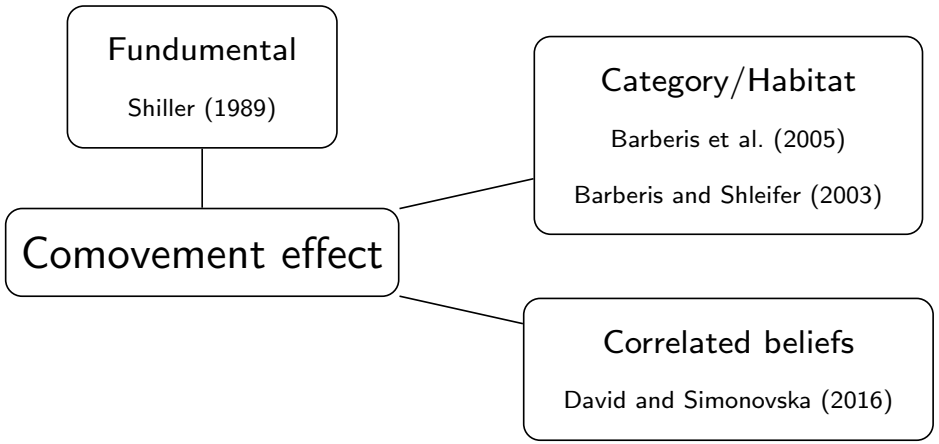

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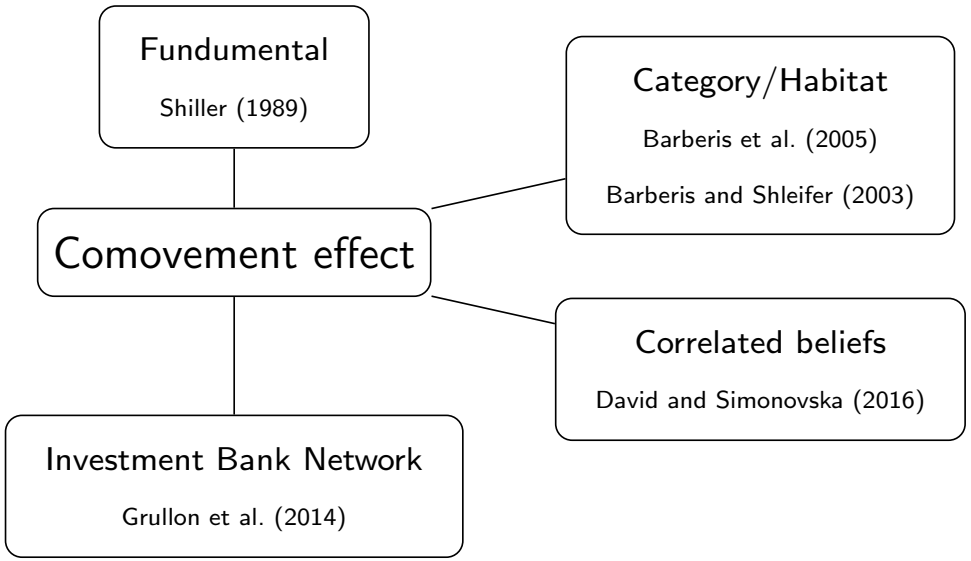

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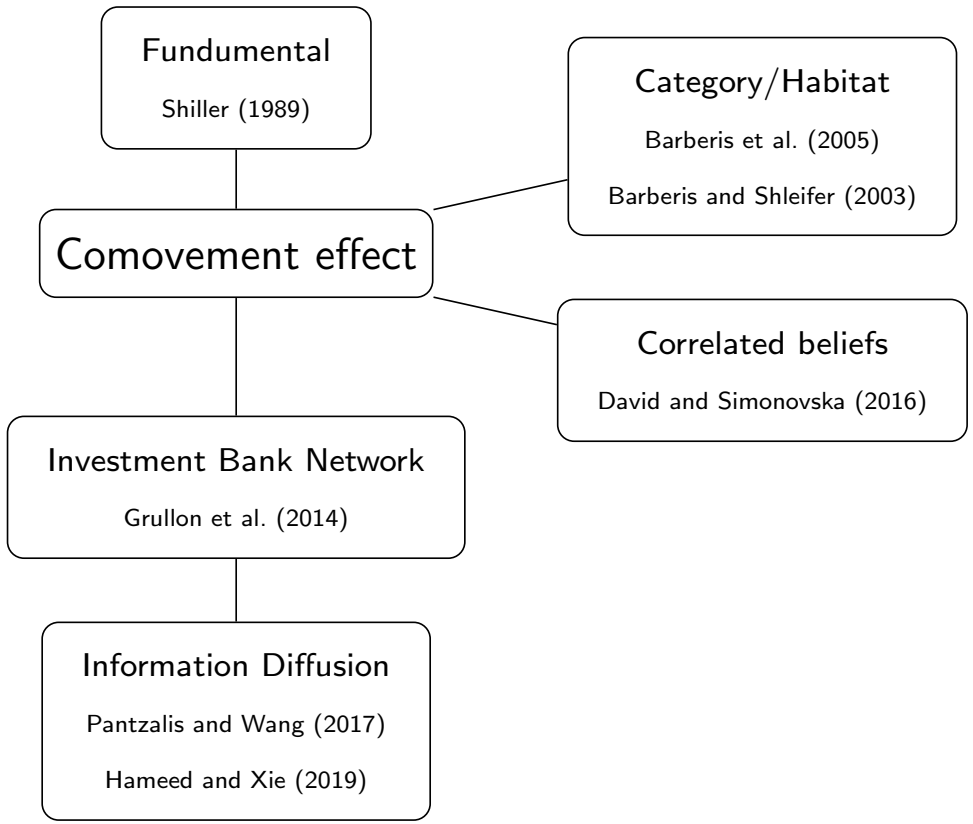

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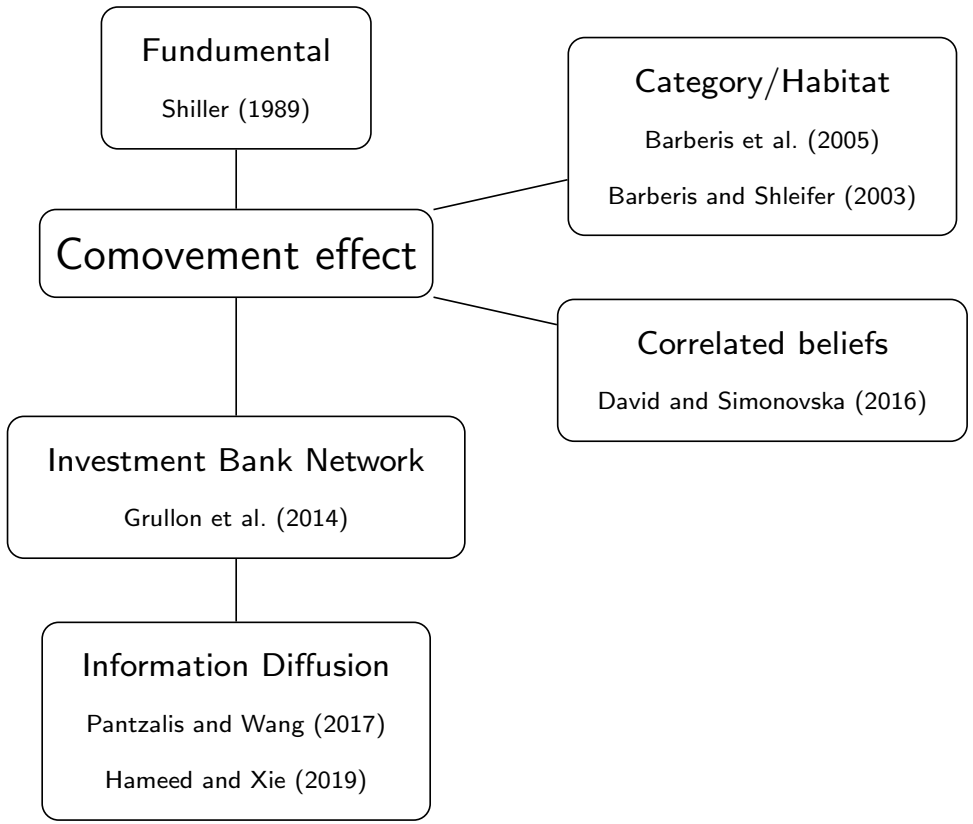
Main effect

Common-ownership



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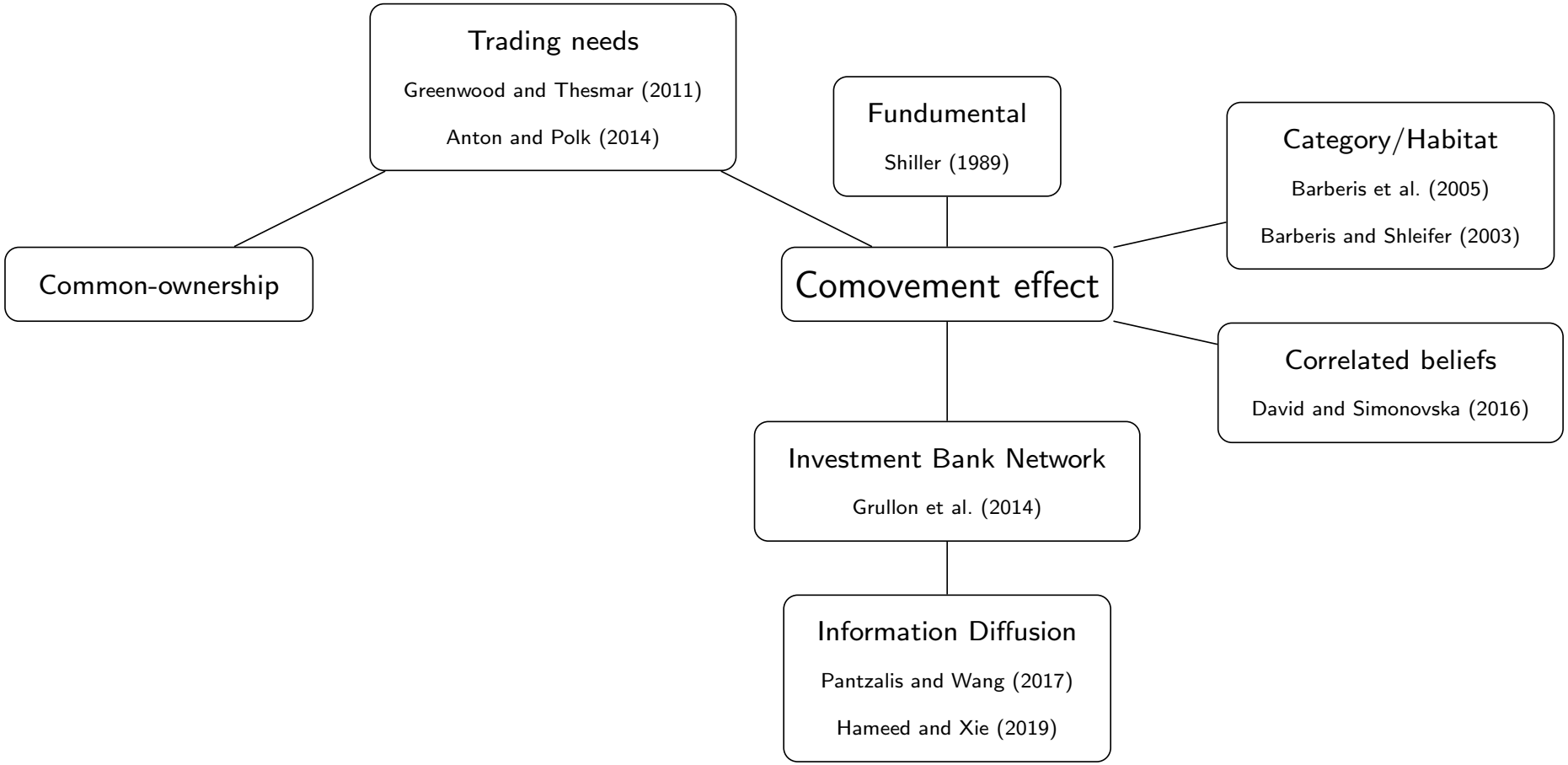

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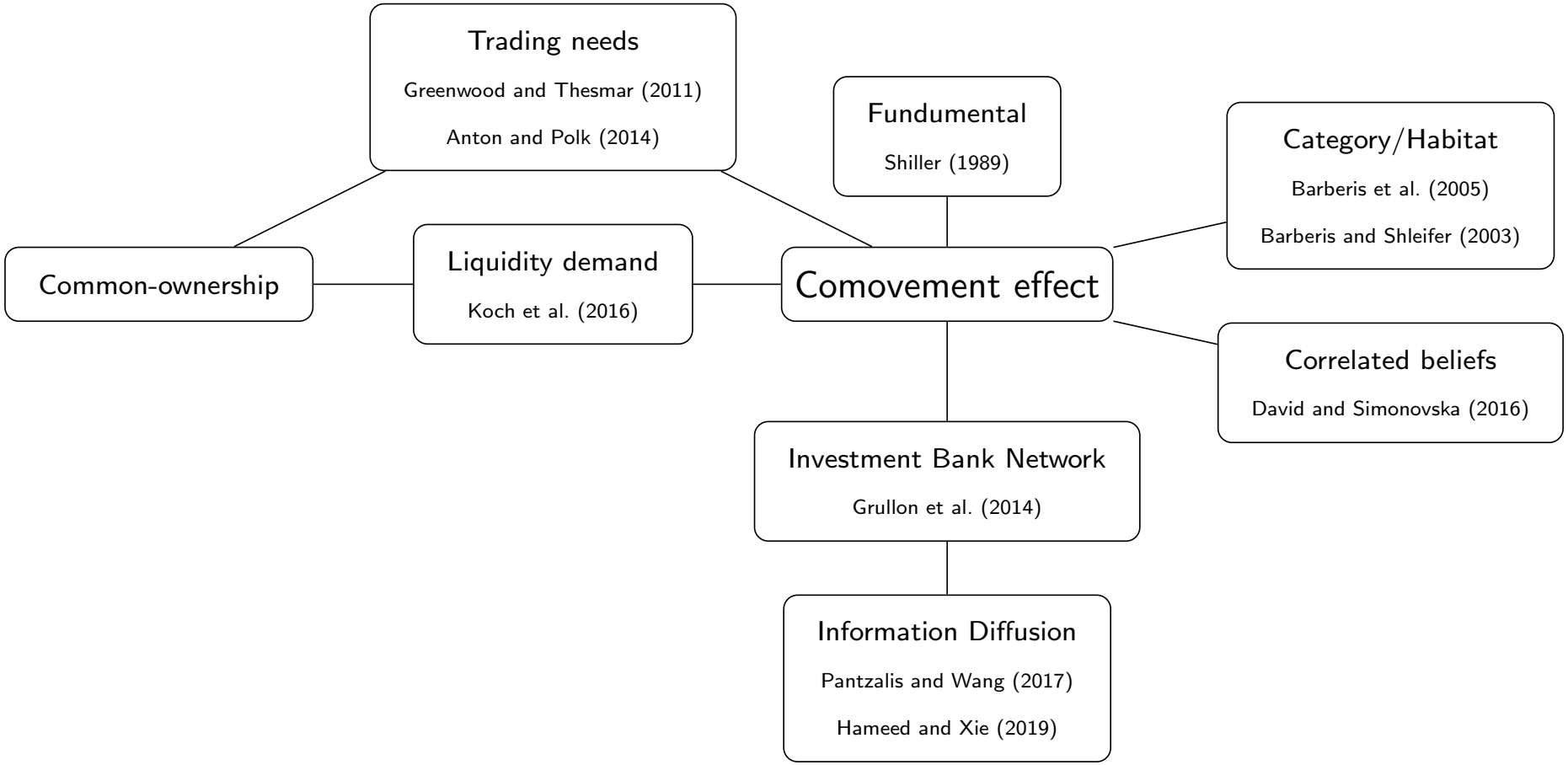

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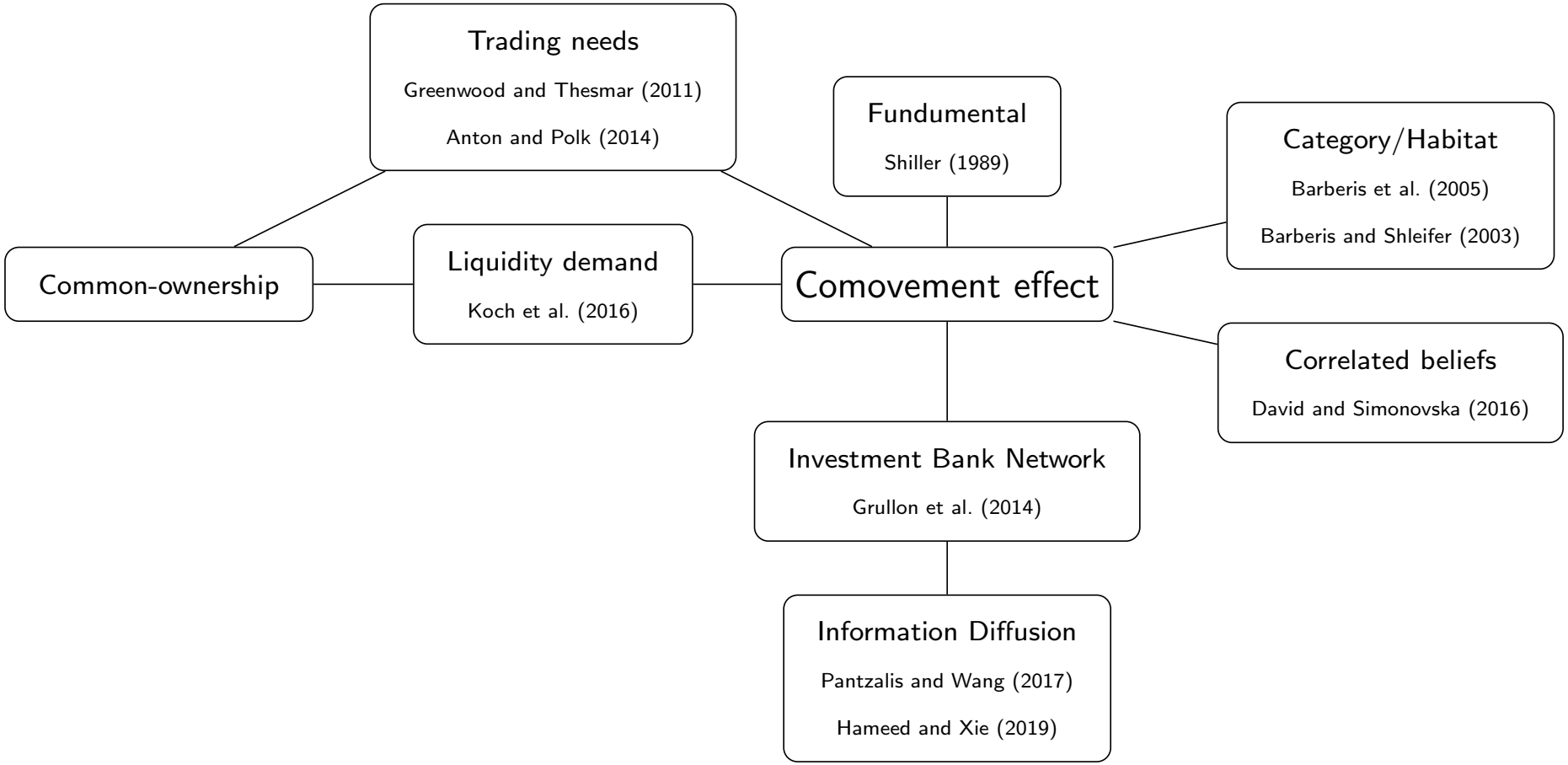

Papers

Our work

- We use daily records of block-holder ownership for firms
- We not restricted to mutual funds ownership
- Furthermore, 80% of market belongs to the business groups
  - Would business groups be able to raise the co-movement of stock returns?
    - Cho and Mooney (2015):
      The strong co-movement between group returns and firm returns is explained by correlated fundamentals.
    - Kim et al. (2015):
      The increase in correlation appears to be driven more by non-fundamental factors such as correlated trading, rather than fundamental factors such as related-party transactions
  - Common ownership or business group (indirect common ownership) ?
  - Through which channel?

Common-ownership measurements

Model based measures

- $HJL_I^A(A,B) = \sum_{i \in I^{A,B}} \frac{\alpha_{i,B}}{\alpha_{i,A}+\alpha_{i,B}}$

  Harford et al. (2011)

- $MHHI = \sum_j \sum_k s_j s_k \frac{\sum_i \mu_{ij}\nu_{ik}}{\sum_i \mu_{ij}\nu_{ij}}$

  Azar et al. (2018)

- $Top5_j = \frac{1}{n-1} \sum_i^5 \sum_{j \neq k} \nu_{ik}$

  Antón et al. (2020)

- $\kappa_{ij} = \cos(\nu_i, \nu_j) . \sqrt{\frac{IHHI_j}{IHHI_i}}$

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- $GGL^A(A,B) = \sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A}) \alpha_{i,B}$

  Gilje et al. (2020) , Lewellen and Lewellen (2021)

- $MHHI_{Delta} = \sum_{j=1}^{J} \sum_{k \neq j}^{K} \frac{\sum_{i=1}^{N} w_j * w_k * \mu_{i,j} * \mu_{i,k}}{\sum_{i=1}^{N} \mu_{i,j} * \mu_{i,k}}$

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Ad-hoc measures

- $Overlap_{AP}(A,B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \frac{\bar{\nu}_A}{\bar{\nu}_A+\bar{\nu}_B} + \alpha_{i,B} \frac{\bar{\nu}_B}{\bar{\nu}_A+\bar{\nu}_B}$
  Anton and Polk (2014)
- $Overlap_{Count}(A,B) = \sum_{i \in I^{A,B}} 1$
  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)
- $Overlap_{HL}(A,B) = \sum_{i \in I^{A,B}} \alpha_{i,A} \times \sum_{i \in I^{A,B}} \alpha_{i,B}$
  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

Table of Contents

Measuring Common-ownership

Anton and Polk (2014)

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

Measuring Common-ownership

Anton and Polk (2014)

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SQRT

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

Quadratic

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

Measuring Common-ownership

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

Quadratic

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

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

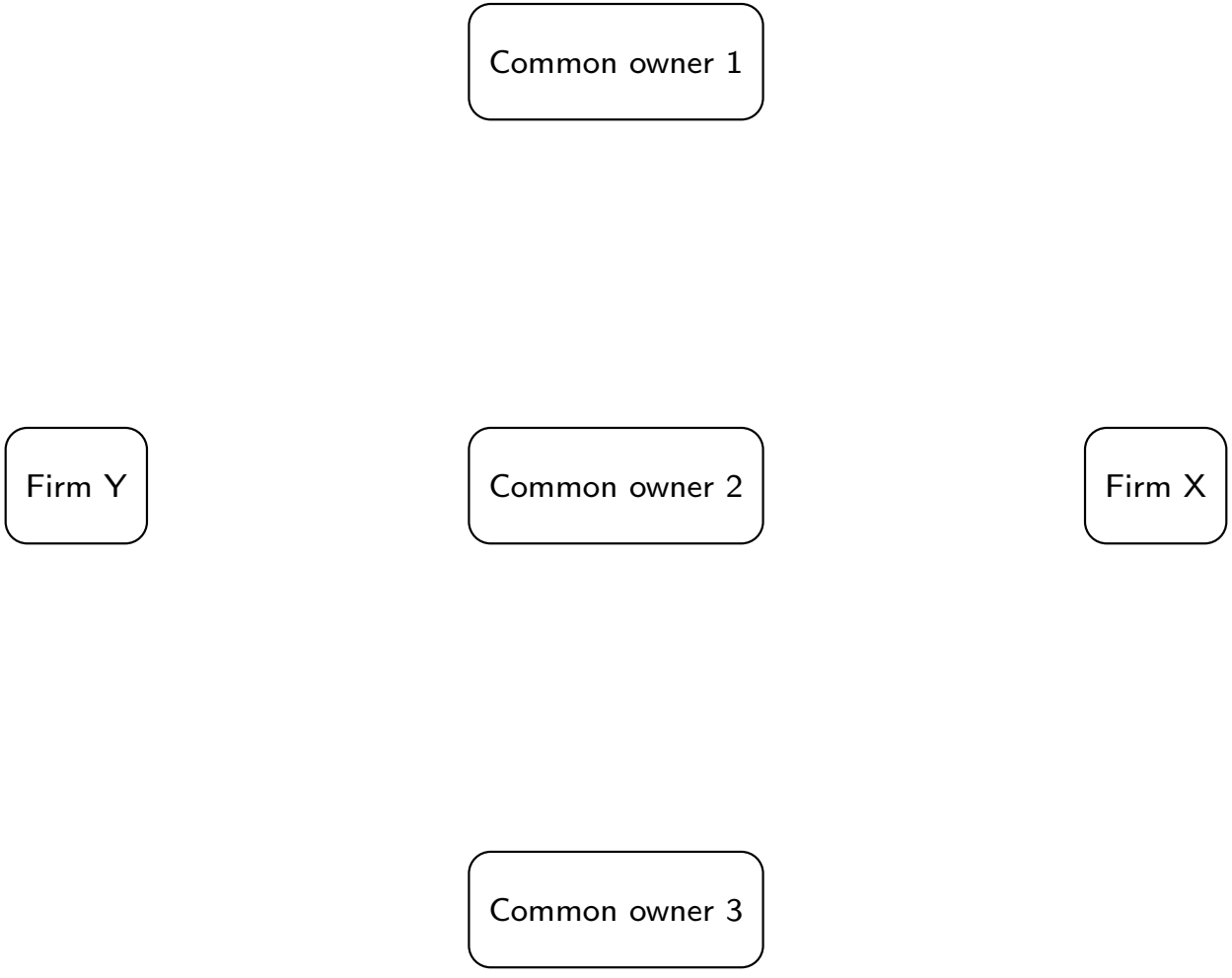
Example of three common owner

Firm Y

Firm X

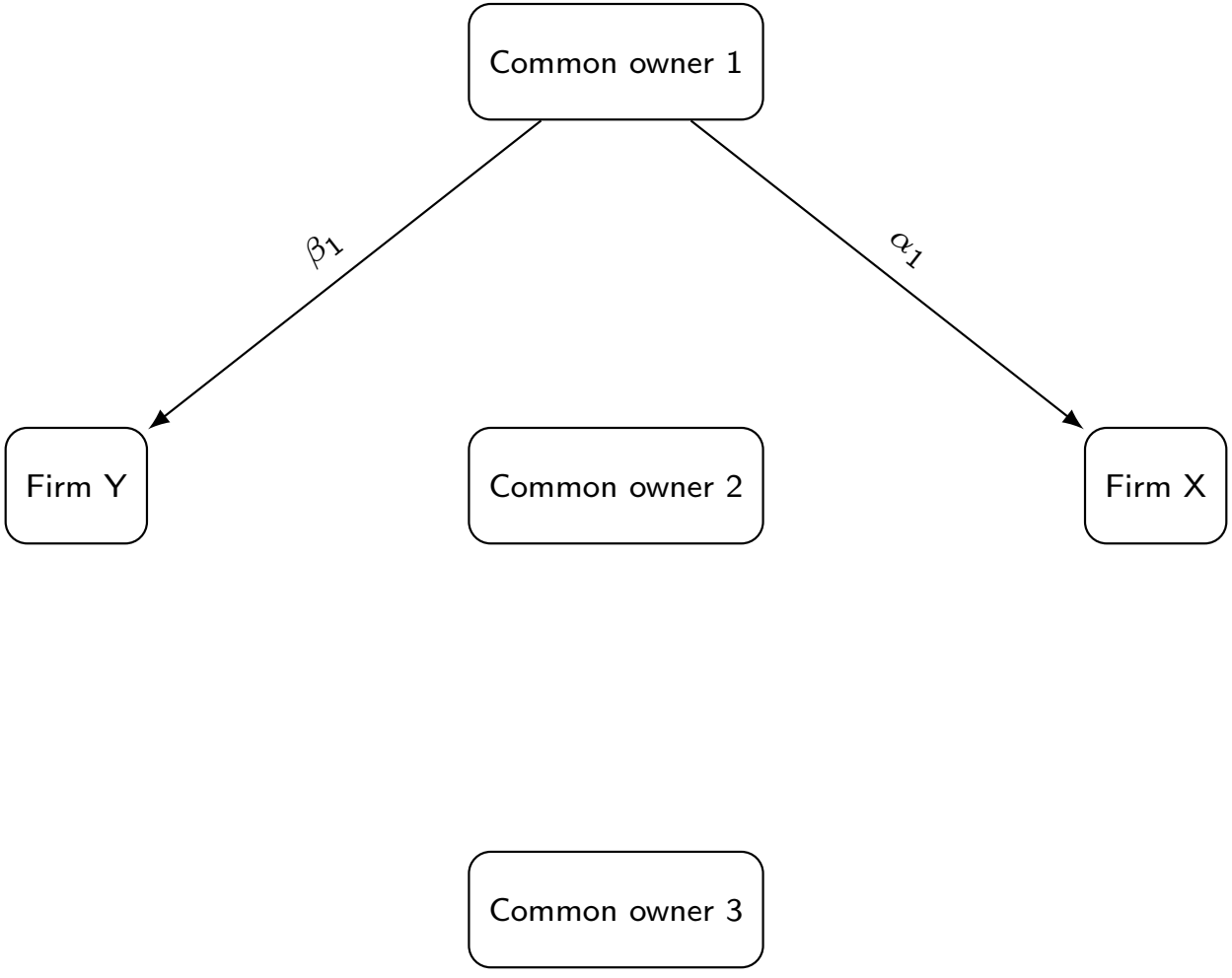
Measuring Common Ownership

Example of three common owner



Measuring Common Ownership

Example of three common owner



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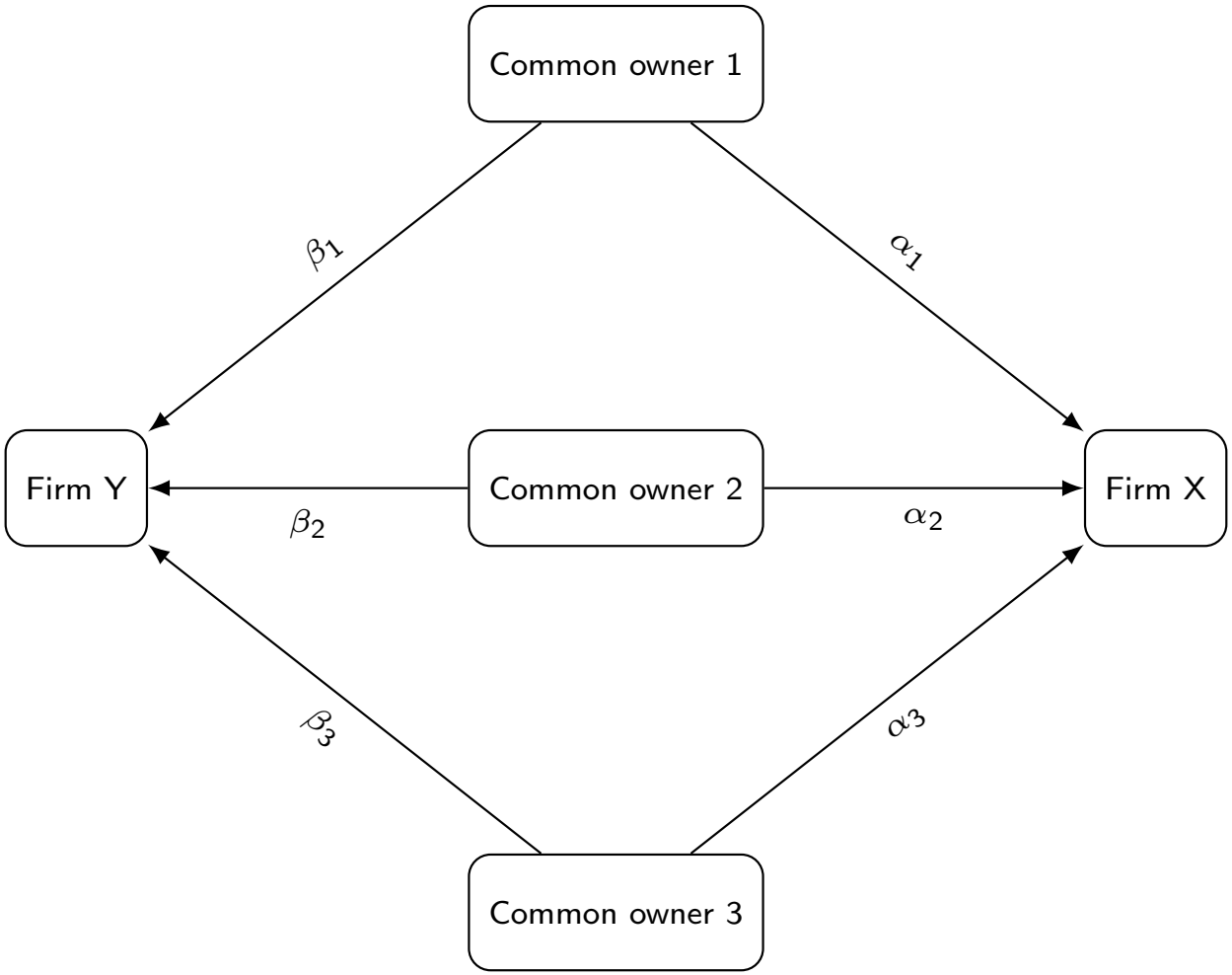


Measuring Common Ownership

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

Measuring Common Ownership

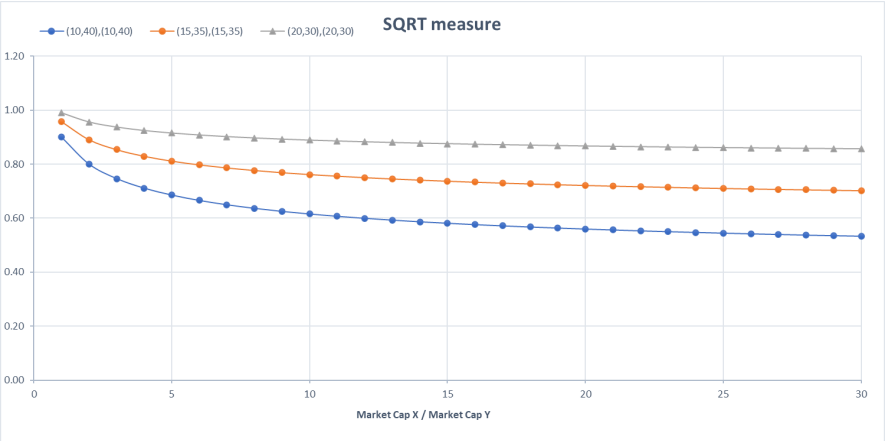
Comparison

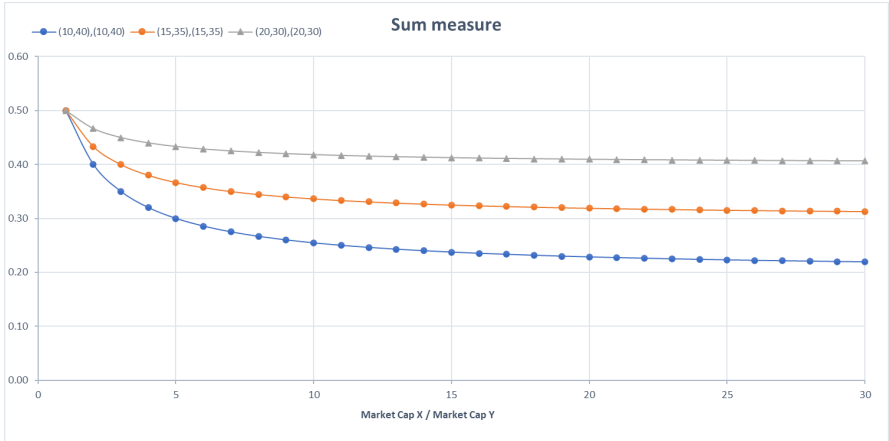
- For better comparison we relax previous assumptions:
  - Two Firms with different market caps.

	$(\alpha_1,\beta_1),(\alpha_2,\beta_2)$					
	(10,40),(10,40)		(15,35),(15,35)		(20,30),(20,30)	
$\frac{\text{MarketCap}_x}{\text{MarketCap}_y}$	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

Measuring Common Ownership

Comparison





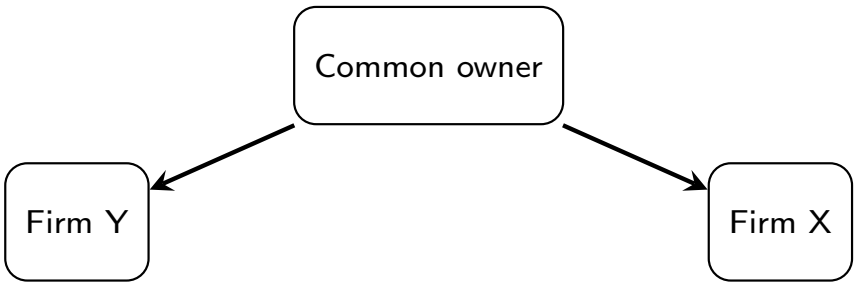
Comparison of two methods for calculating common ownership

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

- Firms with at least one common owner



- In a business group, how can one pair be defined?
  - What is the business group?

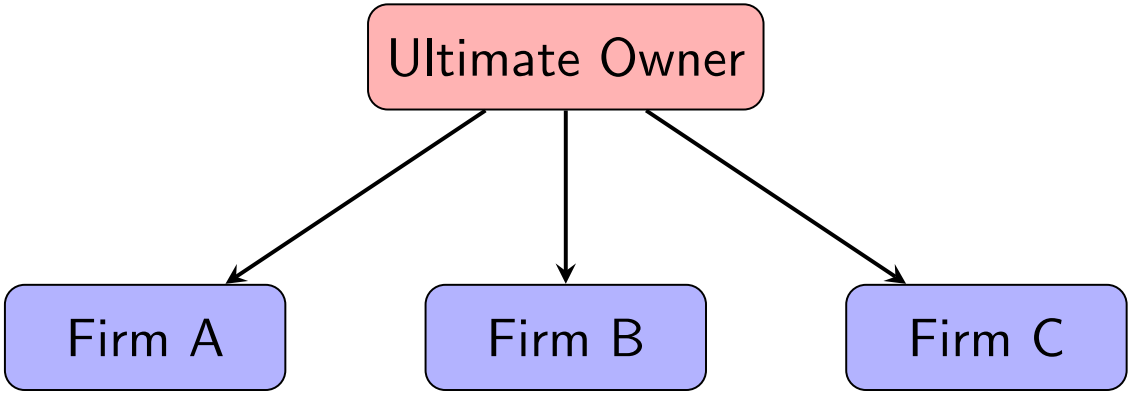
Pair Composition and Business Group

Business Group

Ultimate Owner

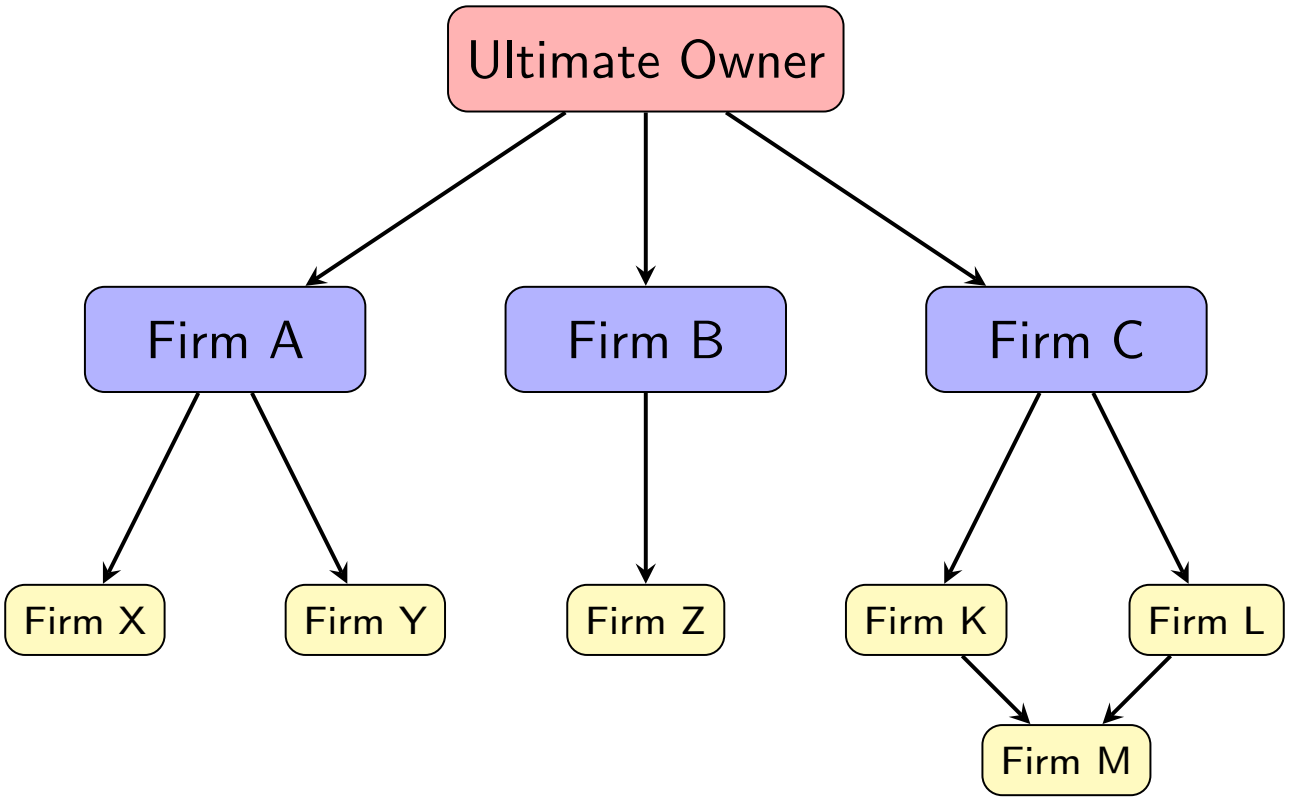
Pair Composition and Business Group

Business Group



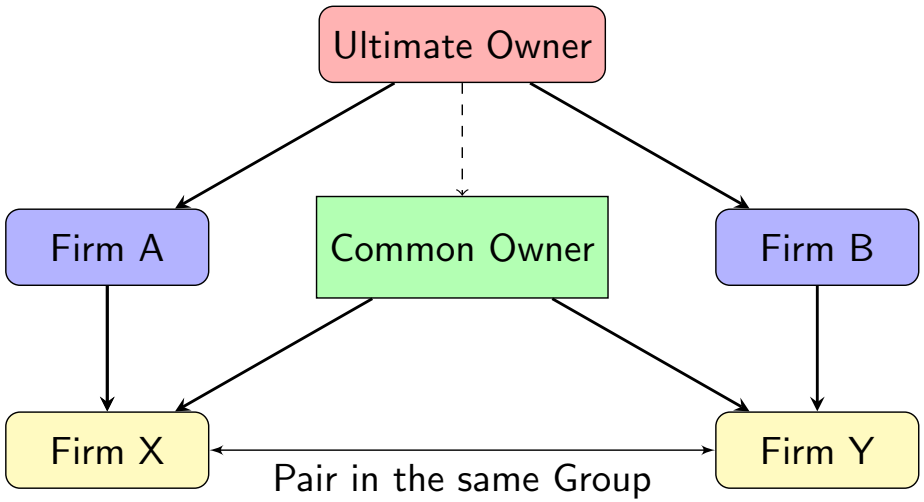
Pair Composition and Business Group

Business Group



Pair Composition and Business Group

Pair in the Business Group



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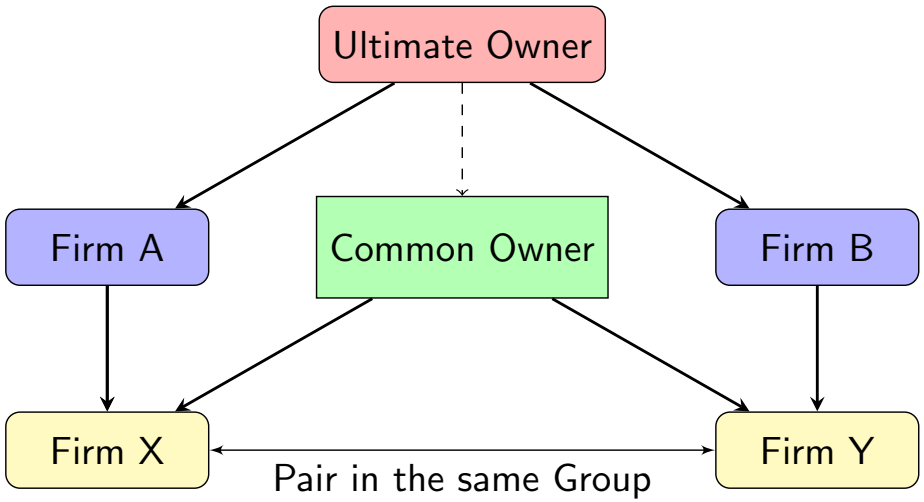
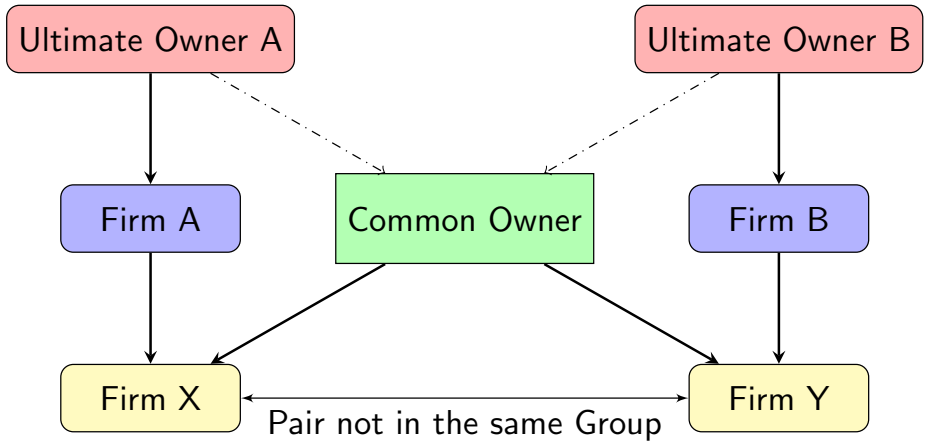
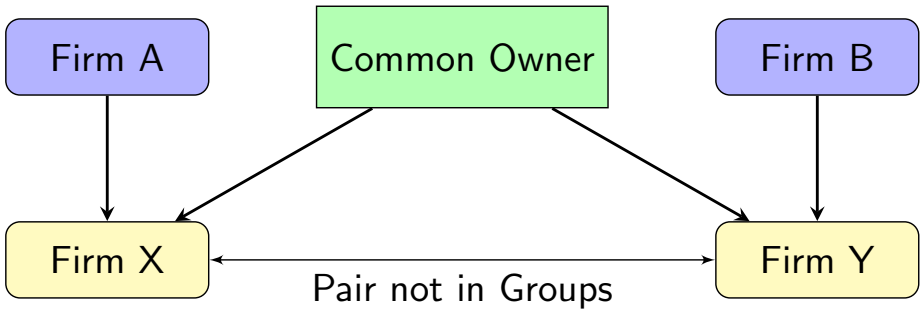
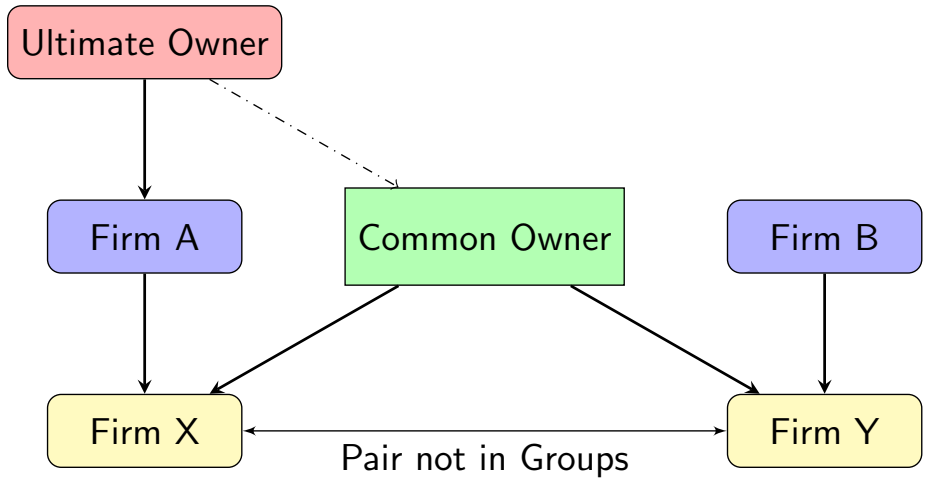




Pair Composition and Business Group

Pair not in any of Business Groups





Data Summary

- We use blockholders' data from 2014/03/25 (1393/01/06) to 2020/03/18 (1398/12/28)
  - Includes of 72 Months
  - Consists of 618 firm inculding 562 firm with common owners

Year	1393	1394	1395	1396	1397	1398
No. of Firms	365	376	447	552	587	618
No. of Blockholders	777	803	984	1297	1454	1458
No. of Groups	38	41	43	44	40	43
No. of Firms not in Groups	116	108	147	216	241	243
No. of Firms in Groups	249	268	300	336	346	375
Average Number of Members	7	7	7	8	9	9
Med. of Number of Members	5	5	5	6	6	5
Average Of each Blockholder's ownership	21	22	22	21	22	23
Med. of Owners' Percent	7	8	8	8	8	9
Average Number of Owners	5	5	5	5	5	5
Med. Number of Owners	4	4	4	4	5	4
Average Block. Ownership	76	77	75	75	75	71
Med. Block. Ownership	82	82	81	80	80	77

Pair Composition

- Pairs consist of two firms with at least one common owner
  - 93442 unique pairs which is 25% of possible pairs ($\frac{612*611}{2} = 373932$)

	mean	min	Median	max
Number of unique paris	24139	13272	23024	45795

year	1393	1394	1395	1396	1397	1398
No. of Pairs	20876	21187	27784	41449	47234	67232
No. of Groups	37	40	42	43	39	43
No. of Pairs not in Groups	11452	11192	15351	26530	29182	43433
Number of Pairs not in the same Group	7962	8731	10971	12916	15366	20745
Number of Pairs in the same Group	923	955	1099	1260	1536	1774
Average Number of Common owner	1	1	1	1	1	1
Med. Number of Common owner	1	1	1	1	1	1
Average Percent of each blockholder	19	19	19	19	19	20
Med. Percent of each blockholder	13	12	12	12	12	14
Average Number of Pairs in one Group	31	30	30	34	39	44
Med. Number of Pairs in one Group	8	10	8	10	9	10
Average Number of Owners	5	5	5	5	4	5
Med. Number of Owners	5	5	5	5	4	5
Average Block. Ownership	73	73	72	70	70	70
Med. Block. Ownership	73	73	73	71	71	71

FCA vs. FCAP Summary

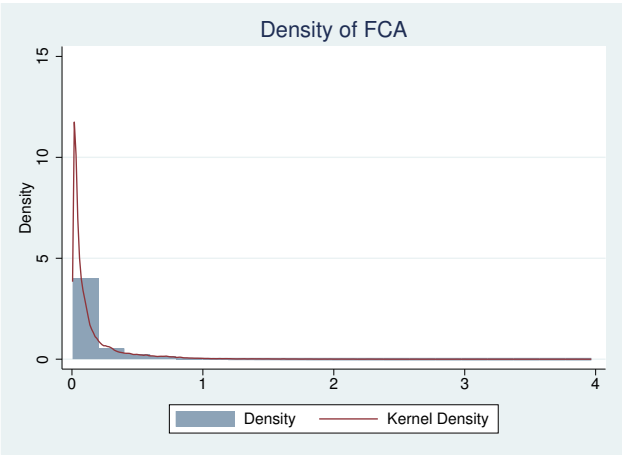
	variable	mean	std	min	25%	50%	75%	max
All	FCA	0.158	0.234	0.002	0.031	0.079	0.191	12.650
	FCAP	0.144	0.166	0.002	0.030	0.077	0.193	1.000
Same Group	FCA	0.474	0.478	0.005	0.096	0.367	0.691	6.174
	FCAP	0.346	0.265	0.004	0.081	0.321	0.561	1.000
Not Same Group	FCA	0.087	0.154	0.003	0.020	0.038	0.087	6.184
	FCAP	0.072	0.102	0.003	0.020	0.037	0.078	0.998
Same Industry	FCA	0.274	0.383	0.003	0.044	0.126	0.351	6.262
	FCAP	0.207	0.215	0.003	0.041	0.120	0.314	0.999
Not Same Industry	FCA	0.150	0.217	0.002	0.030	0.077	0.183	12.650
	FCAP	0.140	0.161	0.002	0.029	0.074	0.187	1.000

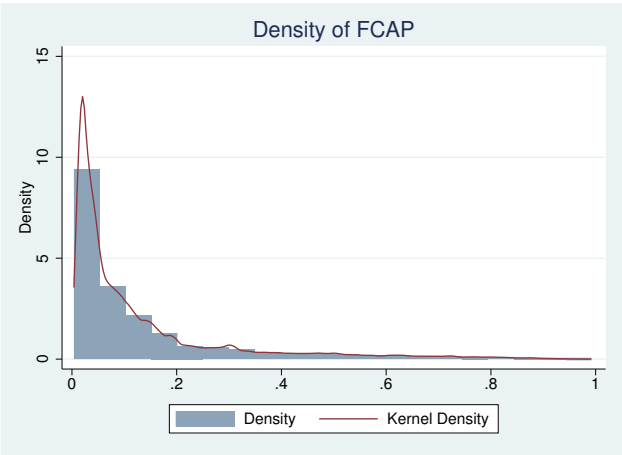
Results

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

FCA vs. FCAP Distributions

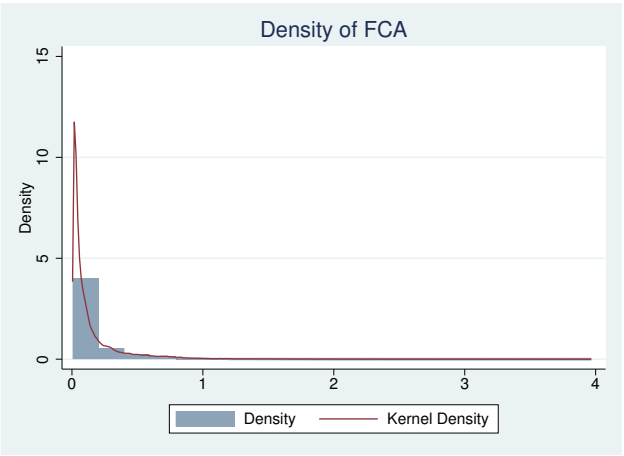
Monthly

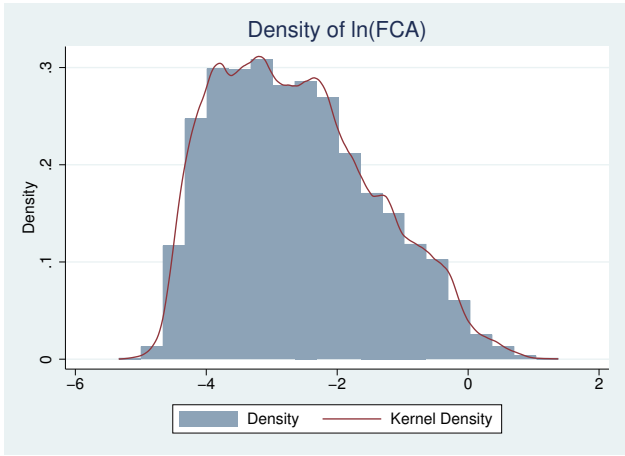


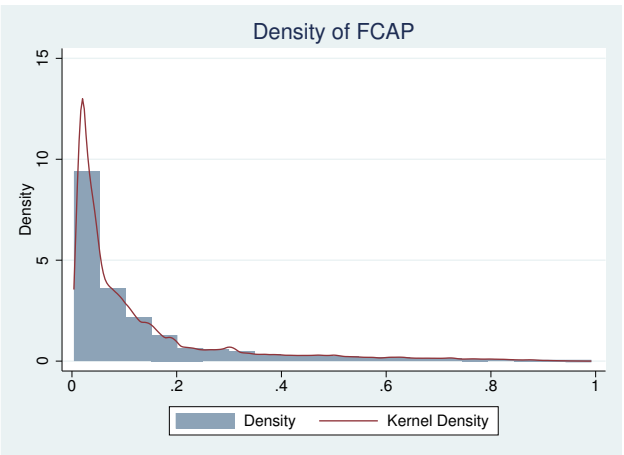


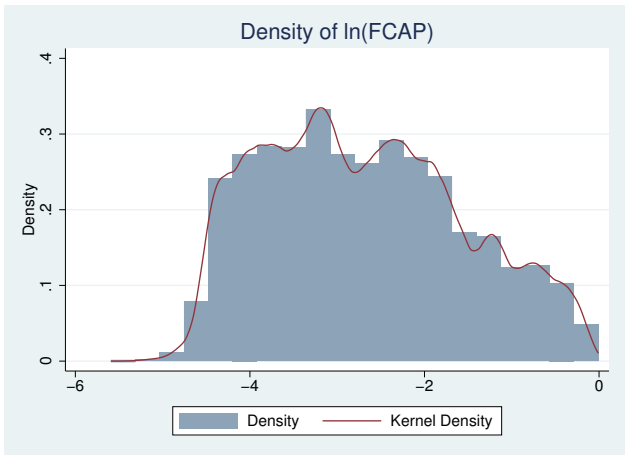
FCA vs. FCAP Distributions

Monthly



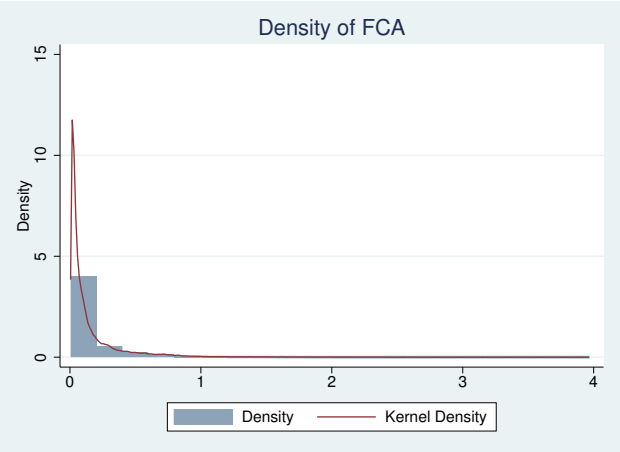


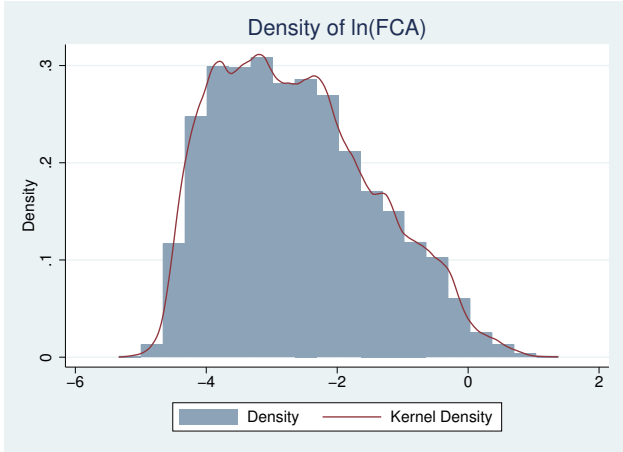


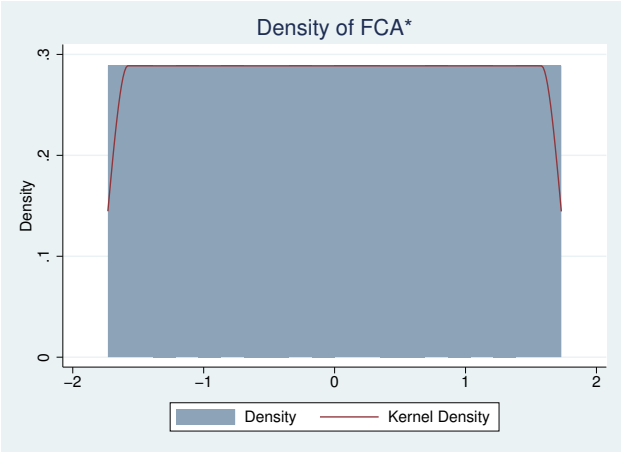


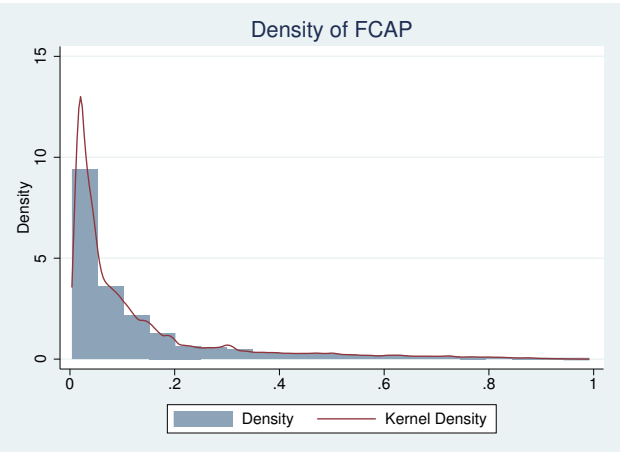
FCA vs. FCAP Distributions

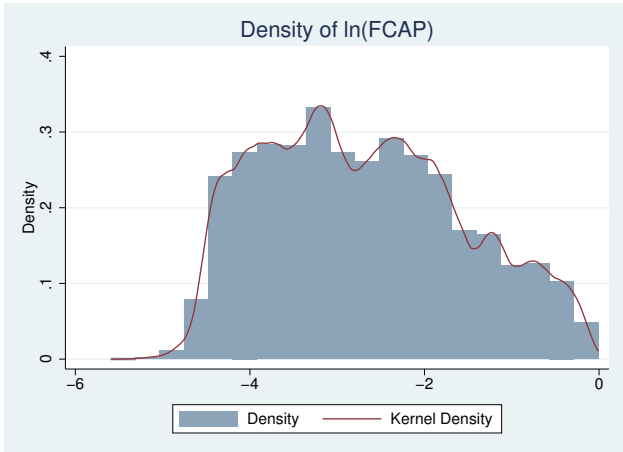
Monthly

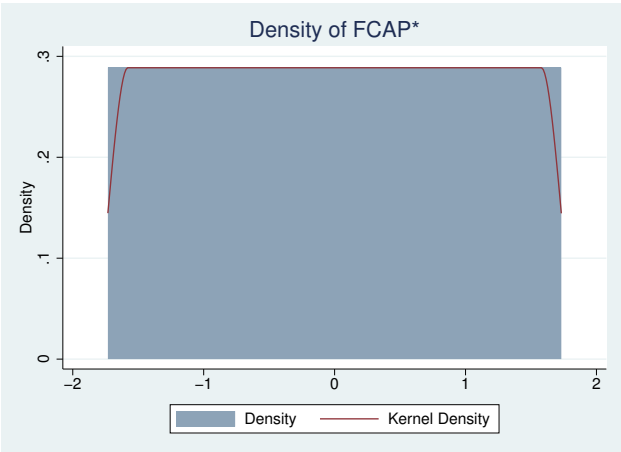












Correlation Calculation

4 Factor + Industry

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 :

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

   - 4 Factor + Industry (5 Factor) :

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

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

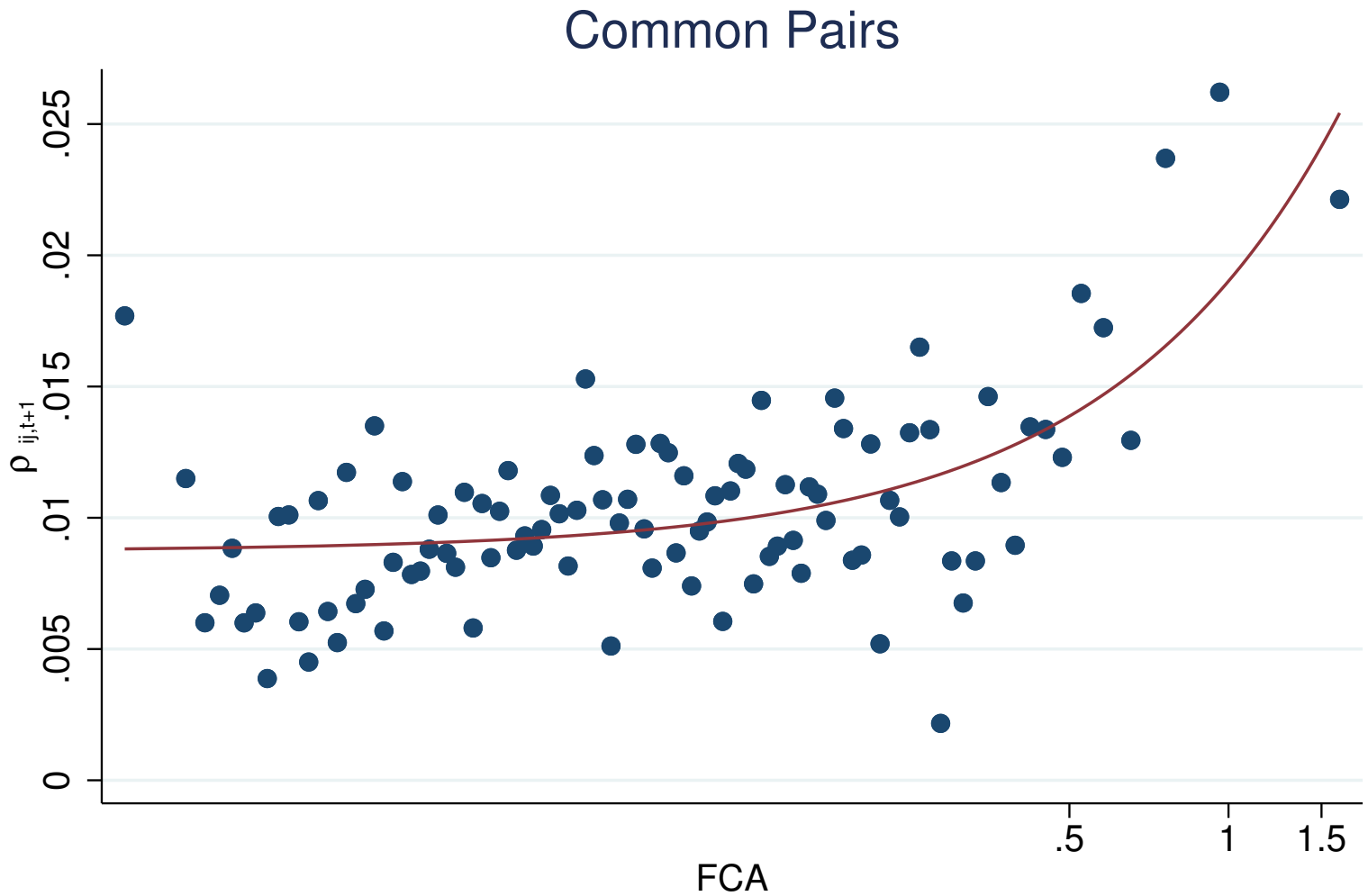
Correlation Calculation Results

	mean	std	min	25%	50%	75%	max
CAPM + Industry	0.021	0.200	-1.0	-0.047	0.016	0.084	1.0
4 Factor	0.032	0.202	-1.0	-0.040	0.025	0.096	1.0
4 Factor + Industry	0.016	0.199	-1.0	-0.051	0.010	0.076	1.0
4 Factor + Industry (With Lag)	0.015	0.198	-1.0	-0.051	0.010	0.076	1.0

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*



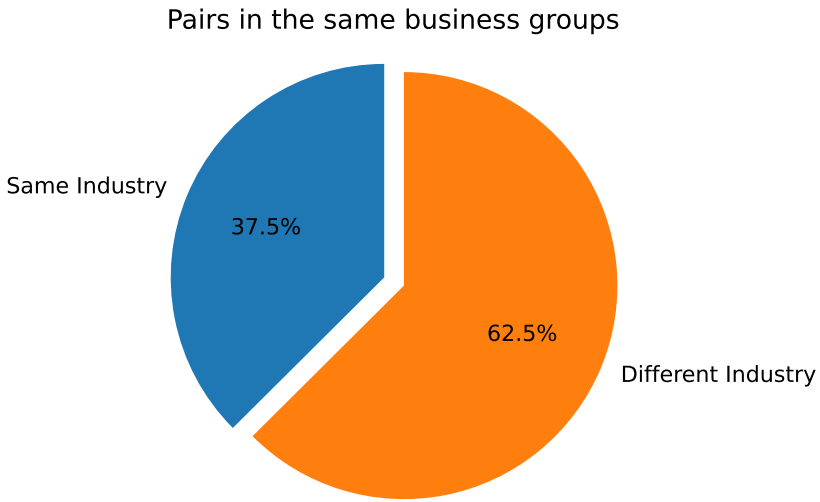
This figure graphs the correlation of daily 4Factor+Industry residuals in monthh t+1 against our measure of institutional connectedness.

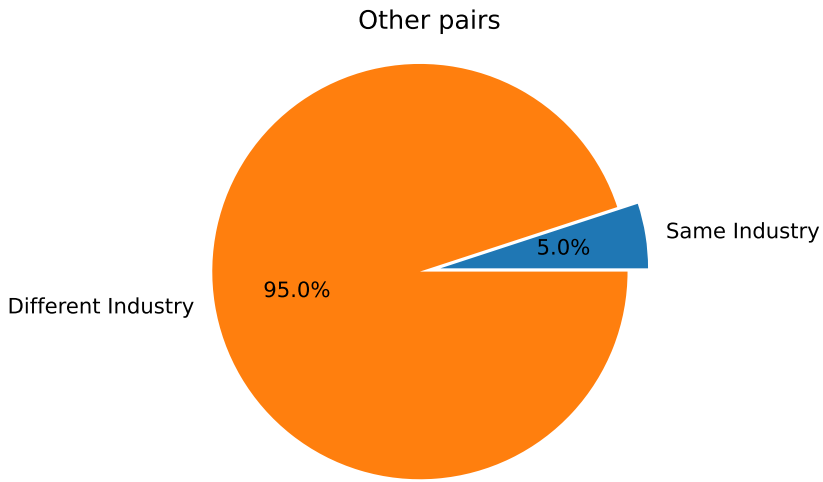
Controls

- **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

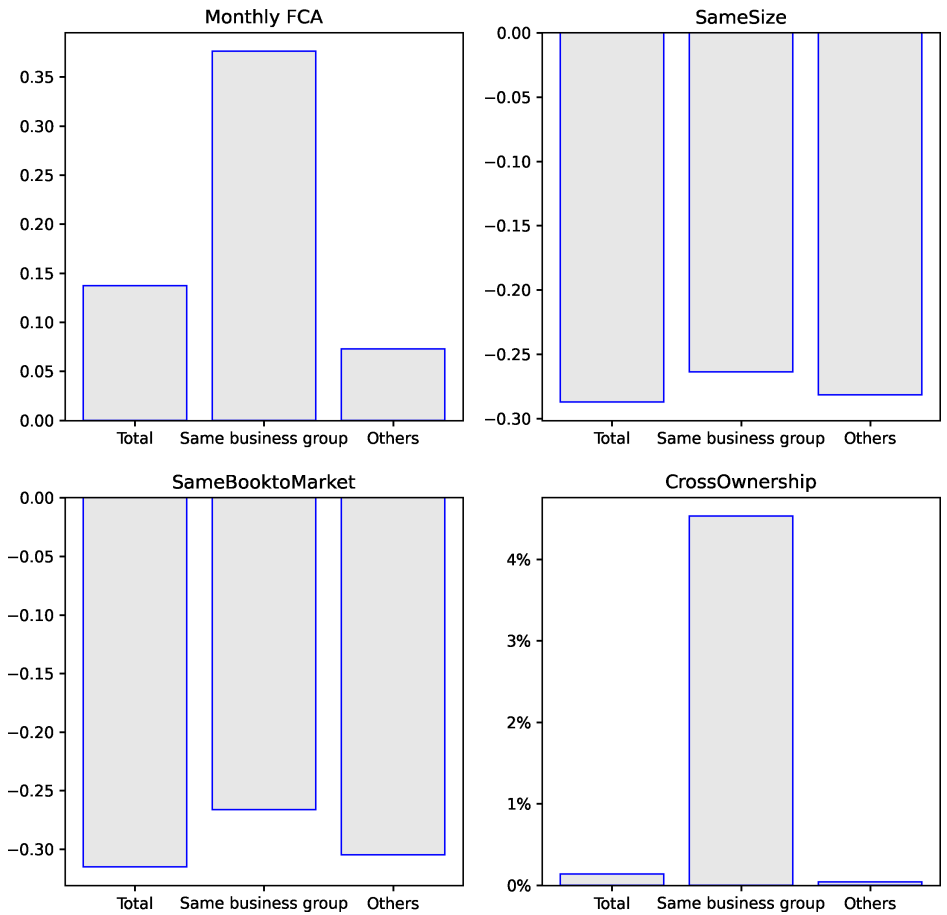
	Yes	No
SameIndustry	4541 (5.7%)	74837 (94.3%)
SameGroup	1834 (6.3%)	27157 (93.7%)
SameGroup & SameIndustry	696 (0.9%)	79378 (99.1%)





Business group

Pairs' characteristic



Summary of Controls

Variables' distribution

	mean	std	min	25%	50%	75%	max
SameIndustry	0.06	0.23	0.00	0.00	0.00	0.00	1.00
SameGroup	0.06	0.24	0.00	0.00	0.00	0.00	1.00
Size1	0.58	0.23	0.01	0.40	0.58	0.77	1.00
Size2	0.30	0.20	0.00	0.13	0.25	0.41	0.99
SameSize	-0.29	0.20	-0.97	-0.41	-0.24	-0.13	-0.00
BookToMarket1	0.54	0.25	0.00	0.36	0.57	0.75	1.00
BookToMarket2	0.55	0.24	0.00	0.36	0.56	0.75	1.00
SameBookToMarket	-0.32	0.20	-0.99	-0.44	-0.27	-0.16	-0.00
CrossOwnership	0.14	2.59	0.00	0.00	0.00	0.00	95.77

Table of Contents

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

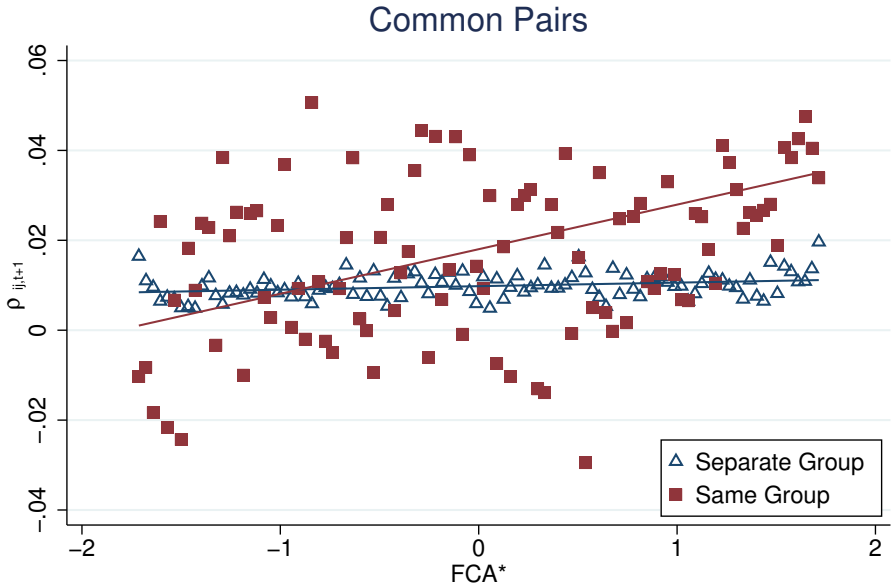
$$Lag = 4(T/100)^{\frac{2}{9}}$$

where T is the number of periods in the time series

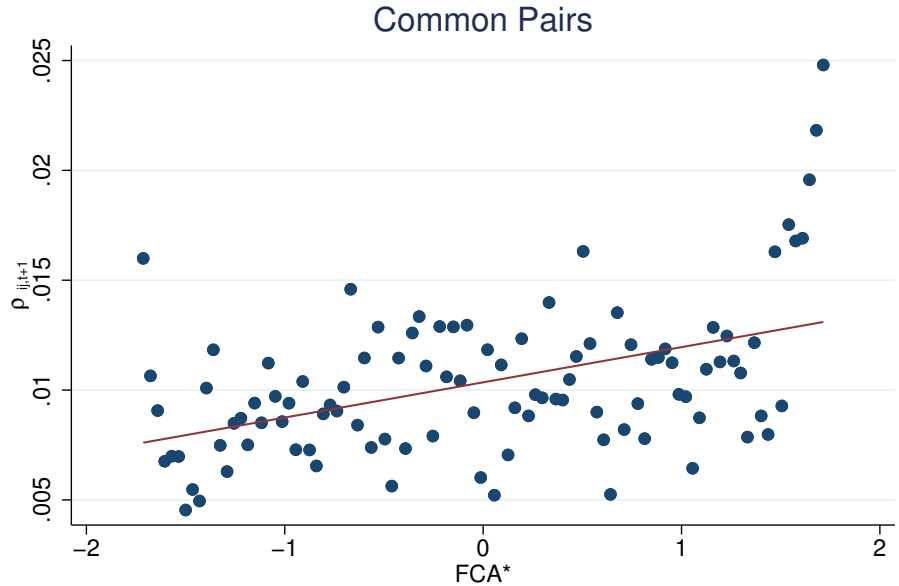
Table of Contents

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

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

- Estimate the model on a monthly frequency
- Adjust standard errors by Newey and West adjustment with 4 lags $(4(70/100)^{\frac{2}{9}} = 3.69 \sim 4)$

Model Estimation

Normalized Rank-Transformed

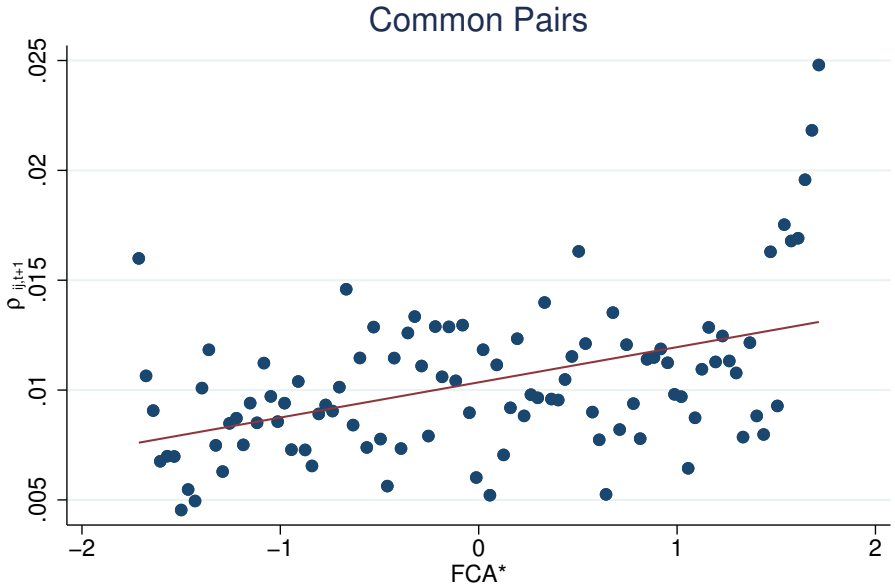
	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Same Group	0.0166***	0.0153***			0.0147***			0.00624***	0.00549**
	(8.54)	(7.90)			(6.97)			(2.81)	(2.27)
FCA*			0.00150***	0.00112**	0.000736	0.00944***	0.000397	0.000377	-0.0000113
			(2.90)	(2.11)	(1.33)	(7.24)	(0.68)	(0.65)	(-0.02)
(FCA*) × SameGroup								0.00992***	0.0107***
								(6.49)	(6.97)
Observations	1665996	1665996	1665996	1665996	1665996	58337	1607659	1665996	1665996
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	0.000180	0.000637	0.000170	0.000652	0.000804	0.0112	0.000577	0.000898	0.00575

t statistics in parentheses

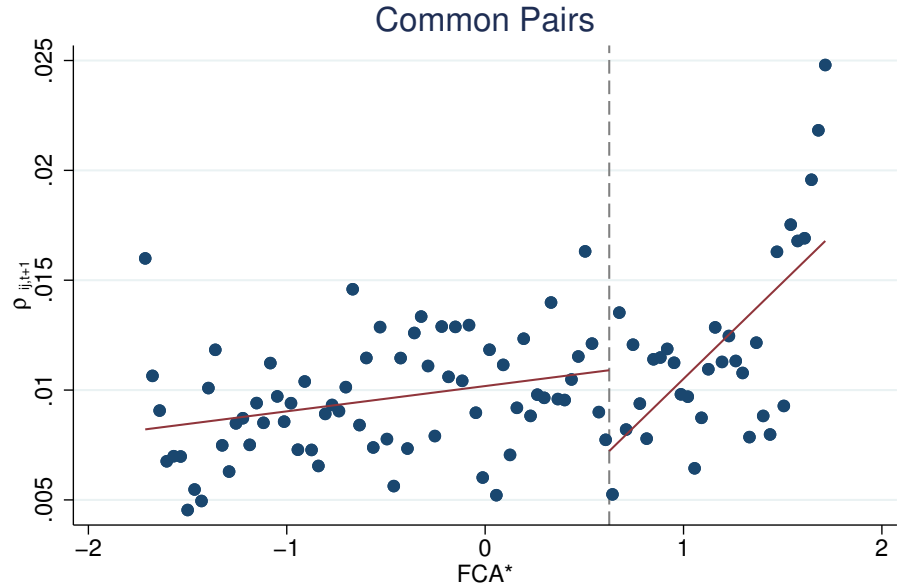
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Future Correlation via *FCA*

Discontinuity



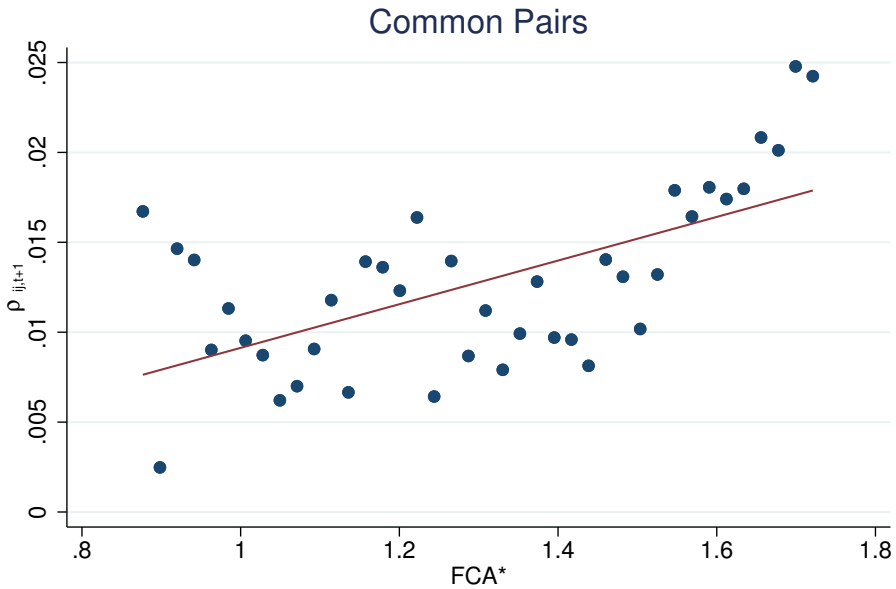
This figure graphs the correlation of daily 4Factor+Industry residuals in month t+1 against our measure of institutional connectedness.



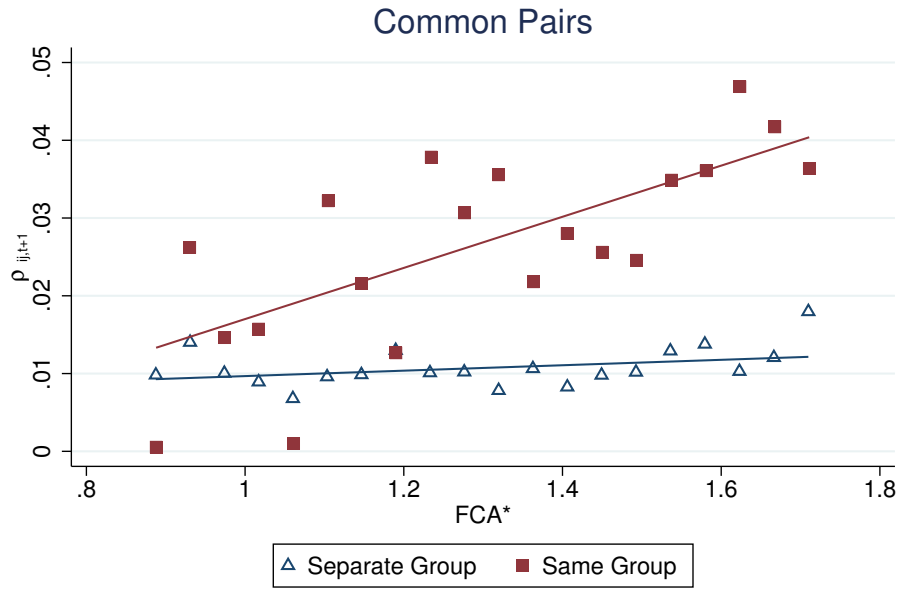
This figure graphs the correlation of daily 4Factor+Industry residuals in month t+1 against our measure of institutional connectedness. Allow for discontinuity in fourth quarter

4 Factor + Industry Future Correlation via *FCA**

Discontinuity & Business Groups

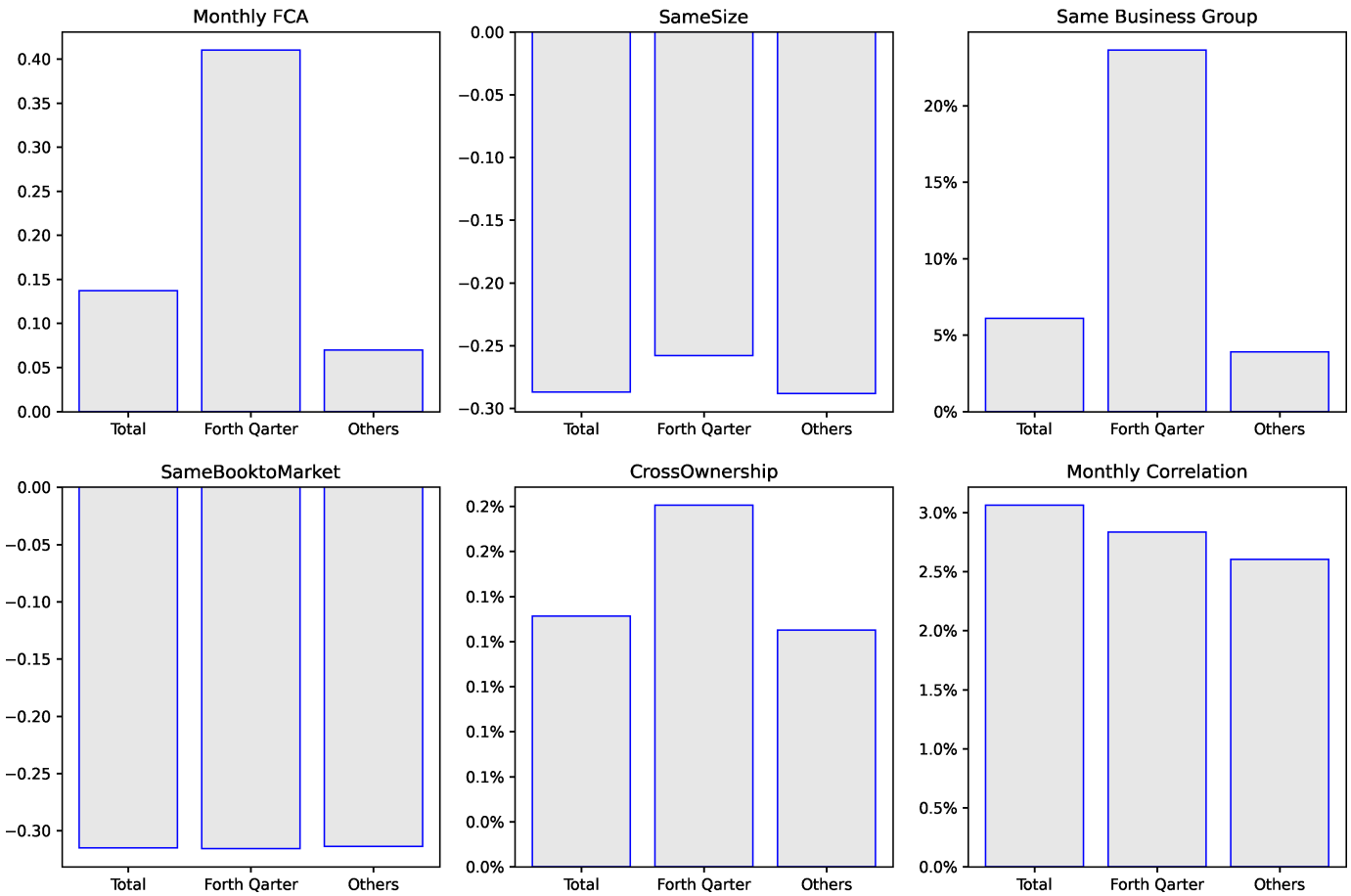


This figure graphs the correlation of daily 4Factor+Industry residuals in month t+1 against our measure of institutional connectedness. Allow for discontinuity in fourth quarter



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

Forth quarter summary



Fama-MacBeth Estimation

Discontinuity (sub-sample)

	Dependent Variable: Future Monthly Correlation of 4F+Ind. Res.						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same Group	0.0229***		0.0220***	0.0206***	0.0195***	-0.0230*	-0.0201
	(9.86)		(8.34)	(7.28)	(7.24)	(-2.21)	(-1.94)
FCA*		0.0122**	0.00516	0.00494	0.00485	0.00270	0.00194
		(3.11)	(1.23)	(1.18)	(1.17)	(0.60)	(0.46)
(FCA*) × SameGroup						0.0287***	0.0269**
						(3.55)	(3.42)
SameIndustry				0.00367	0.00277	0.00232	0.00404
				(1.67)	(1.20)	(0.97)	(1.62)
SameSize					0.00282	0.00233	0.00385
					(0.78)	(0.66)	(1.03)
SameBookToMarket					0.0104***	0.0103***	0.0113***
					(3.55)	(3.54)	(4.04)
CrossOwnership					0.0360	0.0402	0.0487
					(1.46)	(1.62)	(1.99)
Observations	416514	416514	416514	416514	416514	416514	416514
Group FE	No	No	No	No	No	No	Yes
R^2	0.000923	0.000353	0.00124	0.00151	0.00232	0.00253	0.0150

t statistics in parentheses

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

All non-common owner pairs

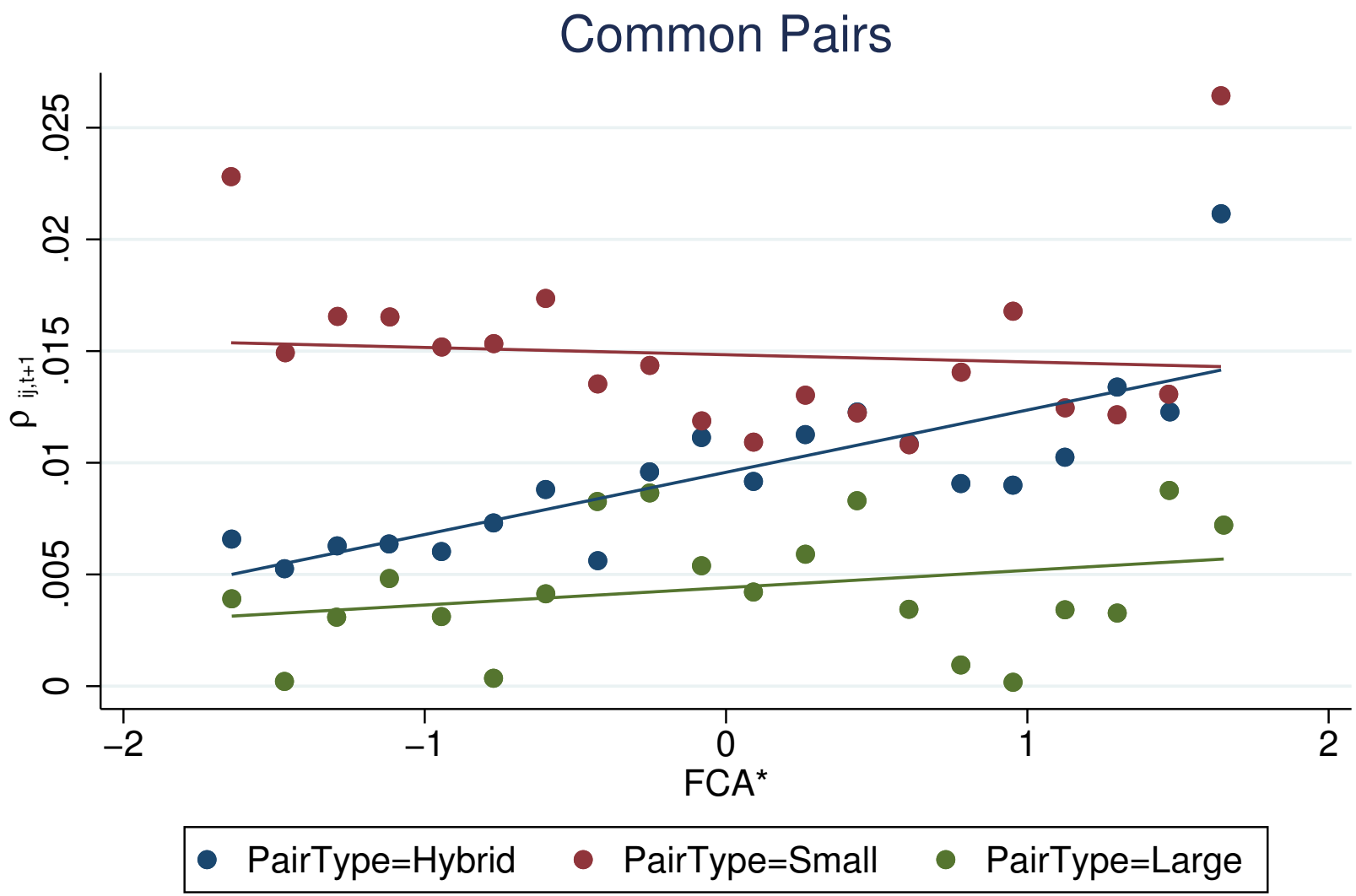
regression

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
SameGroup	0.0153***		0.0150***			0.0134***	0.0124***		0.0151***				0.0104***	0.00926***
	(9.38)		(9.26)			(7.81)	(7.10)		(9.03)				(6.09)	(5.34)
FCA*		0.000676***	0.000496*	0.00212	0.000427*	0.000408*	0.000116							
		(3.50)	(2.56)	(1.79)	(2.20)	(2.11)	(0.67)							
(FCA*) × SameGroup						0.00247*	0.00321**							
						(2.15)	(2.90)							
(FCA > $Q3$[FCA])								0.00226*	0.000744	0.00226*	0.0122***	-0.0000291	-0.0000725	-0.00110
								(2.63)	(0.97)	(2.63)	(4.40)	(-0.03)	(-0.07)	(-1.32)
(FCA > $Q3$[FCA]) × SameGroup													0.0141***	0.0161***
													(4.65)	(5.54)
Observations	6018646	6018646	6018646	114526	5904120	6018646	6018646	6018646	5851137	6018646	114526	5904120	6018646	6018646
Sub Sample	Total	Total	Total	SameGroups	Others	Total	Total	Total	Total	Total	SameGroups	Others	Total	Total
Group Effect	No	No	No	No	No	No	Yes	No	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000445	0.000392	0.000491	0.00699	0.000338	0.000515	0.00330	0.000372	0.00127	0.000372	0.00721	0.000323	0.000508	0.00330

t statistics in parentheses

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

Grouped by size



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

Model Estimation

Grouped by size

	Dependent Variable: Future Monthly Correlation of 4F+Ind. Res.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Same Group	0.00624**	0.0102***	-0.00153	0.0117***	0.00661*	0.0366***	0.0268***	0.00750***
	(2.81)	(3.95)	(-0.53)	(3.76)	(2.15)	(10.31)	(6.57)	(3.53)
FCA*	0.000377	0.000698	-0.000175	0.00199***	0.00177**	-0.00151	-0.00177	-0.0000771
	(0.65)	(1.25)	(-0.31)	(3.56)	(3.00)	(-1.58)	(-1.84)	(-0.14)
(FCA*) × SameGroup	0.00992***		0.0134***		0.00599*		0.0123***	0.0105***
	(6.49)		(4.80)		(2.34)		(4.17)	(6.72)
Observations	1665996	346170	346170	693728	693728	626098	626098	1665996
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample	All Firms	Large Firms	Large Firms	Hybrid Firms	Hybrid Firms	Small Firms	Small Firms	All Firms
Pair Size FE	No	No	No	No	No	No	No	Yes
R^2	0.000898	0.00193	0.00232	0.00135	0.00149	0.00180	0.00198	0.00130

t statistics in parentheses

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

Model Estimation

Grouped by size

	Dependent Variable: Future Monthly Correlation of 4F+Ind. Res.							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SameGroup	0.0134***	0.00954***	0.00853***	0.0136***	0.0118***	0.0314***	0.0267***	0.0138***
	(7.81)	(4.63)	(3.71)	(7.35)	(6.46)	(10.19)	(7.93)	(8.27)
FCA*	0.000408*	-0.0000120	-0.000115	0.000514*	0.000401	-0.00143***	-0.00154***	-0.000390**
	(2.11)	(-0.05)	(-0.47)	(2.09)	(1.67)	(-3.86)	(-3.97)	(-2.70)
(FCA*) × SameGroup	0.00247*		0.00178		0.00272		0.00545**	0.00313**
	(2.15)		(1.30)		(1.59)		(3.38)	(2.80)
Observations	6018646	1753614	1753614	2992221	2992221	1272811	1272811	6018646
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample	All Firms	Large Firms	Large Firms	Hybrid Firms	Hybrid Firms	Small Firms	Small Firms	All Firms
Pair Size FE	No	No	No	No	No	No	No	Yes
R^2	0.000515	0.000796	0.000860	0.000688	0.000735	0.00191	0.00199	0.000829

t statistics in parentheses

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

Table of Contents

Ins Imbalance

- Seasholes and Wu (2007)
  - $$Imbalance_{ins} = \frac{Buy_{ins} - Sell_{ins}}{Buy_{ins} + Sell_{ins}}$$
  - $$Imbalance_{ind} = \frac{Buy_{ind} - Sell_{ind}}{Buy_{ind} + Sell_{ind}}$$

	InsImbalance_value							
	count	mean	std	min	25%	50%	75%	max
Grouped								
Ungrouped	20198	0.01	0.630	-1.0	-0.474	0.016	0.479	1.0
Grouped	12022	-0.04	0.581	-1.0	-0.462	-0.009	0.341	1.0

	IndImbalance_value							
	count	mean	std	min	25%	50%	75%	max
Grouped								
Ungrouped	20198	-0.044	0.265	-1.0	-0.081	-0.0	0.041	1.0
Grouped	12022	-0.027	0.211	-1.0	-0.071	0.0	0.052	1.0

Ins Imbalance

	Future Monthly Corr. of 4F+Ind. Residuals							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
FCA*	0.000308	0.000384	0.000320	-0.0000742	0.00945***	0.0000347	0.000123	0.0000843
	(0.60)	(0.81)	(0.68)	(-0.15)	(6.07)	(0.07)	(0.17)	(0.11)
Same Group	0.0164***	0.0164***	0.00765***	-0.00156		0.00974***	0.00241	0.00154
	(8.68)	(8.68)	(3.64)	(-0.57)		(5.36)	(0.79)	(0.48)
Low Imbalance std		0.00119	0.000325	0.000203	0.0241***	0.000469	0.0000788	0.000481
		(1.29)	(0.35)	(0.22)	(6.15)	(0.52)	(0.08)	(0.31)
Low Imbalance std × SameGroup			0.0238***	0.0245***			0.0142**	0.0142**
			(6.85)	(6.96)			(2.95)	(3.14)
(FCA*) × SameGroup				0.0106***			0.00580**	0.00645**
				(6.16)			(2.77)	(2.94)
Low Imbalance std × (FCA*)							-0.000584	-0.000483
							(-0.77)	(-0.57)
Low Imbalance std × SameGroup × (FCA*)						0.0209***	0.0126***	0.0120***
						(9.69)	(4.44)	(3.91)
Observations	1665996	1665996	1665996	1665996	58337	1665996	1665996	1665996
Group Effect	No	No	No	No	No	No	No	Yes
Pair Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sub-sample	Total	Total	Total	Total	Same Groups	Total	Total	Total
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.00120	0.00132	0.00144	0.00154	0.0210	0.00149	0.00166	0.00643

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)	(5)	(6)
$\Delta\text{TurnOver}_{\text{Market}}$	0.431^{***}	0.453^{***}	0.287^{***}	0.321^{***}	0.288^{***}	0.321^{***}
	(14.56)	(14.49)	(8.23)	(14.03)	(6.92)	(14.14)
$\Delta\text{TurnOver}_{\text{Group}}$			0.245^{***}	0.234^{***}	0.284^{***}	0.273^{***}
			(6.31)	(7.15)	(6.02)	(7.19)
$\Delta\text{TurnOver}_{\text{Industry}}$	0.155^{***}	0.169^{***}	0.174^{*}	0.118^{***}	0.152	0.0430
	(6.53)	(6.99)	(2.08)	(3.68)	(1.47)	(1.19)
Observations	626813	623759	305563	301329	305563	301329
Weight	-	-	MC × CR	MC × CR	MC	MC
Control	No	Yes	No	Yes	No	Yes
R^2	0.141	0.180	0.242	0.282	0.236	0.277

t statistics in parentheses

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

Cross-sectional analyze of Group trunover

	Dependent Variable: β_{Group}							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess	0.355***	0.505***						
	(4.99)	(6.94)						
ExcessDummy			0.00604	0.101**				
			(0.16)	(2.77)				
ExcessDiff					0.716***	0.961***		
					(5.99)	(7.77)		
ExcessHigh							0.344***	0.412***
							(6.61)	(8.48)
Observations	1349	1349	1367	1367	1349	1349	1367	1367
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.0251	0.0970	0.000973	0.0600	0.0436	0.123	0.0436	0.109

t statistics in parentheses

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

Pairwise correlations in trunover

	Dependent Variable: Future Monthly Correlation of Delta turnover						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same Group	0.0349***	0.0217***			0.0227***	0.0182***	0.0176***
	(11.20)	(7.38)			(7.73)	(6.22)	(6.19)
FCA*			0.000871	-0.000438	-0.00110	-0.00134	-0.00171
			(0.63)	(-0.37)	(-0.93)	(-1.08)	(-1.51)
(FCA*) × SameGroup						0.00619*	0.00631*
						(2.45)	(2.42)
Observations	1447955	1341445	1447955	1341445	1341445	1341445	1341445
Group Effect	No	No	No	No	No	No	Yes
Pair Size FE	No	Yes	No	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	Yes	Yes	Yes
R^2	0.000465	0.00431	0.000461	0.00448	0.00471	0.00481	0.0157

t statistics in parentheses

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

Big Business group

	Dep. Var.: Future Monthly Cor. of 4F+Ind. Res.			
	(1)	(2)	(3)	(4)
Same Group	0.00637*	0.0169*	0.00476	0.0127
	(2.22)	(2.25)	(1.83)	(1.78)
FCA*	-0.000339	-0.000551	-0.000108	-0.00121
	(-0.80)	(-1.14)	(-0.19)	(-1.64)
(FCA*) × SameGroup	0.0120***	0.0120***	0.0121***	0.0115***
	(7.57)	(7.74)	(7.14)	(4.07)
ρ_t(Turnover)	0.00515***	0.00609***	0.00373***	0.00638***
	(8.45)	(5.86)	(3.52)	(6.12)
ρ_t	0.0246***	0.0245***	0.0246***	0.0243***
	(17.07)	(17.07)	(17.07)	(10.96)
SameGroup × ρ_t(Turnover)		-0.0104	0.0236***	-0.0129
		(-0.95)	(5.23)	(-1.19)
BigGroup		-0.00148		
		(-1.67)		
BigGroup × SameGroup		-0.0132*		
		(-2.08)		
BigGroup × ρ_t(Turnover)		-0.00233		
		(-1.35)		
BigGroup × SameGroup × ρ_t(Turnover)		0.0336**		
		(3.15)		
Observations	1459585	1459585	957316	502269
Controls	Yes	Yes	Yes	Yes
Pari Size FE	Yes	Yes	Yes	Yes
SubSample	All	All	Big Groups	Others
R^2	0.00241	0.00284	0.00312	0.00399

t statistics in parentheses

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

Bearish/Bullish Market

	Dependent Variable: Future Monthly Correlation of 4F+Industry Residuals						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Same Group	0.00750***	0.00586	4.401	6.193	0.0139*	4.867	0.00429
	(3.53)	(0.65)	(0.98)	(1.06)	(2.39)	(0.98)	(0.61)
FCA*	-0.0000771	-0.000277	-0.00190	-0.00176	0.00141	-0.00692	-0.00140
	(-0.14)	(-0.58)	(-0.34)	(-0.90)	(1.15)	(-1.72)	(-1.79)
(FCA*) × SameGroup	0.0105***	0.0107***	0.194	-3.621	0.00567	-2.787	0.00228
	(6.72)	(7.09)	(1.29)	(-1.05)	(1.21)	(-0.95)	(0.61)
Bearish Market		-0.00425	-0.00327				-0.00252**
		(-1.73)	(-1.63)				(-3.28)
Bullish Market		0.00459	0.0107*				0.00300***
		(1.33)	(2.31)				(4.82)
Bearish Market × SameGroup		-0.0000134	-0.0175				
		(-0.00)	(-0.06)				
Bullish Market × SameGroup		0.00170	-4.388				
		(0.20)	(-0.98)				
Bearish Market × FCA*			-0.00543				-0.000209
			(-1.48)				(-0.26)
Bullish Market × FCA*			0.00328				0.00152*
			(0.59)				(2.34)
(FCA*) × Bullish Market × SameGroup			-0.188				-0.00134
			(-1.26)				(-0.53)
(FCA*) × Bearish Market × SameGroup			-2.703				0.00334
			(-0.99)				(1.11)
Observations	1665996	1665996	1665996	326360	982021	683975	1665996
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pari Size FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SubSample	Total	Total	Total	Bearish Market	Bullish Market	Normal Market	All
Method	FM	FM	FM	FM	FM	FM	FE
R^2	0.00130	0.00174	0.00204	0.0192	0.00266	0.0240	0.0000763

t statistics in parentheses

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

Table of Contents

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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Table of Contents

Measuring Common Ownership

Proof

- 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

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

  - Quadratic

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

Back

Table of Contents

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

Synchronicity and firm interlocks

JFE-2009-Khanna

- 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

Large controlling shareholder and stock price synchronicity

JBF-2014-Boubaker

- 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

- $HJL_I^A(A,B) = \sum_{i \in I^{A,B}} \frac{\alpha_{i,B}}{\alpha_{i,A}+\alpha_{i,B}}$ 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
- $MHHI = \sum_j \sum_k s_j s_k \frac{\sum_i \mu_{ij}\nu_{ik}}{\sum_i \mu_{ij}\nu_{ij}}$ Azar et al. (2018)
  - Capture a specific type of externality
  - Measured at the industry level
  - Assumes that investors are fully informed about the externalities
- $GGL^A(A,B) = \sum_{i=1}^{I} \alpha_{i,A} g(\beta_{i,A}) \alpha_{i,B}$ 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.

Back