Information Pools and Insider Trading: A Snapshot of America's Financial Elite

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Motivation

- Hedge funds managers are a foremost example of economic elite.

- Previous literature showed the importance of personal networks on investment decisions (see, e.g., Cohen, Frazzini, and Malloy, 2008, 2010).

Research question

- Is there an elite informational factor driving a manager's performance?

Executive summary

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- We measure co-movements in returns among groups of alumni.
- Correlations between alumni of top universities are significantly higher than others.
- We link this factor to information pools using an insider trading scandal as a quasi-natural experiment.
- We document that an elite education is linked with a higher AUM at fund launch.

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Biographies

Example of biography:

Uncle Scrooge is an Executive Vice President of McDuck Fund, a position he has held since 1994. From 1981 to 1989, Mr. Scrooge headed the high yield bond departments (including sales, trading and acting as Director of Research) at Prudential Securities (1981 to 1983), Lehman (1983 to 1988) and Barney Harris (1988 to 1990). In these positions, Mr. Scrooge was responsible for the investment of hundreds of millions of U.S. Dollars of each firm's capital in high yield securities and for pricing and marketing approximately USD1.0 billion of new issue high yield bonds. From 1990 to 1994, Mr. Scrooge was a Senior Salesman in the High Yield Bond Department of Alex Brown. Mr. Scrooge holds an MBA from The Wharton School of the **University of Pennsylvania**.

Summary statistics I

	n. observations	n. funds
Full dataset	778,152	13,712
Min. 12 months	768,037	12,412
US only	449,436	7,011
Truncating 1%	444,942	7,011

n. diplomas	0	1	2	3	4	5	6	7	8	9
n. funds	3482	1599	1033	457	299	66	69	5	0	1
% funds	49.66	22.81	14.73	6.52	4.26	0.94	0.98	0.07	0.0	0.01

Summary statistics II

	n. funds	n. obs	mean r	vol	mean r (f)	vol (f)	max r (f)	min r (f)	aum (mil)
Harvard	598	42,500	0.73	3.87	0.61	0.75	5.55	-3.02	1,081
U. of Pennsylvania	568	39,500	0.74	3.88	0.64	0.70	3.63	-3.27	862
Columbia	544	38,038	0.71	3.97	0.65	0.71	4.35	-3.02	296
New York University	518	38,147	0.66	3.55	0.57	0.63	3.63	-3.35	313
U. of Chicago	315	20,822	0.65	3.49	0.59	0.77	5.55	-3.79	326
Stanford	281	21,240	0.79	4.45	0.73	0.66	3.26	-1.78	197
U. of Michigan	202	15,362	0.76	4.01	0.73	0.77	5.36	-1.00	448
U. of C., Berkeley	199	14,234	0.70	4.41	0.67	0.80	5.55	-2.23	182
Northwestern	189	12,446	0.64	3.90	0.52	0.75	4.01	-3.11	186
Dartmouth	181	11,679	0.66	3.61	0.54	0.73	3.47	-2.46	341
M.I.T.	167	10,098	0.80	4.10	0.69	0.71	2.38	-2.56	325
Cornell	166	12,034	0.62	3.96	0.47	0.67	2.68	-2.63	292
Yale	162	10,729	0.64	3.30	0.54	0.71	3.84	-3.27	267
U.of C., Los Angeles	153	11,800	0.73	3.90	0.71	0.83	4.35	-4.13	318
U. of Virginia	147	10,018	0.75	4.28	0.69	0.76	3.28	-1.18	470
Princeton	147	10,038	0.76	4.08	0.61	0.83	5.59	-2.36	2,171
U. of Washington	137	7,949	0.67	3.64	0.66	0.72	3.49	-2.20	307
Boston U.	128	8,251	0.52	4.46	0.35	0.79	2.43	-3.02	664
Duke	127	8,754	0.71	3.65	0.67	0.67	2.65	-1.10	458
Vanderbilt	118	6,959	0.56	3.66	0.45	0.76	3.26	-2.46	446
U. of Wisconsin, Madison	109	8,803	0.67	4.02	0.68	0.75	4.35	-1.18	275
Brown	99	6,917	0.70	3.48	0.67	0.79	3.24	-1.78	196
Fordham	82	6,000	0.73	3.68	0.61	0.66	2.54	-1.19	113
Georgetown	76	4,873	0.75	4.21	0.64	0.66	2.61	-1.10	128

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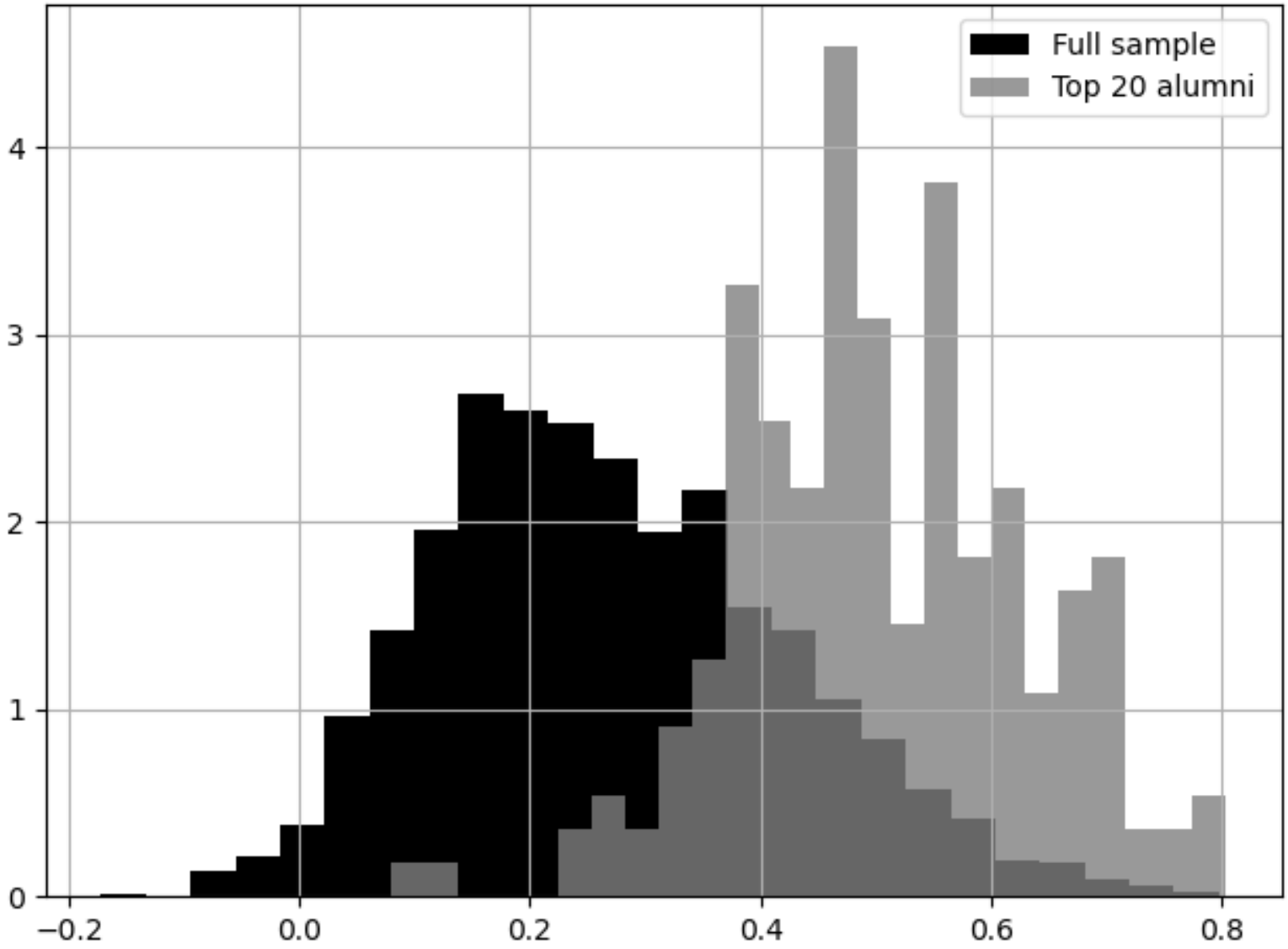
Looking for co-movements

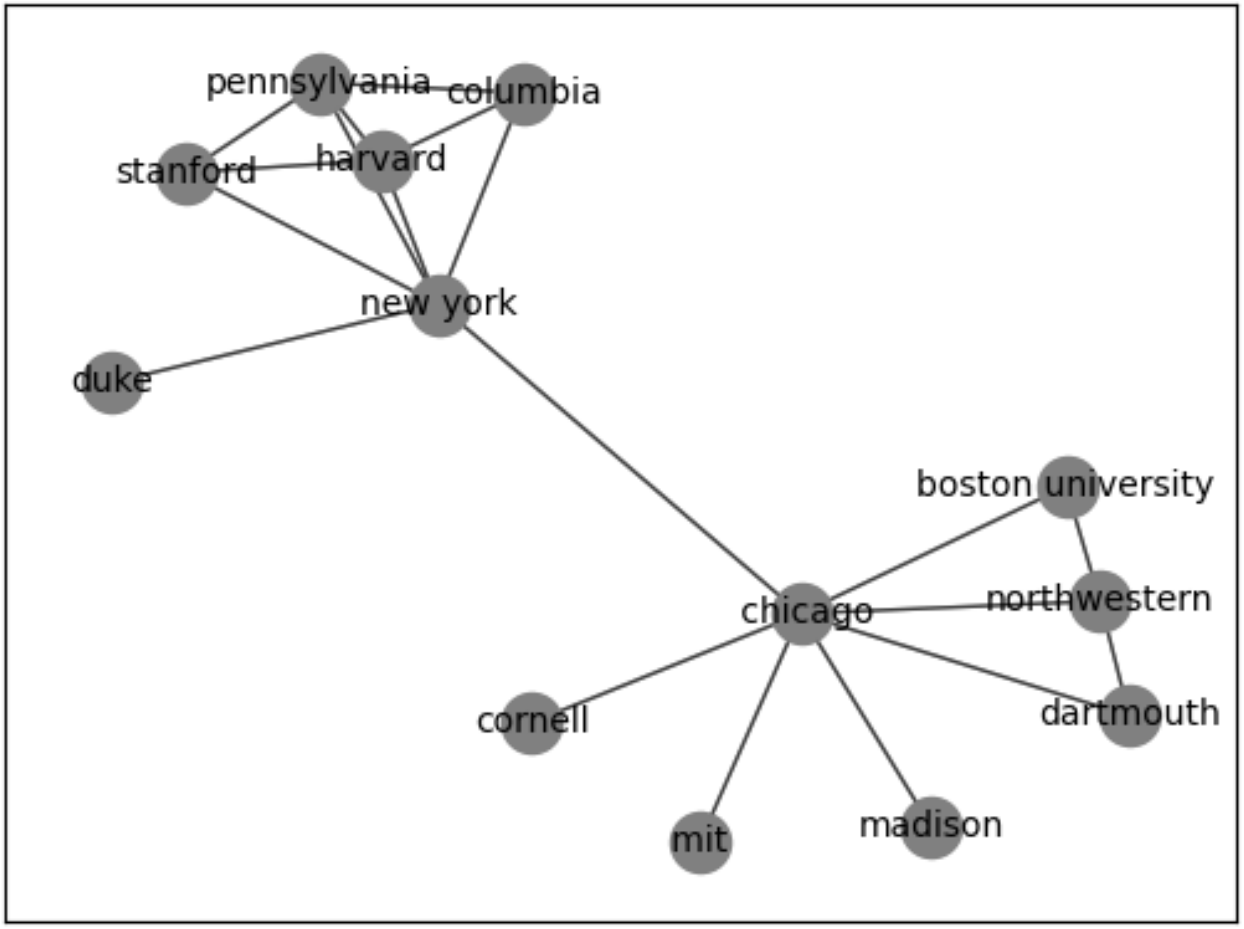
$$y_t = X_t\, a + \epsilon_t \tag{1}$$

- X_i is the vector with the Fung (2001) seven factors.
- We create a time serie for each university by computing the average of its alumni residuals.

Correlation between alumni groups



A snapshot of America's Financial Elite



What are we capturing?

Geographic effect?

- Geography should be marginal, as it should not be limited to elite schools.

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A social phenomenon?

- Social interactions could shape the network.

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Main events

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- According to prosecutors, he earned USD 63.8 million through insider trading in stocks such eBay, Goldman Sachs, and Google.
- He was convicted in May 2011 on nine counts of securities fraud and five counts of conspiracy to 11 years of prison.
- Mr. Rajaratnam obtained an M.B.A. from the Wharton School of the University of Pennsylvania and was resident in Greenwich (CT).

A shock on information sharing?

"what is really worth noting is the unprecedented - and extensive - use of (...) methods so beloved of Hollywood vice-and-action movies"

G. Robinson (2009, Oct 19), Financial Times - Alphaville.

"wire taps are more typically used against the mob or terrorists. The U.S. attorney's implication is that Wall Street ought to watch out because prosecutors are now treating hedge funds like the mafia."

The Wall Street Journal editorial Board (2009, Oct 18)

Unprecedented and unexpected

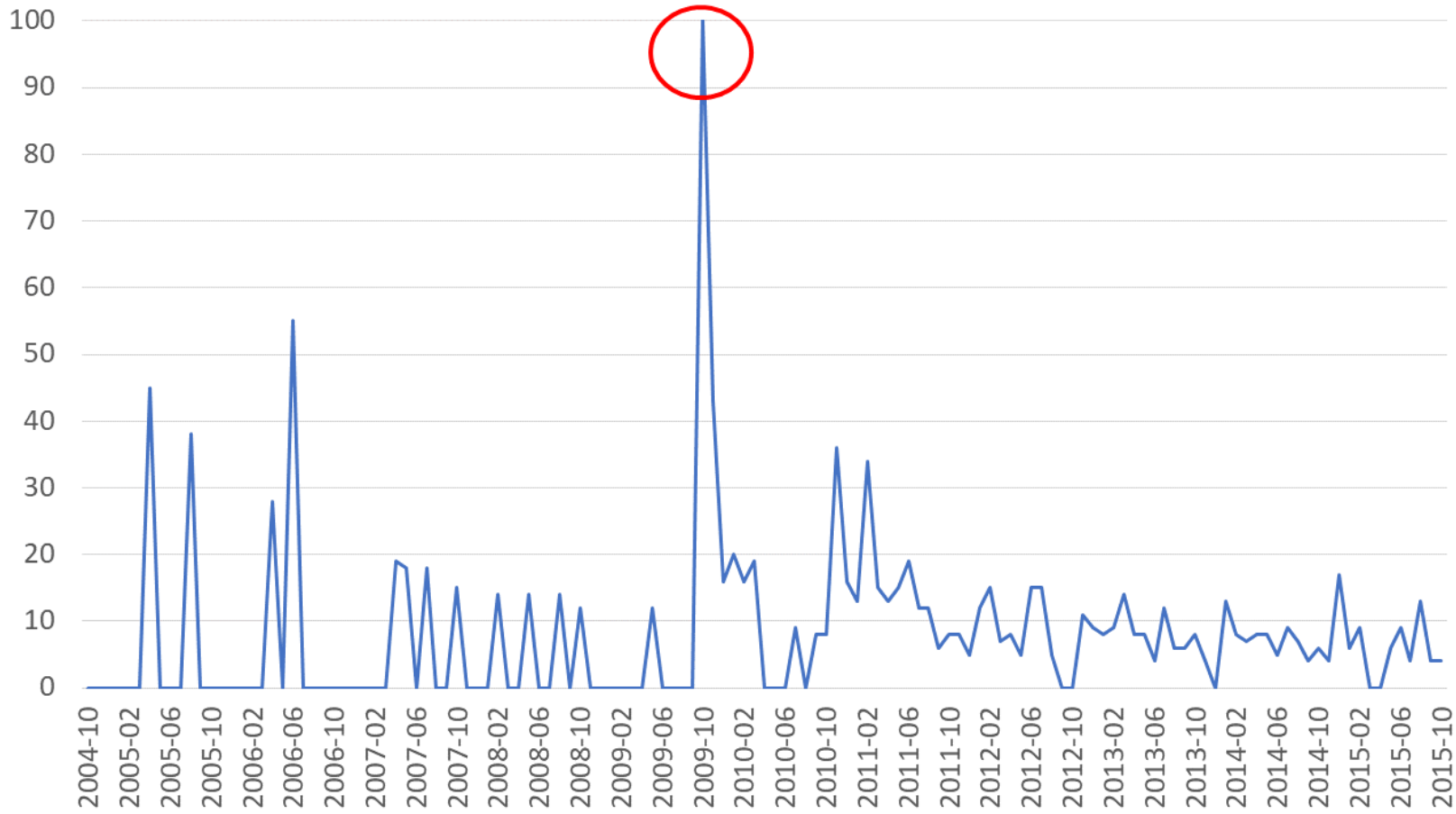

Figure: Google searches for *hedge fund insider trading*

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Relevance and exclusion condition

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The media sensation and the unprecedented investigation methods could have plausibly altered common information-sharing practices

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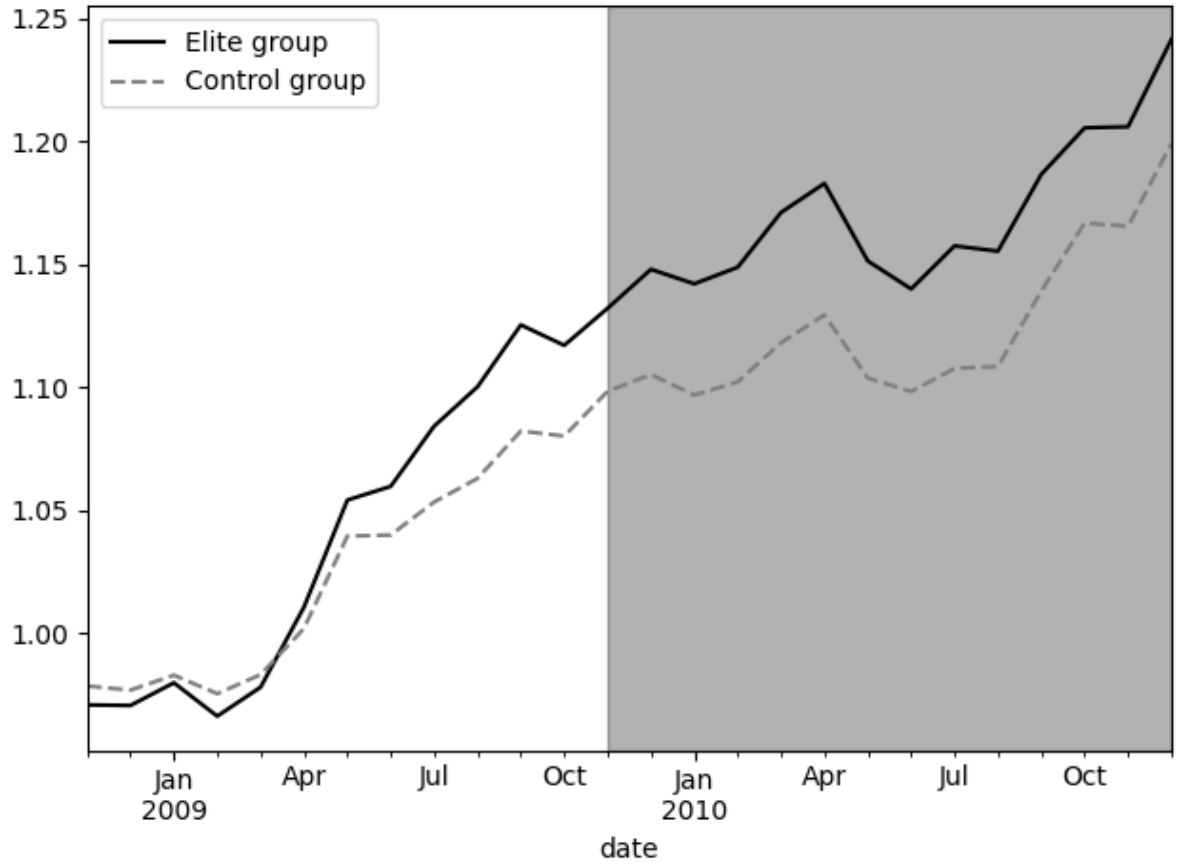
Exclusion condition

The scandal was an isolated criminal investigation with no concrete consequences for those not directly affected

Parallel trend



Main regression

$$y_{i,t} = \alpha + \beta_1\, after + \beta_2\, penn + \beta_3\, (after \times penn) + X'_{i,t}\,\beta + \epsilon_{i,t}. \quad (2)$$

Where:

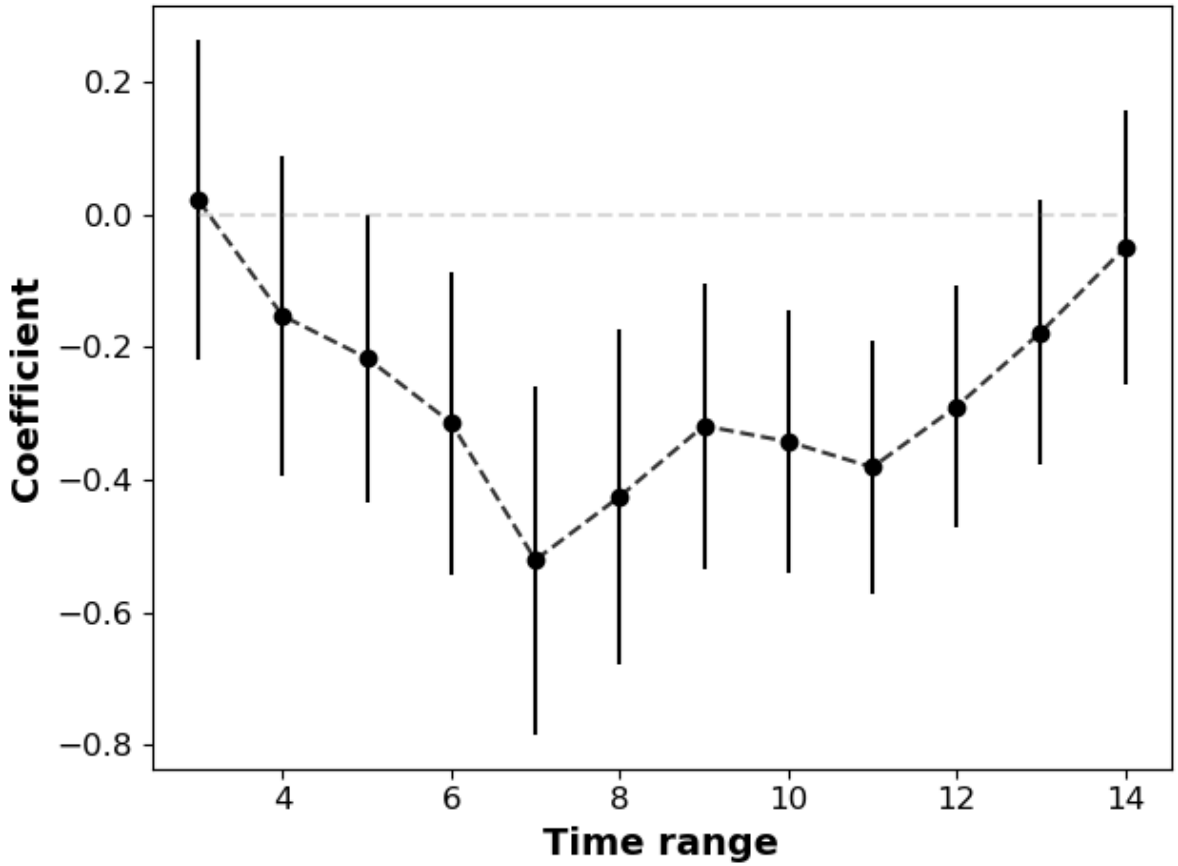
- $y_{i,t}$ is the return of fund i in month t
- *after* is a binary variable equal to 1 if the observation is after the scandal
- *penn* is a binary variable equal to 1 if the fund's manager belongs to the treated network, as defined in the previous section
- $X_{i,t}$ is a vector of controls which include Fama (2015) five factors and US area fixed effects.

University of Pennsylvania network

	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.428***	0.391***	0.504***	0.325**	0.288**	0.4***
	(6.806)	(6.193)	(7.953)	(2.343)	(2.076)	(2.899)
pennsylvania	0.472***	0.472***	0.47***	0.407***	0.407***	0.405***
	(4.346)	(4.354)	(4.359)	(3.704)	(3.71)	(3.714)
after	-0.474***	-0.363***	-0.244***	-0.471***	-0.359***	-0.241***
	(-5.814)	(-4.271)	(-2.877)	(-5.773)	(-4.231)	(-2.836)
after * pennsylvania	-0.296*	-0.299*	-0.294*	-0.306**	-0.309**	-0.305**
	(-1.931)	(-1.953)	(-1.937)	(-1.999)	(-2.02)	(-2.005)
area FE	No	No	No	Yes	Yes	Yes
market controls	1	3	5	1	3	5
n. obs	6740	6740	6740	6740	6740	6740
R^2	0.054	0.056	0.067	0.055	0.057	0.068

Different time horizons

Value of the β_3 coefficient



Robustness: Ivy League

	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.391***	0.354***	0.466***	0.301**	0.264*	0.376***
	(6.101)	(5.497)	(7.228)	(2.169)	(1.901)	(2.72)
ivy	0.545***	0.546***	0.544***	0.484***	0.485***	0.484***
	(5.177)	(5.194)	(5.211)	(4.539)	(4.553)	(4.569)
after	-0.469***	-0.358***	-0.239***	-0.466***	-0.354***	-0.235***
	(-5.633)	(-4.13)	(-2.762)	(-5.592)	(-4.091)	(-2.722)
after * ivy	-0.28*	-0.283*	-0.279*	-0.29*	-0.293**	-0.289**
	(-1.892)	(-1.912)	(-1.9)	(-1.957)	(-1.977)	(-1.965)
area FE	NO	NO	NO	Yes	Yes	Yes
market controls	1	3	5	1	3	5
n. obs	7521	7521	7521	7521	7521	7521
R^2	0.054	0.056	0.068	0.055	0.057	0.068

Robustness: MIT

	(1)	(2)	(3)	(4)	(5)	(6)
constant	0.566***	0.529***	0.64***	0.424***	0.387***	0.498***
	(9.48)	(8.821)	(10.631)	(3.096)	(2.827)	(3.652)
mit	-0.035	-0.035	-0.028	-0.011	-0.011	-0.004
	(-0.274)	(-0.274)	(-0.221)	(-0.084)	(-0.085)	(-0.032)
after	-0.552***	-0.441***	-0.321***	-0.549***	-0.439***	-0.318***
	(-7.177)	(-5.483)	(-3.988)	(-7.15)	(-5.456)	(-3.961)
after * mit	-0.034	-0.034	-0.037	-0.038	-0.038	-0.041
	(-0.19)	(-0.189)	(-0.209)	(-0.212)	(-0.212)	(-0.232)
area FE	No	No	No	Yes	Yes	Yes
market controls	1	3	5	1	3	5
n. obs	4427	4427	4427	4427	4427	4427
R^2	0.053	0.055	0.066	0.054	0.056	0.067

Robustness: Other networks

	Pennsylvania	Harvard	Columbia	Yale	Dartmouth	Cornell	NYU	Stanford
constant	0.4***	0.373***	0.382***	0.414***	0.477***	0.5***	0.437***	0.427***
	-2.899	-2.681	-2.743	-3.009	-3.496	-3.673	-3.156	-3.114
school network	0.405***	0.399***	0.364***	0.389***	0.199	-0.003	0.242**	0.363***
	-3.714	-3.885	-3.476	-3.525	-1.366	(-0.023)	-2.117	-3.201
after	-0.241***	-0.209**	-0.222**	-0.258***	-0.322***	-0.326***	-0.252***	-0.252***
	(-2.836)	(-2.353)	(-2.535)	(-3.064)	(-4.119)	(-4.109)	(-3.037)	(-3.033)
after * school network	-0.305**	-0.33**	-0.318**	-0.248	-0.025	0	-0.305*	-0.301*
	(-2.005)	(-2.317)	(-2.195)	(-1.611)	(-0.122)	(-0.001)	(-1.92)	(-1.891)
area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
market controls	5	5	5	5	5	5	5	5
n. obs	6740	8570	7950	6496	3033	3800	5879	5868
R^2	0.068	0.068	0.068	0.068	0.067	0.067	0.068	0.068

	UCLA	Berkeley	Chicago	Michigan	Northwestern	MIT	Duke	Ivy
constant	0.479***	0.459***	0.498***	0.437***	0.5***	0.498***	0.502***	0.376***
	-3.536	-3.382	-3.652	-3.181	-3.673	-3.652	-3.712	(2.72)
school network	0.417**	0.541***	-0.004	0.289***	-0.003	-0.004	-0.266	0.484***
	-2.524	-3.665	(-0.032)	-2.651	(-0.023)	(-0.032)	(-0.927)	(4.569)
after	-0.295***	-0.278***	-0.318***	-0.258***	-0.326***	-0.318***	-0.329***	-0.235***
	(-3.825)	(-3.562)	(-3.961)	(-3.033)	(-4.109)	(-3.961)	(-4.397)	(-2.722)
after * school network	-0.305	-0.368*	-0.041	-0.242	0	-0.041	0.104	-0.289**
	(-1.342)	(-1.791)	(-0.232)	(-1.602)	(-0.001)	(-0.232)	-0.261	(-1.965)
area FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
market controls	5	5	5	5	5	5	5	5
n. obs	2414	3059	4427	6902	3800	4427	736	7521
R^2	0.068	0.068	0.067	0.068	0.067	0.067	0.067	0.068

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AUM at fund launch

$$log(AUM_i) = \alpha + \beta_1 ivy + \beta_2 year_{exp} + \beta_3 I_{exp} + \beta_4 SR_{exp} + FE + \epsilon_i, \quad (3)$$

Where:

- *ivy* is a binary variable equal to 1 if at least one fund manager has an ivy-league degree
- I_{exp} is a binary variable equal to 1 if the managers already managed a hedge fund before fund i
- $year_{exp}$ indicates the number of years between the date when fund i is open, and the first date in which the manager appears in our database
- SR_{exp} represents the mean sharp ratio estimated across all funds under the same manager as fund's i before the launch of fund i

AUM at fund launch

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
ivy	0.437***	0.446***	0.444***	0.842***	0.848***	0.842***	0.542***	0.559***	0.553***
	(6.612)	(6.793)	(6.767)	(12.881)	(13.091)	(13.027)	(8.268)	(8.57)	(8.504)
$year_{exp}$		0.115***	0.116***		0.171***	0.142***		0.14***	0.112***
		(13.222)	(9.048)		(18.441)	(10.7)		(15.443)	(8.628)
I_{exp}	0.544***		-0.054	0.947***		0.229**	0.791***		0.23**
	(8.474)		(-0.584)	(13.927)		(2.411)	(11.969)		(2.489)
SR_{exp}	0.055		0.118***	0.045		0.12***	0.042		0.101**
	(1.367)		(2.896)	(1.105)		(2.934)	(1.078)		(2.545)
area FE	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
year FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
n. obs	5324	5324	5324	5324	5324	5324	5324	5324	5324
R^2	0.114	0.126	0.127	0.1	0.115	0.118	0.167	0.175	0.178

AUM at fund launch

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
ivy	0.56***	0.538***	0.578***	1.127***	1.031***	1.143***	0.8***	0.729***	0.82***
	(6.415)	(6.897)	(6.663)	(12.826)	(13.24)	(13.136)	(9.183)	(9.375)	(9.477)
$year_{exp}$		0.127***	0.122***		0.195***	0.149***		0.163***	0.12***
		(12.308)	(8.031)		(17.864)	(9.594)		(15.237)	(7.919)
I_{exp}	0.604***		-0.012	1.119***		0.382***	0.947***		0.355***
	(8.053)		(-0.111)	(14.04)		(3.455)	(12.224)		(3.303)
SR_{exp}	0.084*		0.138***	0.074		0.138***	0.066		0.116**
	(1.836)		(2.983)	(1.604)		(2.973)	(1.459)		(2.574)
ivy * $year_{exp}$		-0.041**	-0.022		-0.08***	-0.023		-0.074***	-0.028
		(-2.178)	(-0.776)		(-4.213)	(-0.802)		(-4.005)	(-1.024)
ivy * I_{exp}	-0.199		-0.136	-0.557***		-0.505**	-0.51***		-0.405**
	(-1.384)		(-0.648)	(-3.808)		(-2.389)	(-3.59)		(-1.968)
ivy * SR_{exp}	-0.125		-0.089	-0.127		-0.079	-0.101		-0.071
	(-1.305)		(-0.916)	(-1.316)		(-0.812)	(-1.083)		(-0.748)
area FE	Yes	Yes	Yes	NO	NO	NO	Yes	Yes	Yes
year FE	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
n. obs	5324	5324	5324	5324	5324	5324	5324	5324	5324
R^2	0.115	0.127	0.128	0.104	0.118	0.122	0.17	0.178	0.181

Possible interpretations

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- Managers with an Ivy-league education can raise more money because they tend to perform better.
- An elite education is also associated with a strong personal network.
- Intermediaries have different incentives.
- Consistent with our main argument that an elite education is associated with a superior information pool.

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- By using the Galleon Capital insider trading scandal as an exogenous shock, we take steps towards linking this structure to information sharing.
- Consistent with the existence of an elite information pool, we observe that an Ivy education is associated with 55.3% more AUM at fund launch

Thank You