Empirical Asset Pricing

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Limits of Arbitrage

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Lecture Outline

1. Examples of arbitrage
2. Limits of arbitrage: the theory
3. Empirical evidence on limits of arbitrage

Relevant readings:

- Gromb and Vayanos , 2010, Limits of arbitrage: the state of the theory
- Take a look at: DeLong, Shleifer, Summers, Waldman (DSSW, JPE 1990), Shleifer and Vishny (JF 1997), Gromb and Vayanos (2002), Abreu and Brunnermeier (JFE 2002), Abreu and Brunnermeier (Econometrica, 2003), Brunnermeier and Pedersen (RFS 2009)
- Intermediary Asset Pricing: He, Kelly, Manela (JFE, 2017), Adrian, Etula, Muir (JF, 2014)

- Mitchell and Pulvino (2002, JF), Brunnermeier and Nagel (JF 2004), Ben-David, Franzoni, Moussawi (RFS, 2012), Aragon and Strahan (2012, JFE), Coval and Stafford (JFE 2007), Lou (RFS, 2012), Fleckenstein, Longstaff, Lustig (JF, 2014)

- Also have a look at: Greenwood and Thesmar (2011, JFE), Anton and Polk (2014, JF), Vayanos and Woolley (2013, RFS), Ben-David, Franzoni, and Moussawi (2018), Brav, Heaton, and Li (2010, RoF)

1. Examples of Arbitrage Opportunities

The Palm-3Com Anomaly

- In March 2000, 3Com announced that it would spin off its remaining stake in Palm by distributing 1.525 shares of Palm for each share of 3Com
- Palm was trading at \$95.06 and 3Com was trading at \$81.81
- The law of one price was violated because

$$\$81.81 < 1.525 \times \$95.06 = \$145$$

- Why were investors willing to buy one share of Palm at \$95.95 while they could buy it at $\$\frac{81.81}{1.525} = \$53.646$ with one 3Com share?
- Positive sentiment for dot-com stocks
- However, you need to introduce limits of arbitrage to explain why rational investors did not arbitrage it away
- Short selling costs do the job if large enough
- The evidence is that there was very few Palm stocks available for lending

Mitchell, Pulvino, Stafford (2002, JF)

- They examine systematically the occurence of arbitrage opportunities where the value of the parent company is less than the value of the subsidiary ('negative stub value' firms)

- In a sample running from 1985 to 2000, they find 82 situations of negative stub value

- They typically arise after equity carve outs or partial acquisitions

- The arbitrage trade involves a long position in the parent company and a short position in the subsidiary

- They assess the importance of different types of limits to arbitrage

1. **Fundamental risk**: they define it as the risk that the mispricing does not converge at any point
    - This happens, for example, because the parent goes bankrupt, or third party acquires the subsidiary, or delisting, etc.
    - These events occur for about 30% of the negative stub value situations

2. **Financing risk**: this can take two forms

   (a) **Horizon risk**: uncertainy about the time a position needs to be kept open before convergence occurs

   - In the sample, there is large variability of this horizon: average = 236 days, median = 92 days, min = 1 day, max = 2796 days

   - In the time to convergence, the arbitrage usually underperforms, discouraging investors who are not able to close the mispricing on their own

   (b) **Margin risk**: the long-short strategy involves posting collater to satisfy margins. Margin calls can occur if the strategy underperforms in the interim period which require additional collateral or liquidation. If the fund cannot commit more capital, the position is liquidated at a loss

3. **Cost of shorting and buy-ins**:

   (a) The rebate rate is the interest that is returned to the share-borrower on the proceeds from the short sales. The rebate rate is below the market interest rate (Libor) because the borrower has to pay a short selling fee

$$rebate = libor - shorting\ fee$$

There is wide dispersion in the rebate rate in the sample of stocks. For example, Palm has a rebate rate of -30% (annual). This includes a huge short selling fee. In general, however, short selling fees do not seem extreme and rebate rates are slightly below the Libor rate on average. This limit of arbitrage is not important, rather what matters is the uncertainty about the horizon over which this cost has to be born

(b) A buy-in is a situation in which the share lender recalls the shares because they cannot be found in other ways in the market. In that case the arbitrage trade has to be closed down. This happens for about 15% of the shares in their database. It seems a substantial risk

4. **Imperfect information**: All other risks can be diversified in a portfolio. However, investors still face uncertainty about the actual profitability of this strategy. This is the most important limit to arbitrage. This uncertainty limits the amount of capital that arbitrageurs are willing to commit. The presence of this uncertainty is testified by:

   (a) Low statistical significance of abnormal returns at the end of the 16 year period. Hence, statistical reliability was even lower at the beginning of the sample

   (b) Very extreme and rare events that cause large negative changes in valuation of the profitability of the strategy even 13 years into the sample. There is very few opportunities to learn about these events

(c) When uncertainty is resolved, for example because of public announcements of favorable tax treatment of the deals, there are large swings in the value of the strategies, suggesting that large uncertainty is present

The TIPS-Treasury Bond Puzzle

- Fleckenstein, Longstaff, Lustig (JF, 2014)
- Clear evidence of arbitrage opportunity using TIPS, T-Bonds, and inflation swaps (and STRIPS): the T-Bond appears to be overpriced relative to the TIPS
- TIPS (Treasury Inflation Protected Security)
  - Principal adjusted for Inflation
  - Coupons computed on inflation-adjusted-nominal value
  - Real yield
- Inflation Swaps (zero-coupon)
  - One leg: pays fixed rate on notional value
  - Other leg: pays inflation on notional value
  - It gives one party protection against inflation

- Fixed rate reflects inflation expecations during life of the contract (plus a risk premium)

- STRIPS are zero-coupon bonds obtained from separating (i.e. stripping) dividends and principal payments in a regular bond

- Imagine buying a T-bond with \$100 nominal value and coupon c. The periodic cash flow is:

$$+c$$

- One can create a **synthetic nominal bond replicating this T-Bond** by going:
  - Long TIPS, paying at each date coupon s on inflation adjusted principal I_t
  - Sell inflation protection with an inflation swaps for each date of the coupon and principal payments of the TIPS (F_t is the fixed rate)

$$\begin{aligned} &+sI_t \\ &+s(F_t - I_t) \end{aligned}$$

- Finally, you need STRIPS to equate cash flows from T-Bond and TIPS

$$+c - sF_t$$

- Then, they can compute the difference in prices between the T-Bond and the replicating portfolio. This is the dollar **mispricing**

- They can also compute the difference in yields between the actual and synthetic bonds, as a measure of basis point mispricing

Example

This table shows the cash flows associated with the 7.625% Treasury bond with maturity date January 15, 2025, and the cash flows from the replicating strategy using the 2.375% TIPS issue with the same maturity date that replicates the cash flows of the Treasury bond. The example is based on market prices for December 30, 2008. Cash flows are in dollars per \$100 notional. I_t denotes the realized percentage change in the CPI index from the inception of the strategy to the cash flow date. Date refers to the number of the semiannual period in which the corresponding cash flows are paid.

Date	Treasury	TIPS	Inflation Swaps	STRIPS	Total
0	−169.4793	−101.2249	0	−45.6367	−146.3786
1	3.8125	$1.1875\ I_1$	$1.1856 - 1.1875\ I_1$	2.6269	3.8125
2	3.8125	$1.1875\ I_2$	$1.1638 - 1.1875\ I_2$	2.6487	3.8125
3	3.8125	$1.1875\ I_3$	$1.1480 - 1.1875\ I_3$	2.6645	3.8125
4	3.8125	$1.1875\ I_4$	$1.1467 - 1.1875\ I_4$	2.6658	3.8125
5	3.8125	$1.1875\ I_5$	$1.1307 - 1.1875\ I_5$	2.6818	3.8125
6	3.8125	$1.1875\ I_6$	$1.1376 - 1.1875\ I_6$	2.6749	3.8125
7	3.8125	$1.1875\ I_7$	$1.1566 - 1.1875\ I_7$	2.6559	3.8125
8	3.8125	$1.1875\ I_8$	$1.1616 - 1.1875\ I_8$	2.6509	3.8125
9	3.8125	$1.1875\ I_9$	$1.1630 - 1.1875\ I_9$	2.6495	3.8125
10	3.8125	$1.1875\ I_{10}$	$1.1773 - 1.1875\ I_{10}$	2.6352	3.8125
11	3.8125	$1.1875\ I_{11}$	$1.1967 - 1.1875\ I_{11}$	2.6158	3.8125
12	3.8125	$1.1875\ I_{12}$	$1.2095 - 1.1875\ I_{12}$	2.6030	3.8125
13	3.8125	$1.1875\ I_{13}$	$1.2248 - 1.1875\ I_{13}$	2.5877	3.8125
14	3.8125	$1.1875\ I_{14}$	$1.2466 - 1.1875\ I_{14}$	2.5659	3.8125
15	3.8125	$1.1875\ I_{15}$	$1.2683 - 1.1875\ I_{15}$	2.5442	3.8125
16	3.8125	$1.1875\ I_{16}$	$1.2866 - 1.1875\ I_{16}$	2.5259	3.8125
17	3.8125	$1.1875\ I_{17}$	$1.3058 - 1.1875\ I_{17}$	2.5067	3.8125
18	3.8125	$1.1875\ I_{18}$	$1.3304 - 1.1875\ I_{18}$	2.4821	3.8125
19	3.8125	$1.1875\ I_{19}$	$1.3556 - 1.1875\ I_{19}$	2.4569	3.8125
20	3.8125	$1.1875\ I_{20}$	$1.3792 - 1.1875\ I_{20}$	2.4333	3.8125
21	3.8125	$1.1875\ I_{21}$	$1.4009 - 1.1875\ I_{21}$	2.4116	3.8125
22	3.8125	$1.1875\ I_{22}$	$1.4225 - 1.1875\ I_{22}$	2.3900	3.8125
23	3.8125	$1.1875\ I_{23}$	$1.4427 - 1.1875\ I_{23}$	2.3698	3.8125
24	3.8125	$1.1875\ I_{24}$	$1.4635 - 1.1875\ I_{24}$	2.3490	3.8125
25	3.8125	$1.1875\ I_{25}$	$1.4806 - 1.1875\ I_{25}$	2.3319	3.8125
26	3.8125	$1.1875\ I_{26}$	$1.4979 - 1.1875\ I_{26}$	2.3146	3.8125
27	3.8125	$1.1875\ I_{27}$	$1.5126 - 1.1875\ I_{27}$	2.2999	3.8125
28	3.8125	$1.1875\ I_{28}$	$1.5277 - 1.1875\ I_{28}$	2.2848	3.8125
29	3.8125	$1.1875\ I_{29}$	$1.5407 - 1.1875\ I_{29}$	2.2718	3.8125
30	3.8125	$1.1875\ I_{30}$	$1.5548 - 1.1875\ I_{30}$	2.2577	3.8125
31	3.8125	$1.1875\ I_{31}$	$1.5676 - 1.1875\ I_{31}$	2.2449	3.8125
32	3.8125	$1.1875\ I_{32}$	$1.5823 - 1.1875\ I_{32}$	2.2302	3.8125
33	103.8125	$101.1875\ I_{33}$	$135.9861 - 101.1875\ I_{33}$	−32.1736	103.8125

Results on Mispricing

TIPS		Treasury		Mismatch in Days	Dollar Mispricing Mean	SDev	Min	Max	ρ	Basis-Point Mispricing Mean	SDev	Min	Max	ρ	N
January 15, 2007	3.375	December 31, 2006	3.000	15	0.18	0.39	−0.76	1.10	0.97	34.57	92.03	−255.56	357.23	0.98	506
January 15, 2008	3.625	December 31, 2007	4.375	15	0.34	0.34	−0.25	1.26	0.96	53.82	66.57	−80.99	270.41	0.96	502
January 15, 2009	3.875	January 15, 2009	3.250	0	0.67	0.46	−0.34	2.56	0.95	72.54	135.34	−25.55	723.29	0.98	1,109
January 15, 2010	4.250	January 15, 2010	3.625	0	0.85	0.59	−1.05	4.69	0.91	55.14	71.91	−64.47	420.39	0.97	1,215
April 15, 2010	0.875	April 15, 2010	4.000	0	1.09	0.65	−1.18	4.51	0.93	58.25	57.84	−69.20	316.69	0.96	1,161
January 15, 2011	3.500	January 15, 2011	4.250	0	1.32	0.71	−0.03	4.94	0.92	50.24	33.67	−1.07	231.07	0.94	971
April 15, 2011	2.375	March 31, 2011	4.750	15	1.67	0.70	−0.37	5.03	0.91	56.13	33.04	−15.24	213.25	0.94	736
January 15, 2012	3.375	January 15, 2012	1.125	0	1.84	0.75	0.79	4.64	0.96	72.32	24.20	31.10	163.04	0.95	215
April 15, 2012	2.000	April 15, 2012	1.375	0	1.42	0.41	0.62	2.32	0.91	54.11	14.90	21.83	90.97	0.90	154
July 15, 2012	3.000	July 15, 2012	1.500	0	1.66	0.37	0.94	2.89	0.86	60.25	12.44	35.72	104.19	0.83	91
April 15, 2013	0.625	March 31, 2013	2.500	15	2.19	1.18	−1.07	6.37	0.95	55.44	28.02	−24.54	156.69	0.95	395
July 15, 2013	1.875	June 30, 2013	3.375	15	4.02	1.83	1.77	9.36	0.98	96.27	39.99	49.04	212.92	0.97	353
January 15, 2014	2.000	December 31, 2013	1.500	15	4.38	1.50	2.30	7.86	0.98	103.66	30.32	59.34	173.67	0.97	225
April 15, 2014	1.250	March 31, 2014	1.750	15	1.76	0.30	1.07	2.58	0.85	41.24	6.97	23.77	56.82	0.85	143
July 15, 2014	2.000	June 30, 2014	2.625	15	3.01	0.48	2.04	4.04	0.95	67.20	9.76	46.45	88.47	0.93	101

(Continued)

TIPS		Treasury		Mismatch in Days	Dollar Mispricing Mean	SDev	Min	Max	ρ	Basis-Point Mispricing Mean	SDev	Min	Max	ρ	N
January 15, 2015	1.625	February 15, 2015	4.000	31	3.36	2.04	1.22	12.52	0.99	55.48	37.53	15.62	214.11	0.99	1,204
July 15, 2015	1.875	August 15, 2015	4.250	31	3.61	2.18	1.54	13.24	0.99	56.39	36.45	22.68	207.57	0.99	1,079
January 15, 2016	2.000	February15, 2016	4.500	31	4.01	2.29	1.63	13.14	0.99	59.66	35.41	22.46	206.56	0.99	950
July 15, 2016	2.500	June 30, 2016	3.250	15	3.76	0.59	2.46	4.99	0.98	62.34	9.63	40.75	82.58	0.98	101
January 15, 2017	2.375	February 15, 2017	4.625	31	4.27	2.35	1.51	12.56	0.98	58.22	31.97	18.92	166.06	0.98	698
July 15, 2017	2.625	August 15, 2017	4.750	31	4.43	2.34	1.70	11.20	0.97	57.29	29.83	20.51	143.82	0.97	573
January 15, 2018	1.625	February 25, 2018	3.500	31	5.00	2.51	2.13	12.05	0.98	65.33	31.57	26.99	147.04	0.97	446
July 15, 2018	1.375	August 15, 2018	4.000	31	5.38	2.62	1.78	12.31	0.98	65.78	29.84	21.72	137.22	0.97	320
January 15, 2019	2.125	February 15, 2019	2.750	31	5.32	2.08	2.56	10.14	0.99	68.36	24.60	33.66	123.37	0.99	194
July 15, 2019	1.875	August 15, 2019	3.625	31	3.94	0.78	2.40	5.09	0.99	47.98	9.44	29.05	62.51	0.99	68
January 15, 2025	2.375	February 15, 2025	7.625	31	4.27	3.57	−0.89	23.06	0.98	29.40	23.45	−5.51	138.97	0.98	1,342
January 15, 2026	2.000	February 15, 2026	6.000	31	4.90	3.16	−0.06	18.49	0.97	36.85	21.96	−0.50	118.59	0.96	961
January 15, 2027	2.375	February 15, 2027	6.625	31	5.30	3.46	0.54	18.53	0.97	36.42	22.03	3.70	108.12	0.96	709
January 15, 2029	2.500	February 15, 2029	5.250	31	6.84	3.49	1.68	15.22	0.98	48.43	23.69	12.22	103.74	0.98	205

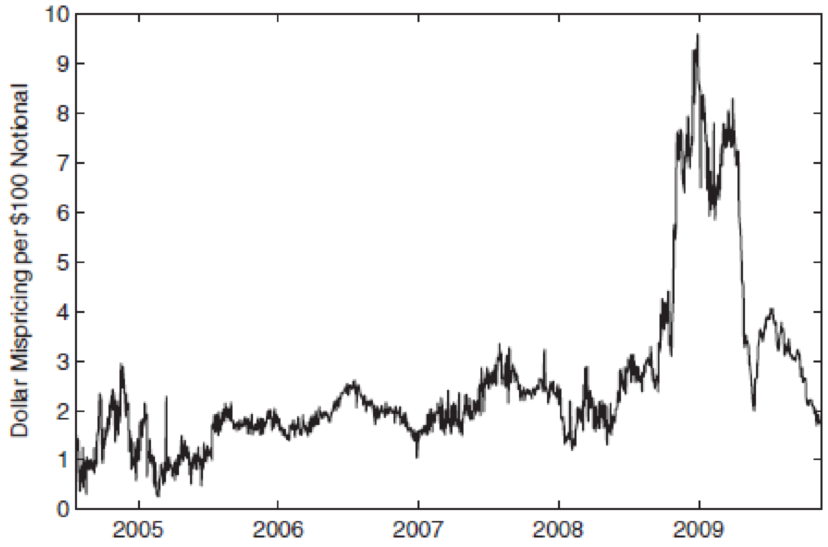
- 29 pairs between 2004 and 2009

- The mispricing is mostly positive: the TBonds are more expensive than the TIPS

- The mispricing is very large. E.g. it is up to \$23 for the Jan2025 bond

- The mean mispricing is also large. E.g. it is \$6.84 for the Jan2029 bond

- There is time variation in average mispricing across bonds. Much larger during the Global Financial Crisis



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Can it be due to transaction costs or mispricing of swaps?

- No, transaction costs are very small for all the instruments involved
  - Average bid-ask spread for T-bond is 0.78 ticks (tick $= 1/32$ of \$1)
  - For TIPS up to 7.3 ticks
  - For STRIPS 3 ticks
- No, inflation swaps mispricing does not seem to be the explanation
  - They re-do the exercise with Corporate bonds (nominal and inflation-protected) and find no mispricing there
  - They compute the credit spread (= yield corporate - yield treasury) for nominal and inflation-protected bonds. They find credit spread for nominal is up to 86 bps larger than for inflation-protected, suggesting that nominal treasuries have excessively low yields (i.e. high prices)
  - This computation does not involve inflation swaps

Why is the mispricing there?

- Why are T-Bonds overpriced relative to TIPS?
- Not much empirical evidence
- Arguments:
  - TBonds are perceived to be extremely liquid and safe (cash-like) instruments
  - Investors are willing to forego some returns to hold TBonds
  - **Treasury convenience yield**

Why does the mispricing persist?

- There are limits to arbitrage
- In particular, they refer to slow-moving capital (see later, Duffie 2010)
- Arbitrageurs' capital is scarcer during the crisis
- They show correlation with mispricing in other fixed income strategies (e.g. on-the-run vs. off-the-run TBonds, CDS-Bond basis)
  - Meaning that arbitrageurs are constrained across multiple strategies
- They show that when arbitrageurs are doing well mispricing goes down
  - I.e. when stock/bond markets go up, when hedge funds perform well

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2. Limits of arbitrage: the theory

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A simple model

- Based on Gromb and Vayanos (2010)
- Two periods: 1 and 2
- Two assets with correlated payoffs: A and B
- Risk-free rate exogenously set to 0
- Arbitrageurs are risk averse with CARA utility and risk aversion α
- Arbitrageurs trade at time 1 and receive dividends at time 2
- Normally distributed random dividends: d_A and d_B , with mean $\bar{d}_i$ and variance σ_i, $i = A, B$
- Assets are in zero net supply
- Asset B's price is exogenously set to the expected dividend $p_B = \bar{d}_B$

- There are exogenous demand (=liquidity) shocks in asset A: u

- Arbitrageurs provide liquidity: take the opposite side of liquidity demand

- The equilibrium price of asset A is

$$p_A = \bar{d}_A + \alpha\sigma_A^2 \left(1 - \rho^2\right) u \tag{1}$$

  where ρ is the correlation between the dividends of the two assets

- Notice: demand shocks u in equation (1) affect the price

- That is: arbitrageurs earn a premium from providing liquidity

- Assets with more risk (σ_A) and fewer substitutes (lower ρ) are more subject to demand shocks because arbitrageurs are less able to hedge risks

- Similarly, higher risk aversion (α) gives rise to a larger price impact

- Notice that if $\rho = 1$ there exists a perfect substitute of asset A. So, arbitrage is riskless and price equals fundamentals

- In all other cases, arbitrage is not riskless

Fundamental vs. non-fundamental risk

- Assume that there is a period 0 in which trading occurs
- At time 0, even the expectations of the dividends ($\bar{d}_i$) are random (e.g. think of a coarser information set about fundamentals at time 0)
- And the demand shock u at time 1 is random from the point of view of time 0
- Then, at time 0 arbitrageurs who need to liquidate at time 1 (short horizon) bear two sources of risk
    1. Fundamental risk: related to uncertainty about $\bar{d}_A$ and $\bar{d}_B$
    2. Non-fundamental risk: related to uncertainty about demand shocks u
- So, arbitrageurs with short horizons at time 0, may refrain from trading against time 0 demand shocks because of non-fundamental risk

- As a result, the volatility of p_A at t=1 as of t=0 is

$$\sigma_A \left[1 + \alpha^2 \sigma_A^2 \left(1 - \rho^2\right)^2 \sigma_u^2\right]^{1/2}$$

and the correlation between p_A and p_B is

$$\frac{\rho}{\left[1 + \alpha^2 \sigma_A^2 \left(1 - \rho^2\right)^2 \sigma_u^2\right]^{1/2}}.$$

Note that the volatility is larger than σ_A and the correlation is smaller than ρ because the denominator is larger than one

- Hence, demand shocks create volatility and lower the correlation between the two assets

- As a result of this volatility and reduced correlation, arbitrageurs require a higher premium and prices diverge further from fundamentals

- DSSW (1990) generate divergence from fundamentals in a model with two identical assets, but with autocorrelated demand shocks for one asset

- Crucial assumptions:

- arbitrageurs with finite horizons
- infinite horizon economy

- They call this: **noise trader risk**
- Short horizons can be endogenized as a form of financial constraints (e.g. Shleifer and Vishny 1997, see below)
- Bottom line: non-fundamental risk can affect asset prices if arbitrageurs have short horizon

Short-selling costs

- In case of positive demand shocks, arbitrageurs would like to short the asset
- Short-selling is not free. Arbitrageurs need to post cash as collateral
- The interest rate earned on the collateral can be below the market interest rate
- That is: rebate rate $<$ market interest rate
- The difference between the two is the short-selling fee
- This is a short-selling cost
- You can model the short-selling cost as c
- In this case, the equilibrium price of asset A at time 1 is

$$
\begin{aligned}
p_A &= \bar{d}_A + \alpha\sigma_A^2\left(1-\rho^2\right)u \qquad &\text{if} \quad u \leq 0 \\
p_A &= \bar{d}_A + \alpha\sigma_A^2\left(1-\rho^2\right)u + c \qquad &\text{if} \quad u > 0
\end{aligned}
$$

- In case $u > 0$, arbitrageurs are selling short asset A, and the price has to rise by c to compensate them for short selling costs

- So, two assets with identical payoffs ($\rho = 1$) that are subject to demand shocks can have different prices if there are short-selling costs. That is

$$
\begin{aligned}
p_A &= \bar{d}_A + c \\
p_B &= \bar{d}_A
\end{aligned}
$$

- This result can explain the Palm-3Com anomaly

Wealth Effects

- The ability to correct deviations from fundamentals due to demand shocks requires capital
- In previous model arbitrageurs' wealth does not appear because of CARA utility
- With more general utility functions, wealth increases risk bearing capacity, that is, it decreases risk aversion (e.g., logarithmic utility in Xiong, 2001, and Kyle and Xiong, 2001)
- So, as wealth decreases, arbitrageurs are less willing to take the other side of liquidity shocks and price correction is smaller (liquidity decreases)
- This channel is called **wealth effects**
- The empirical paper by Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (JF, 2010) on NYSE specialists provides empirical evidence of wealth effects
- The specialists withdraw from liquidity provision when they lose money
- Note, however, that the authors provide a justification based on 'financial constraints'. But specialists are not using outside finance

Leverage constraints

- Then, one can let wealth enter the model through the constraints on arbitrageurs' ability to invest more than their wealth
- This channel is labeled **financial constraints**
- One version of financial constraints is limits on leverage
- Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009) and others model these limits as margin constraints
- Buying on margin: to buy a security, investors borrow money from broker, and post the security as collateral
- Similarly, to buy fixed income securities, arbitrageurs do Repo transactions, also involving haircuts
- The value of the security is discounted (haircut). So, you cannot borrow 100% of the value of the security

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- You still need your own capital (margin requirement)

- The broker wants to minimize the risk of this operation. So, the margin is the larger the more risky the security is

- Similarly, to short sell a security, you need to post cash (margin) that exceeds the proceeds from the short sale because the broker wants to be protected against upward movements in the price

- So, arbitrageurs need to have at least some equity capital in the presence of limits on leverage

- If there are demand shocks (u) arbitrageurs would like to take the other side

- However, it's possible that their capital is not enough, so that they cannot borrow enough to enforce the law of one price

- That is: when arbitrageurs capital is small, the leverage constraint is binding, and arbitrageurs' liquidity provision is not perfect

- These arguments have led to the rise of a new strand of literature in asset pricing that makes asset prices depend on the balance sheet of financial intermediaries (see below: Adrian, Etula, and Muir, 2014; He, Kelly, Manela, 2017): **intermediary asset pricing**

- For a critical assessment of this literature, see Cochrane (2016, "The Habit Habit"). In brief, why don't long term investors (wealthy individuals, endowments, pension funds) buy when short term investors sell in a stressed market? Cochrane's answer: because everybody's risk aversion goes up in bad times

- Other possible answer: because these investors revise their allocation at a very low frequency. Hence, they are not marginal investors when prices start falling rapidly

Fire Sales

- See Shleifer and Vishny (1992, 2011)
- A fire sale is defined as a forced sale of a real or financial asset at a price below its best-use valuation
- A fire sale may occur if the asset holders (investors, banks, firms) are required to return cash to their capital providers (shareholders or creditors) and they are not able to come up with this cash
- A necessary condition for a fire sale is that the other ‘specialized’ holders of this asset are also in financial distress, so that they are ‘sidelined’
- Hence, the asset is bought by investors that have lower valuations than the best-use value
- Fire sales can lead to amplication and contagion

Amplification

- Suppose arbitrageurs enter period 1 with wealth that is invested in period 0
- There is a negative demand shock that lowers the value of the assets in arbitrageurs' portfolio
- This makes the leverage constraint binding in period 1
- Arbitrageurs receive margin calls from their brokers and they are forced to liquidate
- Arbitrageurs' sales reinforce the negative demand shock
- Arbitrageurs are consuming liquidity in this case
- Amplification

Contagion

- In a multi-asset setting, a demand shock to one asset may force liquidation of other securities in the portfolio

- For example, arbitrageurs may choose to liquidate the more liquid securities first

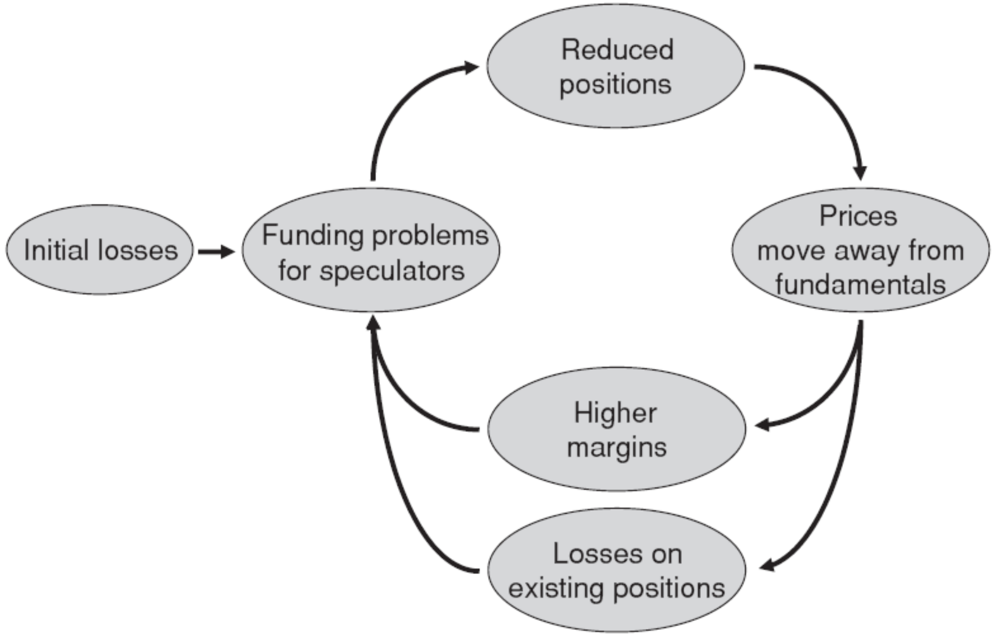
- Or, they can choose to liquidate the most volatile securities that impose higher capital charges (**flight to quality**)

- In any case, a shock to one security can propagate to other securities because of leverage constraints

- Propagation of shocks to correlated assets can also emerge in models with risk averse investors that hedge the demand for one asset with demand for a correlated asset (see Greenwood, 2005, JFE)

Funding liquidity and market liquidity

- Brunnermeier and Pedersen (2009) use leverage constraints in a multi-asset setting to generate amplification and contagion
- Similar concepts were previously explored by Gromb and Vayanos (2002, JFE)
- Brunnermeier and Pedersen talk about *funding liquidity*: the availability of capital for arbitrageurs, which depends on the performance of their portfolio
- And *market liquidity*: the proximity of securities prices to fundamentals following demand shocks
- The two forms of liquidity affect each other in what the authors label ‘loss spirals’ and ‘liquidity spirals’
- The action comes from forced liquidations after initial losses, which reinforce the negative price impact, and cause further losses



- The paper also predicts ‘flights to quality’: after negative shocks, arbitrageurs sell high volatility stocks and buy low volatility stocks to reduce the amount of collateral that they need to post
- This effect reinforces the initial shocks because in the model conditional volatility depends positively on past returns (GARCH)

Constraints on equity capital

- These constraints operate similarly to leverage constraints
- If capital is limited, arbitrage ability is limited, and liquidity provision is not perfect
- They can emerge if arbitrageurs' wealth belongs to other investors (agency problems)
- Shleifer and Vishny (1997) postulate that mutual/hedge fund investors redeem their capital following losses
- This fact constraints arbitargeurs' ability to correct mispricing, triggers liquidations, and amplification
- S&V show that these constraints limit liquidity provision not only when they are binding, but also when there is a chance that they will bind in the future
- That is, arbitrageurs fear that future losses will cause forced liquidations. So, they limit their exposure to risky assets

- Risk management emerges as a response to capital constraints
- Leverage and equity constraints are exogenous in these models
- But they can be micro-founded on asymmetric information about the skill of the manager (e.g. Berk and Green, 2004)

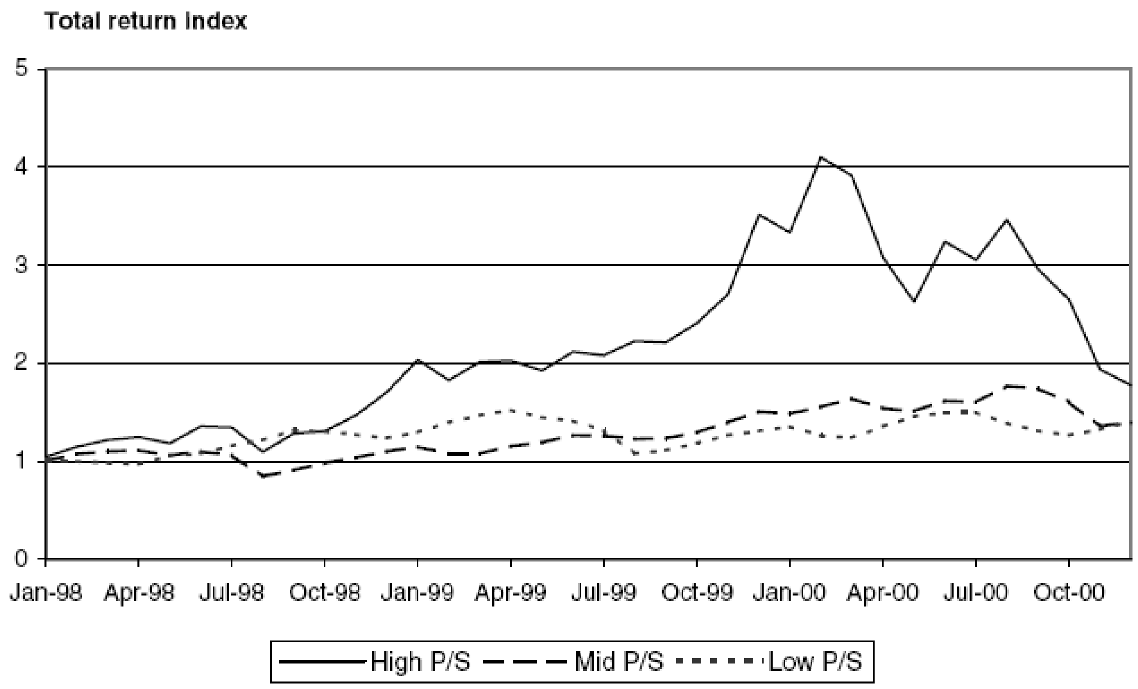
Synchronization risk

- Abreu and Brunnermeier (2002) postulate that arbitrageurs have limited capital
- So, a single arbitrageur cannot correct mispricing alone
- Also, arbitrageurs are not simultaneously aware about profit opportunities
- So, they do not necessarily jump in together to correct mispricing
- Finally, there are ‘holding costs’. That is, it is costly to hold open positions in the expectation that mispricing will be corrected
- As a result, mispricing can last for some time because arbitrageurs fail to coordinate in entering the market (**synchronization risk**)
- In Abreu and Brunnermeier (2003), given these assumptions, it can make sense for arbitrageurs to trade in the direction of the mispricing (*ride the bubble*) in anticipation that the bubble will continue for some time
- Kondor (JF, 2009) similarly generates persistent price divergence arising from the dynamic choices of arbitrageurs that need to decide when to enter the market. They may decide not to invest all their capital right away and save some capital for later in case the arbitrage opportunity widens

2. Empirical evidence

Brunnermeier and Nagel (JF, 2004)

- Technology stocks on Nasdaq rose to unprecedented levels during the two years leading up to March 2000
- Valuations were implicitly assuming growth rates of earnings exceeding what was previously experienced even by the fastest growing stocks
- Also valuations were implicitly assuming very low discount rates



- High price-to-sales (P/S) stocks (mostly high tech stocks) experienced a four-fold price increase and a huge correction after March 2000

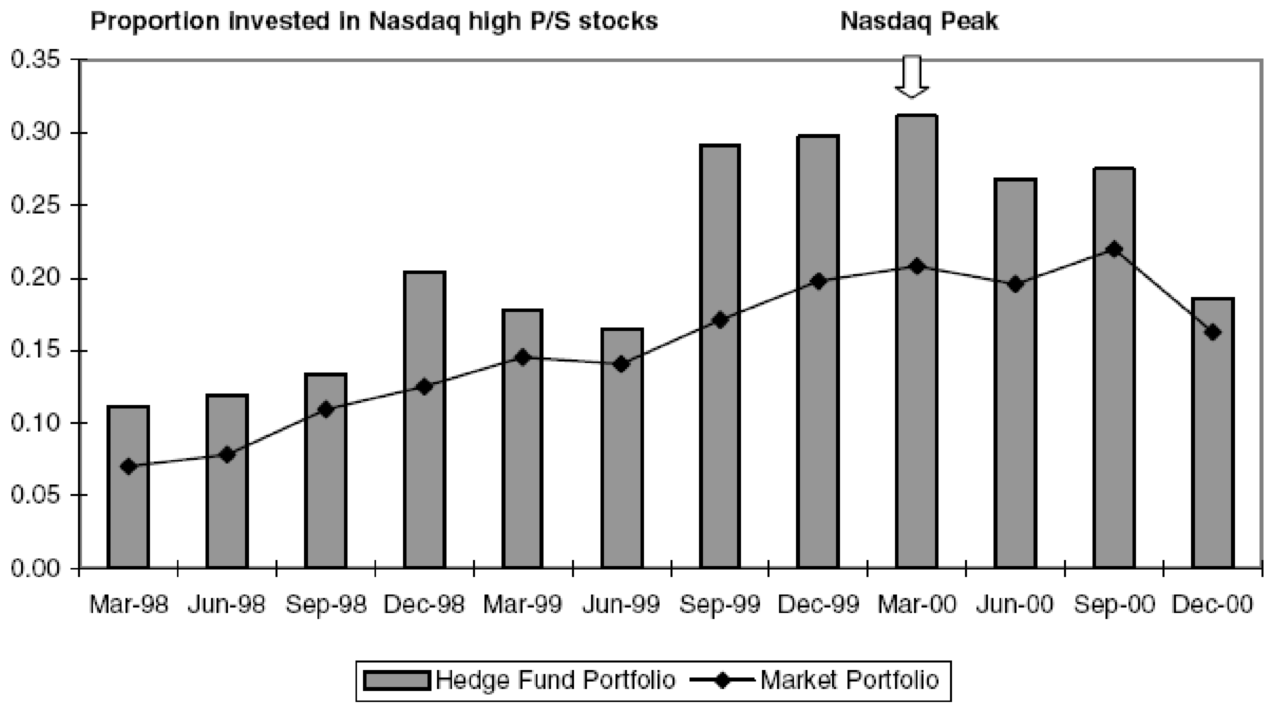
- These high valuations have been argued to be an example of asset price bubble

Question

- This seems a manifestation of investor irrationality
- However, this cannot survive without limits to arbitrage
- What were arbitrageurs doing during this period?
- They look at the trading behavior of the most sophisticated investor class: hedge funds (HFs)
- They draw data from 13F filings: all institutions with more than $100M in U.S. equity have to report their end-of-quarter long positions
- No data on short positions
- Did HFs attack or ride the bubble?

The weights of HFs in the tech sector

- They use HFs' long portfolio holdings of high P/S stocks and compare to weight of the same stocks in the market portfolio



- HFs were overweight (larger weight than the market weight) in tech stocks at least until the peak of the Nasdaq (March 2000)

- So, they did not attack the bubble, rather they were riding it

How about the short side?

- HFs could also have increased their short positions in tech stocks
- In this case, the impression of riding the bubble would be mitigated
- But shorts not reported in the 13F
- So, look at style regressions for returns:

$$R_t = \alpha + \beta R_{M,t} + \gamma \left(R_{T,t} - R_{M,t} \right) + \varepsilon_t$$

  where $R_{M,t}$ is the market return and $R_{T,t}$ is the tech sector return (high P/S stocks)

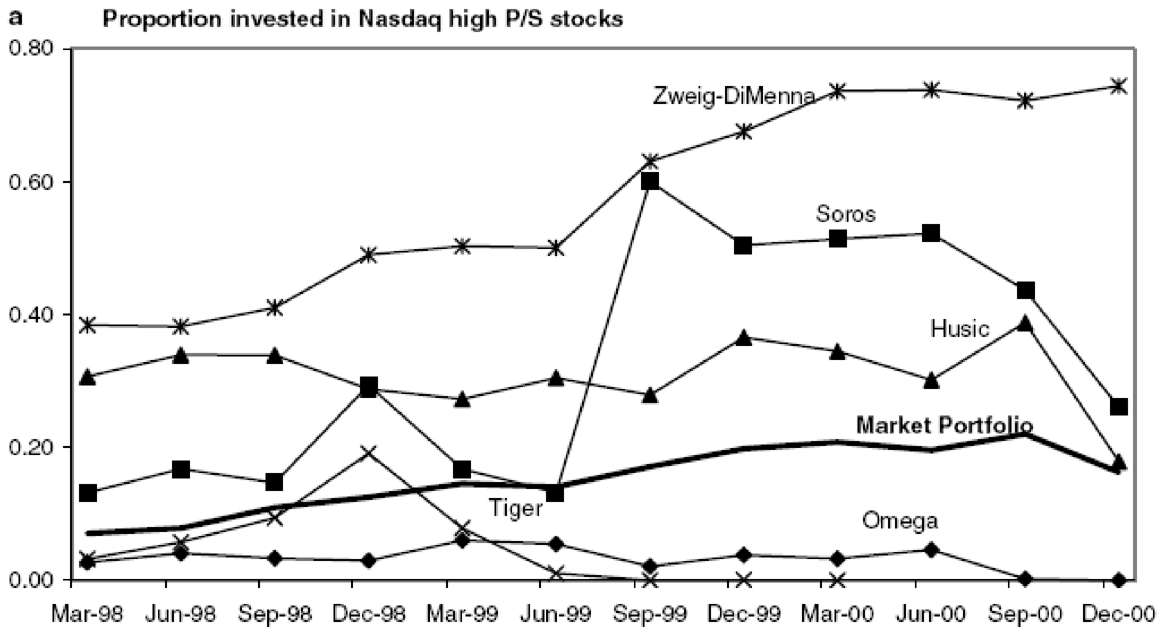
- γ captures the exposure to tech stocks on top of what you get through the exposure to the market portfolio
- For a long only fund replicating the market portfolio: $\beta = 1$ and $\gamma = 0$

	Factor Loadings			Implied Tech-Weight
Index	β	γ	Adj. R^2	w_T
Panel A: Equal-weighted Index of Largest Funds in Our Sample (1998–2000)				
Large	0.42	0.17	0.56	0.49
	(3.51)	(2.51)		(0.08)
Panel B: HFR Hedge Fund Style Indexes (1998–2000)				
Equity-hedge	0.45	0.15	0.80	0.44
	(6.36)	(3.92)		(0.04)
Equity nonhedge	0.74	0.16	0.86	0.34
	(9.07)	(3.57)		(0.03)
Equity market-neutral	0.07	0.01	0.10	0.32
	(1.54)	(0.53)		(0.15)
Market timing	0.25	0.07	0.48	0.38
	(3.45)	(1.67)		(0.08)
Short-selling specialists	−1.00	−0.43	0.80	
	(−5.93)	(−4.57)		
Macro	0.13	0.09	0.34	0.70
	(1.84)	(2.13)		(0.21)
Sector technology	0.71	0.57	0.86	0.84
	(5.29)	(7.62)		(0.08)
Panel C: Aggregate Long Portfolio (As in Figure 2)				
13F	1.13	0.29	0.89	0.37
	(9.97)	(4.49)		(0.03)

- For most funds (except for short-selling specialists), there is an over-exposure to the tech sector
- Short positions were used, but only to reduce exposure to the market ($\beta < 1$)
- To summarize, the results strengthen the evidence from the previous table that HFs were riding the bubble

Evidence for individual HFs

- So far, aggregate data
- Did some funds behave differently? What were the consequences on their performance?
- What about the money flows from investors? These are relevant for the limits of arbitrage
- Focus on a few selected funds, especially Soros and Tiger

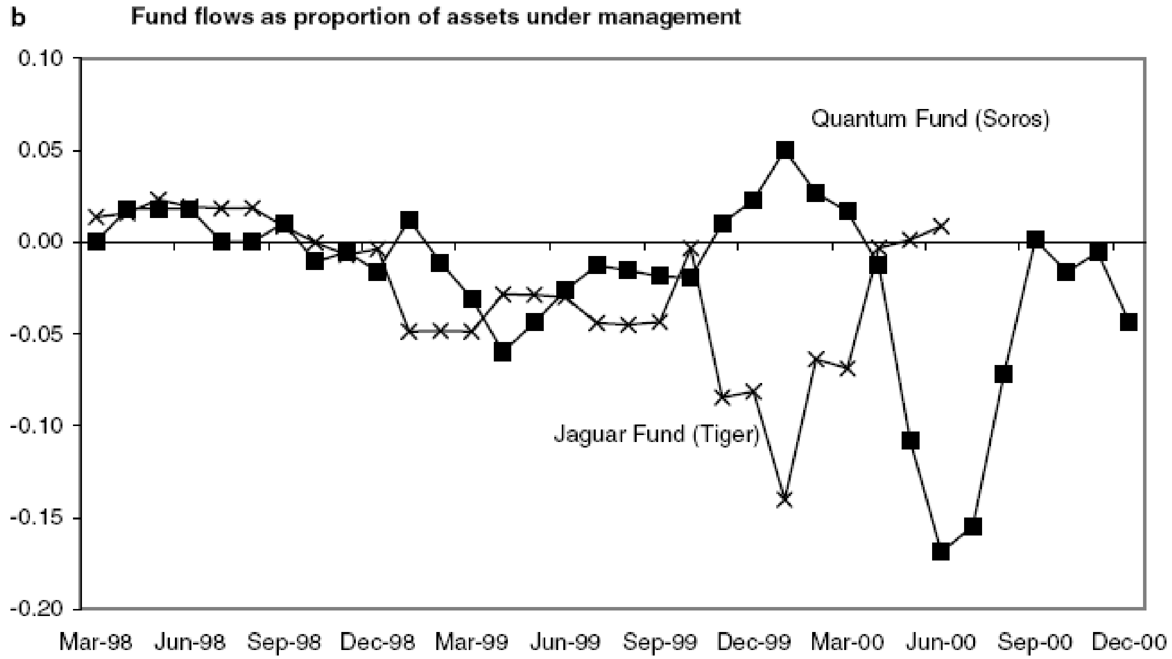


- Soros was riding the bubble especially after June 1999

- Tiger was a value manager, definitely not riding the bubble. Exposure to tech stocks went to zero in June 1999

- Diverging paths

- Look at fund flows:



- Soros did well during the bubble. So, investors kept pouring in money
- As Tiger's performance was poor during the bubble, it suffered from redemptions
- Eventually, the Tiger fund was liquidated in March 2000 because its asset base eroded too much. Just before the bubble burst!

Conclusions

- B&N also show that at the stock level, HFs managed to time the the market correctly
- On average, they got out of stocks before they declined
- Evidence is consistent with 'synchronization risk' theories (Abreu and Brunnermeier, 2002 and 2003)
- Not only do we observe that arbitrageurs do not correct mispricing (as predicted by financial constraints)
- But also we see that arbitrageurs ride the bubble, possibly because they anticipate that it will continue for some time
- The example about Tiger is consistent with the limits on equity capital, as described by Shleifer and Vishny (1997)
- That is, temporary losses trigger redemptions that prevent arbitrageurs to hold on to a strategy that would pay off in the longer run

Ben-David, Franzoni, Moussawi (2012, RFS)

- Hedge funds (HFs) resemble the textbook arbitrageurs
  - Sophisticated: trade across assets and markets
  - Use leverage
  - Engage in short selling
- However, HFs depend on outside financing
  - Vulnerable to investor redemption of capital
  - Vulnerable to margin calls
- Did HFs continue to provide liquidity in the crisis of 2007-2009 or did they run into financial constraints?
- Evidence that liquidity provision was hampered: Aragon and Strahan (2012), Nagel (2012)

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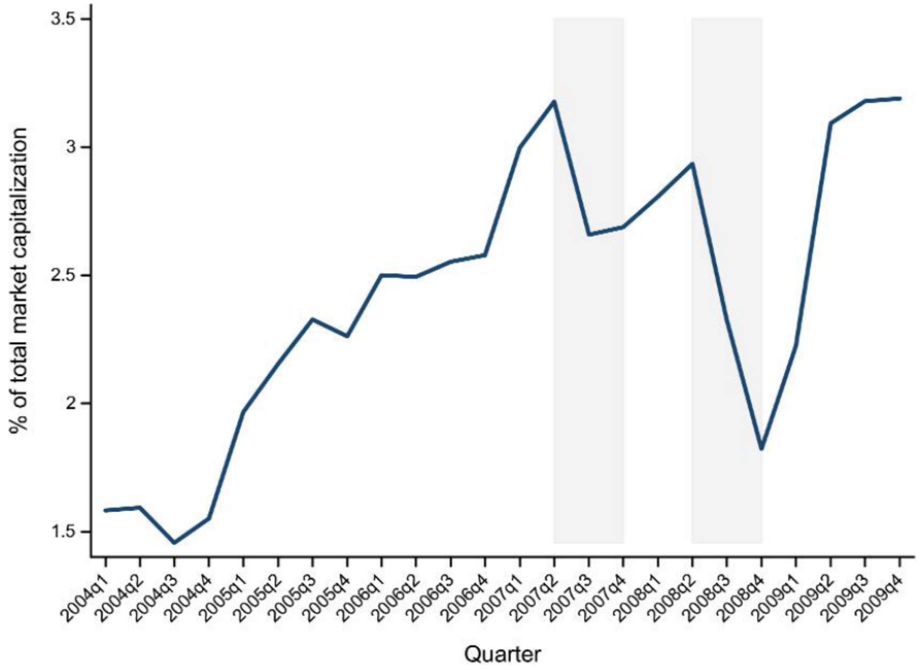
The data

- HFs long equity holdings in U.S. stocks at quarterly frequency:
  - Thomson 13F Institutional Ownership
  - No survivorship/self-reporting biases
  - All management companies with more than \$100 million in U.S. equity
- Match with proprietary HF identification list provided by Thomson
- Using ADV filings, keep pure-play HF (e.g., no Goldman Sachs)
- Manually match a subset with TASS for returns and characteristics
- Sample period: 2004Q1– 2009Q4

Year	Number of Mgrs. 13F	Number of Mgrs. TASS match	Total AUM in TASS ($bn)	Equity portfolio ($m, TASS match) Mean
	(1)	(2)	(3)	(4)
2004	436	104	93	466
2005	530	124	112	597
2006	606	133	147	747
2007	693	136	189	910
2008	696	114	149	610
2009	612	98	147	521

Results: HF trading

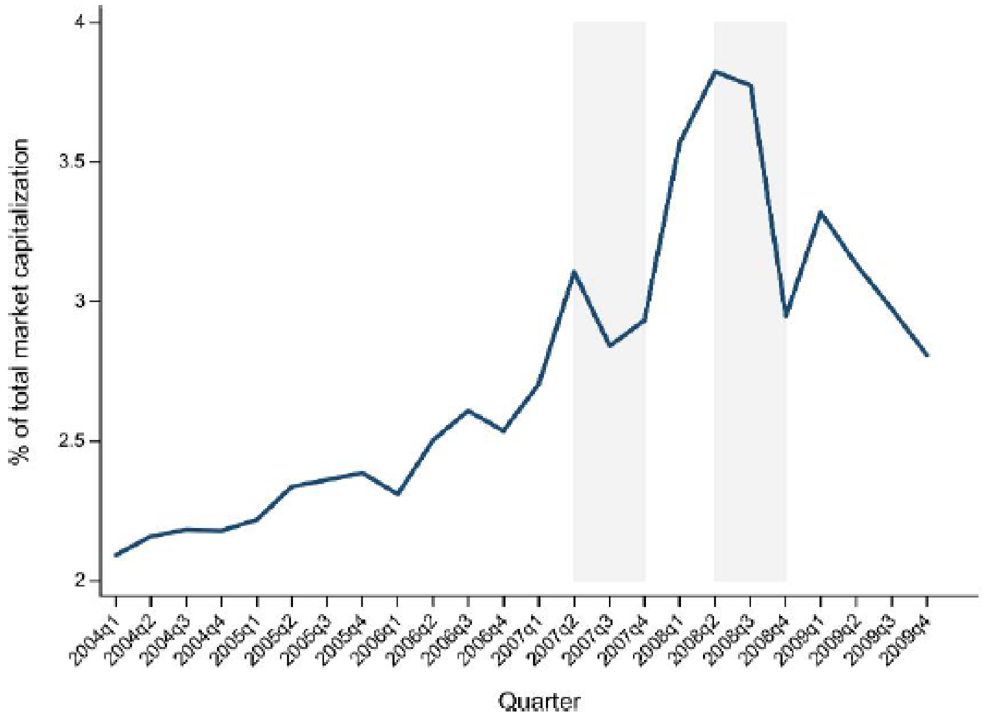


- Drastic declines in the fraction of the stock market owned by HFs around two critical events
- Look at actual trades evaluated at prior period prices (to filter out the change in prices during the quarter)

		Avg Qtr Δ Holdings Hedge Funds	
		%	% of total mktcap
		(1)	(2)
Pre-crisis	2004Q1-2007Q2	6.13	0.13
Crisis	2007Q3-2009Q1	-3.06	-0.10
Post-crisis	2009Q2-2009Q4	5.60	0.17
Selloff quarter	2007Q3	-9.87	-0.31
Selloff quarter	2007Q4	-2.74	-0.08
	2008Q1	4.72	0.13
	2008Q2	3.57	0.10
Selloff quarter	2008Q3	-16.70	-0.49
Selloff quarter	2008Q4	-14.26	-0.33
	2009Q1	13.88	0.25

- The selloffs took place in four quarters: Q3/Q4 of 2007 and 2008

What about the short side?



- High correlation of short interest with HF long equity holdings (42%)
- The correlation is 79% during the crisis period
- Long and short positions move in tandem

Net effect?

- Do the changes in short positions cancel out with the changes in long position, so that net effect on liquidity is zero?

- At the stock level, regress change in HF long position onto the change in short interest

	Dependent variable: Δ HF holdings (%)			
	(1)	(2)	(3)	(4)
Δ Short interest	0.071***	0.071***	0.071***	0.071***
	(8.382)	(11.173)	(10.659)	(13.354)
× Selloff quarter	0.022	0.021**		
	(0.909)	(2.026)		
Selloff quarter	-0.449**	-0.402***		
	(-2.225)	(-21.630)		
Firm FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
Observations	103982	103982	103982	103982
Adj. R^2	0.017	0.016	0.029	0.028
Number of stocks	6242	6242	6242	6242

- Correlation is at most 9%

- Liquidity is removed from stocks that hedge funds hold ("undervalued"), and added to stocks that hedge funds short sell ("overvalued").

- Hence, the exit of hedge funds and short-sellers leads to greater mispricing

Why did HFs sell?

- Balance sheet of a HF

Assets	Liabilities
U.S. Stocks	Equity (AUM)
Other investments (including Cash)	Debt (including Short positions)

$$\Delta U.S.Stocks = \Delta AUM + \Delta Debt - \Delta OtherInvestments$$

- We can construct fund flows (ΔAUM) using TASS
- But. . .
  - No time-series dimension on leverage
  - No direct information on other investments

- No fund level information on short positions

- We need empirical proxies to identify channels other than ΔAUM

Financial constraints

- We test whether the large selloffs were due to financial constraints in the form of:
  - Investor redemptions
  - Margin calls
  - Risk management constraints

Investor redemptions

	Dependent variable: Δ HF equity portfolio (%)	
Selloff quarter	-11.529***	-6.516
	(-4.130)	(-1.718)
Fund flows		0.160
		(0.874)
lead(Fund flows)		0.396***
		(3.892)
lead2(Fund flows)		0.157*
		(2.036)
Observations	2053	2053
Adj R^2	0.009	0.038

- Fund-quarter level regressions
- Dependent variable: % change in equity portfolio value
- Selloff quarter dummy: Q3/Q4 of 2007 and 2008
- Future fund flows explain 43% of selloff dummy
- Most direct evidence of selling motive

Margin calls + Risk limits

	Dependent variable: Δ HF equity portfolio (%)		
Selloff quarter	-12.118***	-6.991	-2.653
	(-4.445)	(-1.564)	(-0.544)
× Avg. leverage		-5.982**	-5.711***
		(-2.281)	(-2.903)
Fund flows			0.193
			(1.461)
lead(Fund flows)			0.384**
			(2.400)
lead2(Fund flows)			0.060
			(0.954)
Avg. leverage		4.476***	4.326***
		(4.293)	(4.382)
Observations	1332	1332	1332
Adj R^2	0.009	0.016	0.039

- Conjecture: higher leverage $\longrightarrow$ higher likelihood of forced deleveraging
- Confirmed by the data
- Financial constraints (Redemptions + Leverage): explain 78% of selloffs

Which stocks are sold?

- Analysis of stock characteristics can reveal motives of selloffs
- We find that during the crisis HFs sold:
  - High volatility stocks rather than low volatility stocks
    - Consistent with margin calls and risk management (Brunnermeier and Pedersen 2009)
  - Low price impact stocks rather than high price impact stocks
    - Consistent with management of price impact during fire sales
- Also, short interest is mostly closed on high volatility stocks
- Overall, evidence is consistent with financial constraints channel

HFs vs. Mutual Funds

- Use mutual funds as benchmarks for hedge fund behavior
- Similarities:
  - Investment in the equity market
  - Active investing
- Major differences:
  - Hedge funds use high leverage and short positions
  - Hedge funds have restrictions on capital withdrawals
  - Hedge fund investors are more sophisticated (institutional investors)

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Difference in behavior

Panel A: Summary Statistics for Hedge Funds

		Hedge funds		
		Quarterly returns (%)	Trades/Total equity portfolio (%)	Flows/AUM (%)
		(1)	(2)	(3)
Pre-crisis	2004Q1-2007Q2	2.82	6.13	2.76
Crisis	2007Q3-2009Q1	-2.37	-3.06	-3.69
Post-crisis	2009Q2-2009Q4	4.01	5.60	-2.94
	2007Q3	-0.09	-9.87	5.71
	2007Q4	1.84	-2.74	-6.21
	2008Q1	-2.57	4.72	-1.80
	2008Q2	3.05	3.57	8.06
	2008Q3	-9.78	-16.70	1.64
	2008Q4	-9.12	-14.26	-8.87
	2009Q1	0.11	13.88	-24.35

Panel B: Summary Statistics for Mutual Funds

		Mutual funds		
		Quarterly returns (%)	Trades/Total equity portfolio (%)	Flows/AUM (%)
		(1)	(2)	(3)
Pre-crisis	2004Q1-2007Q2	2.82	1.37	1.17
Crisis	2007Q3-2009Q1	-7.22	0.20	0.12
Post-crisis	2009Q2-2009Q4	11.82	0.54	1.63
	2007Q3	1.86	0.75	0.79
	2007Q4	-2.39	1.34	0.46
	2008Q1	-8.90	-0.52	0.08
	2008Q2	0.15	-1.70	0.79
	2008Q3	-11.12	-0.12	0.59
	2008Q4	-22.13	-0.24	-0.92
	2009Q1	-7.97	1.86	-0.92

- Compared to MFs, HFs had:

– Higher redemptions

– Higher sales of stocks (MF almost did not sell)

Flow-Performance Sensitivity

- It has to be the case that investors of the two types of funds react differently to negative performance
- Prior literature:
  - Mutual fund investors exhibit **convex** performance-flow sensitivity
    - Strong inflows following good past performance
    - Weak outflows following bad past performance
- Hedge fund investors exhibit **linear or concave** flow-performance sensitivity (Li, Zhang, Zhao 2011)
- Hedge funds' flow-performance relation is more sensitive when liquidity restrictions are stricter (Ding, Getmansky, Liang, and Wermers 2010)
- Liquidity restrictions:

- Lockup period
- Redemption notice
- Redemption frequency

- Sophisticated investors react more strongly to past performance (Calvet, Campbell, and Sodini 2009)

Performance-flow sensitivity: MFs vs HFs

- TRank_i (i=1,2,3): is a dummy that categorizes prior-quarter performance in three terciles
- The dependent variable is the Flows into the fund as a fraction of AUM

	Dependent variable: Flows (q+1) / AUM (q)					
Ranking / sample:	Absolute ranking			Within-style ranking		
Sample period:	All qtrs	Non-Crisis	Crisis	All qtrs	Non-Crisis	Crisis
TRank1	0.072**	0.116**	-0.036	0.094***	0.129***	0.010
	(2.067)	(2.715)	(-0.929)	(3.146)	(3.353)	(0.393)
× I(Hedge fund)	0.133***	0.147***	0.111*	0.120***	0.123**	0.115**
	(3.601)	(3.062)	(1.970)	(3.425)	(2.618)	(2.542)
TRank2	-0.049**	-0.091***	0.057	-0.050**	-0.093***	0.056
	(-2.061)	(-3.661)	(1.941)	(-2.093)	(-3.723)	(1.865)
× I(Hedge fund)	0.099***	0.118***	0.038	0.117***	0.154***	0.020
	(3.831)	(3.691)	(0.967)	(3.771)	(4.004)	(0.649)
TRank3	0.538***	0.593***	0.402***	0.523***	0.584***	0.372***
	(11.253)	(11.001)	(4.832)	(10.851)	(10.716)	(4.783)
× I(Hedge fund)	-0.096*	-0.159**	0.060	-0.124**	-0.192***	0.042
	(-1.744)	(-2.721)	(0.562)	(-2.137)	(-3.077)	(0.402)
Calendar Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	204240	145262	58978	204240	145262	58978
Adj R^2	0.082	0.080	0.084	0.080	0.078	0.081

Controls: I(Hedge fund), log(AUM)

- Hedge funds have higher sensitivity of flows to bad performance

HF behavior and investor base

- Are individual investors less sensitive than institutional investors to bad performance?
- Exploit heterogeneity in HF investor base
- Dependent variables: Δ HF equity holdings or Flows into the fund
- Explanatory variable of interest: Fraction of fund owned by institutions*Crisis dummy

	Δ HF equity portfolio (%)		Flows (q+1) / AUM (q)	
I(Crisis) defined as:	07Q3-09Q1	Selloff Qtrs	07Q3-09Q1	Selloff Qtrs
I(Crisis)	0.117	-3.321	-1.678	-16.458**
	(0.034)	(-1.622)	(-0.196)	(-2.480)
× Institution ownership	-2.633***	-1.137**	-2.491**	-0.034
	(-4.995)	(-2.586)	(-2.410)	(-0.119)
× I(Lockup period)	3.903	0.380	4.039	1.508
	(0.554)	(0.120)	(0.552)	(0.417)
× I(Redemption period > 90)	12.358	7.790*	12.496	8.510**
	(1.344)	(2.016)	(1.400)	(2.131)
Observations	1474	1477	1474	1477
Adj R^2	0.043	0.057	0.043	0.060

Controls: Institutional ownership, I(Lockup period), I(Redemption period > 90), constant

- High institutional ownership $\rightarrow$ higher sales, greater outflows during the crisis
- Potential driving factors:
  - Institutional investors more sophisticated, hence more reactive
  - Risk management controls in the institutions that force them to sell
  - Career concerns for managers within the institutions that need to justify poor performance

Conclusions

- Hedge funds drastically decreased their equity holdings during the last crisis
- Main driving force is capital withdrawals and pressure by lenders
- Hedge funds are different because:
  - Investors react aggressively to past losses
  - Stronger selloffs and redemptions for hedge funds with high institutional investors
- Strong support for limits to arbitrage in bad times (Shleifer and Vishny, 1997, Gromb and Vayanos, 2002, Brunnermeier and Pedersen, 2009)
- For the most part, HFs liquidity provision seems to be pro-cyclical

Aragon and Strahan (2012, JFE)

- Do hedge funds provide liquidity?
- Same as: are HFs beneficial to financial markets?
- Test of Brunnermeier and Pedersen (2009)
- Funding liquidity impacts market liquidity
- But feedback effect (market liquidity $\rightarrow$ funding liquidity) complicates identification
- Need an exogenous shock to funding liquidity
- Also, HFs' strategy is to get into illiquid positions to provide liquidity and get out when liquidity improves
- So, there is correlation between HF presence in an asset and the evolution of liquidity
- Need exogenous variation in HF presence in the market
- Lehman bankruptcy (September 15, 2008) provides this natural experiment

The prime-broker

- Lehman Brothers, among other activities, operated as prime broker to many HFs
- A prime-broker for a HF acts as: custodian for securities, security lender (short sales), financier (buying on margin), risk manager (for smaller funds)
- The authors focus on re-hypothecation activities of prime-broker
- Re-hypothecation: a broker is allowed to lend a client's pledged securities to another client who wants to do short sales
- Counterparty risk: if the prime-broker goes bankrupt, the lent-out securities may never return to their original owner
- This is a problem for the original HF that loses part of its capital
- The paper uses the bankruptcy of Lehman as an exogenous shock to the HF's capital, for the HFs that had Lehman as a prime-broker

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- Data on prime-brokers from TASS
- Then, they look at the liquidity of the stocks that were largely owned by the HFs which had Lehman as a broker around its bankruptcy
- Did liquidity decrease?
- Data on ownership from 13F filings

2002	2003	2005
18.16% Bear Stearns	18.05% Bear Stearns	19.41% Morgan Stanley
16.24% Morgan Stanley	16.43% Morgan Stanley	18.38% Goldman Sachs
13.65% Goldman Sachs	14.47% Goldman Sachs	13.98% Bear Stearns
4.30% Bank of America	5.81% ABN AMRO	8.51% UBS
3.67% ABN AMRO	5.14% Bank of America	6.03% Bank of America
3.65% Morgan Stanley Dean Witter	2.91% Merrill Lynch	3.33% Lehman Brothers
3.40% Merrill Lynch	2.64% Morgan Stanley Dean Witter	3.25% Citigroup
2.77% Man Group	2.50% Man Group	3.12% Credit Suisse First Boston
2.23% ING Group	1.96% Salomon Smith Barney	2.69% Deutsche Bank
1.85% Salomon Smith Barney	1.62% Credit Suisse First Boston	2.39% Man Group
2006	2007	2008
19.67% Morgan Stanley	20.67% Morgan Stanley	20.60% Morgan Stanley
18.24% Goldman Sachs	17.21% Goldman Sachs	16.64% Goldman Sachs
13.21% Bear Stearns	12.00% Bear Stearns	9.13% Bear Stearns
8.61% UBS	8.24% UBS	8.58% UBS
5.53% Bank of America	4.53% Bank of America	4.14% Deutsche Bank
3.88% Citigroup	4.15% Citigroup	3.90% Citigroup
3.55% Lehman Brothers	3.68% Deutsche Bank	3.46% Merrill Lynch
3.29% Credit Suisse First Boston	3.58% Credit Suisse First Boston	3.37% Credit Suisse First Boston
2.57% Deutsche Bank	3.31% Lehman Brothers	3.04% Bank of America
2.36% Man Group	2.96% Merrill Lynch	2.36% Lehman Brothers

Effect of Lehman's bankruptcy on HFs

- First, they want to show that Lehman's bankruptcy had a negative impact on the connected HFs
- Estimate hazard rate models
- These are econometric models that estimate the impact of covariates on the failure probability
- Failure proxied by disappearance of HF from TASS
- Explanatory variable of interest: 2008 dummy * Lehman fund dummy
- Estimated coefficient > 1 positive effect

	1	2	3	4	5	6
2008 Dummy	1.88	1.53	1.50	1.65	1.64	1.66
	(13.18)**	(6.81)**	(5.75)**	(7.03)**	(6.98)**	(7.14)**
Lehman Fund Dummy	0.67	0.65	0.47	0.46	0.47	0.43
	(1.94)+	(2.05)*	(2.68)**	(2.48)*	(2.43)*	(2.69)**
2008 Dummy*Lehman Fund Dummy	2.42	2.67	3.37	3.13	3.14	3.06
	(3.15)**	(3.57)**	(3.53)**	(3.18)**	(3.21)**	(3.12)**
Raw Fund Return	-	0.84	0.85	0.87	0.86	0.86
	-	(6.73)**	(5.64)**	(5.12)**	(5.30)**	(5.32)**
Percentage Net Fund Flow	-	-	0.68	0.62	0.62	0.63
	-	-	(7.23)**	(8.19)**	(8.15)**	(8.17)**
Ln(Fund Assets)	-	-	-	0.70	0.69	0.69
	-	-	-	(12.87)**	(12.99)**	(12.81)**
Ln(1+ Lockup Period)	-	-	-	-	0.97	0.96
	-	-	-	-	(1.23)	(1.36)
Ln(1+Redemption Notice Period)	-	-	-	-	1.07	1.03
	-	-	-	-	(2.10)*	(0.90)
Hedge Fund Style Fixed Effects?	No	No	No	No	No	Yes
N	9,557	9,557	7,847	7,122	7,122	7,122

- In all specifications, the variable of interest (being a Lehman connected fund, in year of Lehman bankruptcy) is > 1

- Magnitude: 2.42 means that Lehman funds in 2008 were 2.42 times as likely to fail compared to Lehman funds before the crisis and compared to other funds

- Authors' conclusion: the bankruptcy of the prime-broker had a negative impact on connected funds

- Alternative story: Funds that had Lehman as a broker were undertaking more risky strategies

Effect on liquidity

- Next, they want to show that connected HFs decreased their liquidity provision

- Notice first that liquidity decreased across the board in the stock market after Lehman's collapse

	Pre-crisis			*Post-crisis*		
	25th Percentile	Median	75th Percentile	25th Percentile	Median	75th Percentile
Panel A: Distribution of liquidity measures						
Bid-ask spread	0.16%	0.32%	1.11%	0.34%	0.82%	2.98%
Overall price impact (Amihud illiquidity)	0.27%	2.53%	37.87%	0.77%	8.14%	113.30%

- Next, use regression analysis to show that liquidity decreased for stocks owned by connected funds (as defined in June 2008)

$$\begin{aligned} \textit{Post-Crisis Illiquidity}_i &= \alpha + \beta \textit{Pre-Crisis Illiquidity}_i + \gamma^1 \textit{Lehman-HF holdings}_i + \\ &+ \gamma^2 \textit{Non-Lehman HF holdings}_i + \gamma^3 \textit{Other Institutional holdings}_i + \\ &+ \textit{Pre-Crisis Control Variables}_i + \varepsilon_i \ , \qquad \text{(1a)} \end{aligned}$$

- Pre-crisis and Post-crisis: 3 months before and 3 months after September 15, 2008

- Excluded category from regression is holdings by non-institutional investors (notice that you cannot have this variable in the regression because of perfect collinearity with the other ownership variables, as they add up to 1)

- Relevant tests:
  - $\gamma^1 = 0$, test if Lehman connected HF ownership effect is different from non-institutional ownership
  - $\gamma^1 = \gamma^2$, test if Lehman connected HF ownership had same effect as other HF
  - $\gamma^1 = \gamma^3$, test if Lehman connected HF ownership had same effect as other non-HF-institution

	Log of Relative Spread		Log of Amihud Illiquidity		Daily Stock Return	
Pre-Crisis Market Beta	0.050	0.050	0.140	0.110	-0.090	-0.090
	(7.07)**	(5.45)**	(10.18)**	(4.94)**	(5.78)**	(3.18)**
Pre-Crisis Liquidity Beta	0.030	0.020	0.070	0.060	-0.050	-0.040
	(5.08)**	(3.44)**	(5.82)**	(4.01)**	(2.91)**	(2.22)*
Pre-Crisis Liquidity Level[1]	0.790	0.780	0.850	0.850	-0.020	-0.020
	(75.11)**	(31.95)**	(69.58)**	(16.42)**	(1.71)+	(0.78)
Log(Market Capitalization)	0.150	0.150	-0.050	-0.060	-0.220	-0.230
	(10.21)**	(2.63)**	(2.08)*	(2.03)*	(7.23)**	(6.28)**
Market Capitalization Rank	-1.830	-1.890	-1.080	-1.080	1.350	1.360
	(16.62)**	(4.63)**	(5.65)**	(1.25)	(5.84)**	(2.30)*
NASDAQ Stock Dummy	-0.080	-0.040	0.180	0.190	0.080	0.070
	(5.68)**	(2.26)*	(6.20)**	(6.34)**	(2.20)*	(1.33)
(a) Share Held By Lehman Hedge Funds	0.880	0.800	1.110	0.530	-2.320	-2.200
	(2.88)**	(2.71)**	(2.34)*	(0.94)	(3.45)**	(3.08)**
(b) Share Held By Non-Lehman Hedge Funds	-0.210	-0.170	-0.350	-0.390	0.180	0.210
	(2.89)**	(1.39)	(2.71)**	(2.30)*	(1.23)	(1.12)
(c) Share Held By Other Institutions	-0.210	-0.170	-0.170	-0.180	0.150	0.170
	(5.00)**	(2.75)**	(2.52)*	(2.05)*	(1.72)+	(1.18)
P-value for F-Test that: (a)=(b)	0.00	0.01	0.00	0.12	0.00	0.00
P-value for F-Test that: (a)=(c)	0.00	0.00	0.01	0.20	0.00	0.00
P-value for F-Test that: (b)=(c)	0.95	1.00	0.31	0.26	0.89	0.89
Observations	5,606	5,606	5,586	5,586	5,507	5,507
R-squared (within industry)	88%	88%	94%	94%	2%	2%
Estimation of Industry Effects	Random	Fixed	Random	Fixed	Random	Fixed

+ significant at 10%; * significant at 5%; ** significant at 1%

- Lehman connected HF ownership increased illiquidity in most specifications (and decreased returns)
- The three null hypotheses above are rejected
- It turns out that ownership by other HFs and institutions mitigated the drop in liquidity due to Lehman connected HF ownership (negative coefficient)
- The negative impact on returns of Lehman connected HF ownership suggests fire sales by these HFs

Placebo: Bear Stearns

- They want to show that it is the disappearance of the brokerage services that caused the drop in liquidity, as opposed to the news that a major bank went bust
- Compare with Bear Stearns failure
- BS was acquired by JP Morgan, which took over its activities
- No disruption to BS-connected HFs
- Focus on March 2008

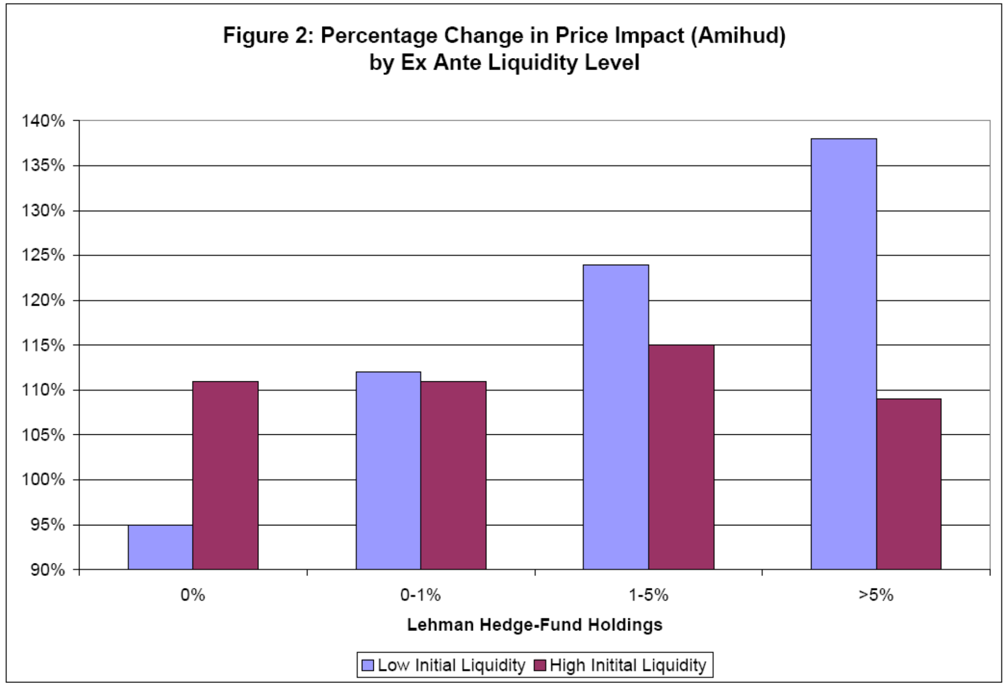
	Log of Relative Spread		Log of Amihud Illiquidity		Daily Stock Return	
Pre-Bear Crisis Market Beta	0.012	-0.004	-0.006	-0.018	0.004	0.000
	(2.48)*	(0.55)	(0.64)	(1.15)	(0.30)	(0.03)
Pre-Bear Crisis Liquidity Beta	0.022	0.016	0.022	0.020	-0.032	-0.030
	(4.59)**	(2.41)*	(2.43)*	(1.84)+	(2.64)**	(2.46)*
Pre-Bear Crisis Liquidity Level[1]	0.940	0.879	0.916	0.886	-0.005	-0.007
	(132.55)**	(51.42)**	(89.26)**	(33.32)**	(0.59)	(0.64)
Log(Market Capitalization)	0.070	0.053	0.044	-0.001	-0.042	-0.047
	(5.38)**	(5.21)**	(2.29)*	(0.05)	(2.08)*	(2.06)*
Market Capitalization Rank	-0.773	-0.879	-1.359	-1.367	0.230	0.245
	(8.73)**	(7.80)**	(10.46)**	(4.74)**	(1.64)	(1.77)+
NASDAQ Stock Dummy	0.104	0.042	0.211	0.156	0.079	0.065
	(10.72)**	(3.41)**	(10.39)**	(6.50)**	(3.04)**	(1.97)*
(a) Share Held By Lehman Hedge Funds (as of 12/2007)	0.310	0.055	-0.423	-0.382	0.139	-0.002
	(1.10)	(0.20)	(0.99)	(0.74)	(0.26)	(0.01)
(b) Share Held By Bear Funds (as of 12/2007)	0.019	-0.205	-0.307	-0.497	-0.142	-0.103
	(0.13)	(0.84)	(1.04)	(1.27)	(0.41)	(0.31)
(c) Share Held By All Other Hedge Funds (as of 12/2007)	-0.060	-0.204	-0.198	-0.319	0.090	0.074
	(0.98)	(2.53)*	(1.96)+	(2.02)*	(0.94)	(0.72)
(d) Share Held By Other Institutions (as of 12/2007)	0.065	-0.053	-0.060	-0.163	0.147	0.111
	(2.20)*	(1.13)	(1.22)	(2.20)*	(2.52)*	(1.83)+
P-value for F-Test that: (a)=(c)	0.37	0.52	0.83	0.87	0.65	0.86
P-value for F-Test that: (b)=(c)	0.20	0.35	0.61	0.91	0.93	0.89
P-value for F-Test that: (a)=(d)	0.39	0.69	0.40	0.66	0.99	0.83
P-value for F-Test that: (b)=(d)	0.12	0.01	0.30	0.44	0.65	0.78
Observations	5,717	5,717	5,590	5,590	5,490	5,490
R-squared (within industry)	92%	92%	96%	96%	1%	1%
Estimation of Industry Effects	Random	Fixed	Random	Fixed	Random	Fixed

+ significant at 10%; * significant at 5%; ** significant at 1%

- No effect on liquidity of connected HF ownership
- Consistent with their conjecture

Effect by liquidity groups

- The increase in illiquidity due to Lehman connected HF ownership was larger for stocks that were already illiquid



- Consistent with liquidity betas (β^2 in Acharya and Pedersen 2005) being larger for more illiquid stocks

Which dimension of liquidity deteriorated?

- Following Sadka (2006) they decompose liquidity into two dimensions
- Using transaction data, they estimate price impact components that are due to:
  - Information asymmetry (permanent impact of order flow on prices)
  - Transitory price impact (due to inventory and other transaction costs)
- For stocks owned by Lehman connected HFs they find that:
  - Permanent price impact $\downarrow$ (improvement in liquidity)
  - Transitory price impact $\uparrow$ (deterioration in liquidity)
- Interpretation:
  - HFs are liquidity providers, they trade patiently, and take the other side of liquidity demand (u)
  - But HFs are also informed traders. So they increase the cost of trading for their counterparties (the market-makers)

Conclusions

- The authors find a plausible source of exogenous variation in arbitrageurs' ability to provide liquidity
- They find evidence that when funding liquidity deteriorates also market liquidity deteriorates
- They focus on one direction of the liquidity spiral in Brunnermeier and Petersen (2009)

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Intermediary Asset Pricing

- Adrian, Etula, Muir (JF, 2014) use *broker-dealer leverage* as an additional pricing factor in a two-factor asset pricing model, including the market factor

- The price for risk of broker-dealer leverage is positive, consistent with pro-cyclical leverage. That is, leverage increases in good times for broker-dealers

- The new factor does a good job in pricing 25 Fama-French portfolios, Momentum portfolios, and treasuries' portfolios

- He, Kelly, and Manela (JFE, 2017) instead use the aggregate *capital ratio of primary dealers* as the additional factor

$$\eta_t = \frac{\sum_i Market\ Equity_{i,t}}{\sum_i \left(Market\ Equity_{i,t} + Book\ Debt_{i,t}\right)}$$

- Primary dealers are a restricted set of about 20 financial institutions that are counterparties to the NY Fed in its implementation of monetary policy

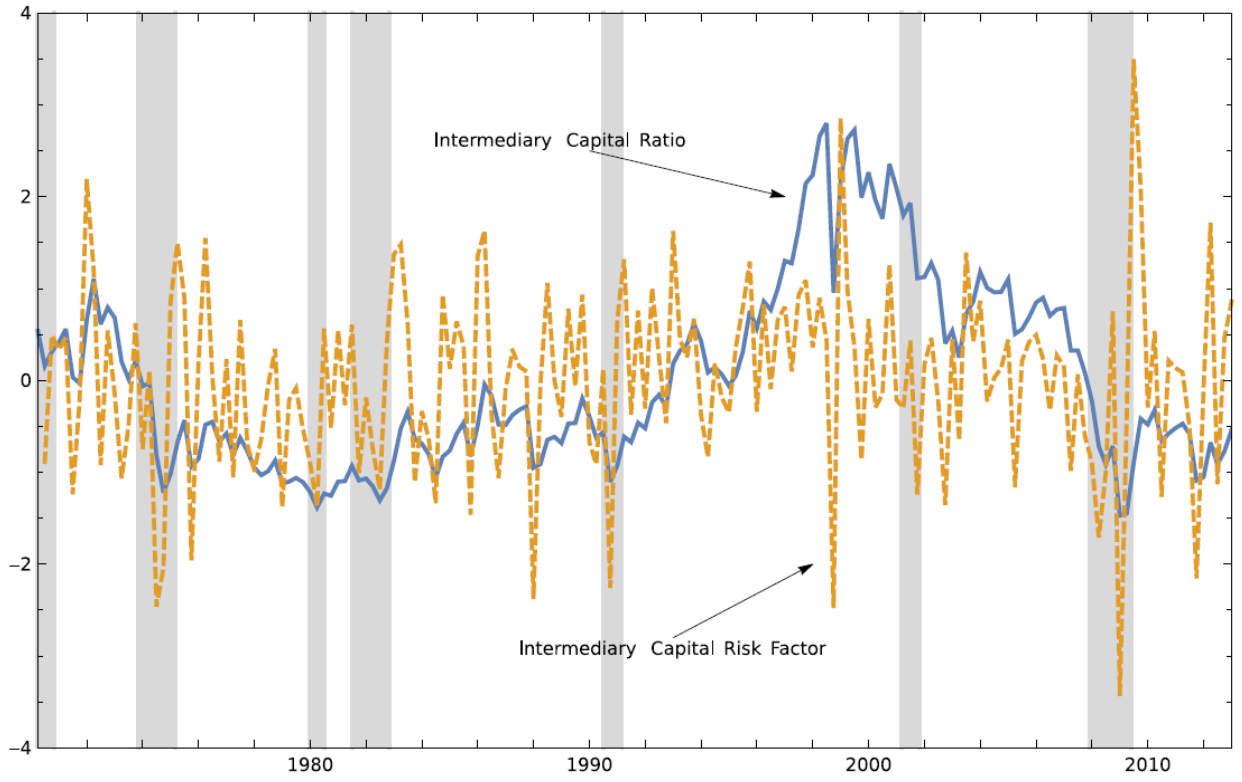
- Justification for why intermediary capital enters the pricing kernel (i.e. the marginal utility of wealth):

  1. Intermediaries are marginal investors in pricing assets, especially in specialized markets different from equity. E.g. intermediaries are dealers in 95% of OTC bond transactions. 50% of CDS are sold by top 5 dealers

  2. When their capital is low (in bad times), intermediaries need to pass up on attractive investment opportunities. Hence, a marginal dollar is more valuable when capital is low

- They show that the capital ratio is pro-cyclical. Hence, its price of risk should be positive

- They construct the intermediary capital ratio factor as the AR(1) innovations for η_t



- Incidentally, notice the drop in the factor in 1998 (LTCM crisis). This drop is useful in pricing assets (e.g. options, but not equities) that were affected by this shock

Main Results of HKM

- In a two-factor model, they price seven categories of assets: 25 FF portfolio, Bonds, Sovereign, Options, CDS, Commodities, Currencies

	FF25	US bonds	Sov. bonds	Options	CDS	Commod.	FX	All
Capital	6.88	7.56	7.04	22.41	11.08	7.31	19.37	9.35
	(2.16)	(2.58)	(1.66)	(2.02)	(3.44)	(1.90)	(3.12)	(2.52)
Market	1.19	1.42	1.24	2.82	1.11	−0.55	10.14	1.49
	(0.78)	(0.82)	(0.32)	(0.67)	(0.41)	(−0.25)	(2.17)	(0.80)
Intercept	0.48	0.41	0.34	−1.11	−0.39	1.15	−0.94	−0.00
	(0.36)	(1.44)	(0.33)	(−0.31)	(−2.77)	(0.83)	(−0.83)	(−0.00)
R^2	0.53	0.84	0.81	0.99	0.67	0.25	0.53	0.71
MAPE, %	0.34	0.13	0.32	0.14	0.18	1.15	0.44	0.63
MAPE-R, %	0.40	0.26	0.45	0.68	0.39	1.40	0.62	0.63
RRA	2.71	3.09	2.52	8.90	3.61	2.88	8.26	3.69
Assets	25	20	6	18	20	23	12	124
Quarters	172	148	65	103	47	105	135	172

- The price of risk is 'similar' across asset classes, as it should be if the pricing kernel is correct. I.e. the same investors pricing assets in different markets implies that the pricing kernel/price of risk is the same across markets

- They cannot reject the null that the price of risk is 9% across all asset classes (but they can reject 0%, hence there's sufficient power)

- An extensive definition of intermediaries does not do as well. Hence, primary dealers are more important

- Using leverage of non-financial institutions does not have any pricing power

- When they decompose the capital ratio into equity (the numerator) and debt (at the denominator), equity is much more important

Comparison with AEM

- AEM do better in pricing equity (including momentum) and bonds, KHM do much better with all other asset classes

- What are the differences?

- AEM find that leverage of *broker-dealers* is pro-cyclical, while KHM find that leverage of *primary dealers* (the reciprocal of the capital ratio) is counter-cyclical

- How to reconcile this puzzle?

- The different behavior is not due to using market leverage instead of book leverage, the two versions of leverage are highly correlated

- What makes the difference is the focus on different levels of aggregation and different entities

- HKM argue that focusing on the balance sheet of the individual broker-dealers (considered by AEM), which can be a small institution, misses out on the role of *internal capital markets* within financial conglomerates, which is the level of aggregation that HKM consider

- Indeed, the conglomerates are diversified entities that are subject to different shocks than individual broker-dealers

- Moreover, the parent company can transfer funds, if needed, to its subsidiaries to finance asset purchases (e.g. as Lehman was doing before its collapse)

- Hence, what matters more is the holding company capital availability, not the individual subsidiary

- A similar notion is present in Franzoni and Giannetti (JFE, 2019) who show that hedge funds that have an affiliation with a financial conglomerate are better positioned to hold risky assets in bad times

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Differences in theoretical motivation

- The background for pricing kernels with counter-cyclical leverage (as in HKM) is provided by models with *constraints on equity* (He and Krishnamurthy 2012, 2013; Brunnermeier and Sannikov 2014)
- In these models, a negative shock to intermediaries' capital reduces their risk bearing capacity, they drop assets, causing a further reduction in the value of equity
- If there is a constraint on leverage, intermediaries also reduce debt. But the drop in equity is more important
- On the other hand, a pro-cyclical leverage emerges from models with constraints on leverage, a la Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009)
- In these models, intermediaries are forced to reduce leverage in bad times, which triggers fire sales
- Different financial intermediaries are subject to different types of constraints (e.g. commercial banks more likely exposed to capital ratio constraints, hedge funds to leverage constraints)
- Hence, the true pricing kernel is possibly a combination of the two types of kernels in different states of the world and asset markets

Coval and Stafford (JFE 2007)

- Focus on fire sales
- A fire sale occurs when a distressed firm/investor has to liquidate its assets. Because the assets are specialized, few buyers are present in the market. Then, the price has to decline enough to attract buyers to the market (see Shleifer and Vishny, JEP, 2011)
- The evidence of price pressure from fire sales is indirect evidence of limits of arbitrage
- The price deviates from fundamentals for an extended period of time and no other investor jumps in immediately to provide liquidity
- Possibly because the other investors in that security are also experiencing financial distress and limits on their capital
- The authors focus on stock sales by mutual funds that experience significant capital outflows (redemptions)
- Reason: identify an exogenous reason for the fire sale
- That is: a reason that is unrelated to the value of the asset that is sold

Identifying fire sales

- They show that mutual funds experiencing outflows reduce their positions more than other funds
- Symmetrically, funds experiencing inflows increase their positions
- Then, define a flow induced trade for stock i in quarter t as:

$$PRESSURE\_1_{i,t} = \frac{\sum_j \left(\max\left(0, \Delta Holdings_{j,i,t}\right) | flow_{j,t} > Percentile\left(90th\right)\right)}{AvgVOLUME_{i,t-12:t-6}} - \frac{\sum_j \left(\max\left(0, -\Delta Holdings_{j,i,t}\right) | flow_{j,t} < Percentile\left(10th\right)\right)}{AvgVOLUME_{i,t-12:t-6}} \tag{2}$$

- That is, sum the positive change in stock holdings for the funds that are top decile in flows and substract the sum of the negative change in holdings for the funds that are in the bottom decile of flows
- Fire sale stocks are those that rank in the lowest decile of the $PRESSURE\_1_{i,t}$ variable

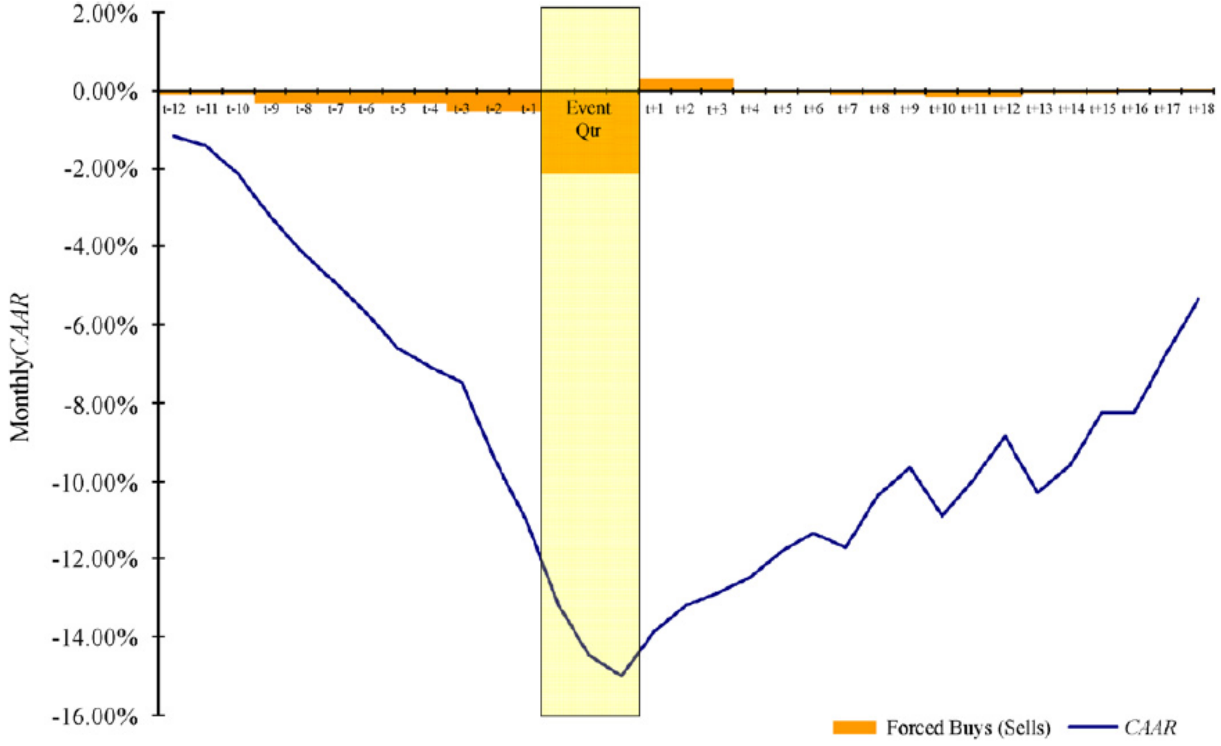
Price behavior of fire sale stocks

- One would like to disentangle the effect of selling due to negative information on the stock from the effect of fire sales

- The assumption is that price pressure induced by fire sales is going to revert

- Instead, for information driven sales, the price should remain permanently at the lower level

- Here's the price pattern for stocks with flow induced sales (bottom decile stocks by $PRESSURE\_1_{i,t}$). They average across stocks and then across quarters

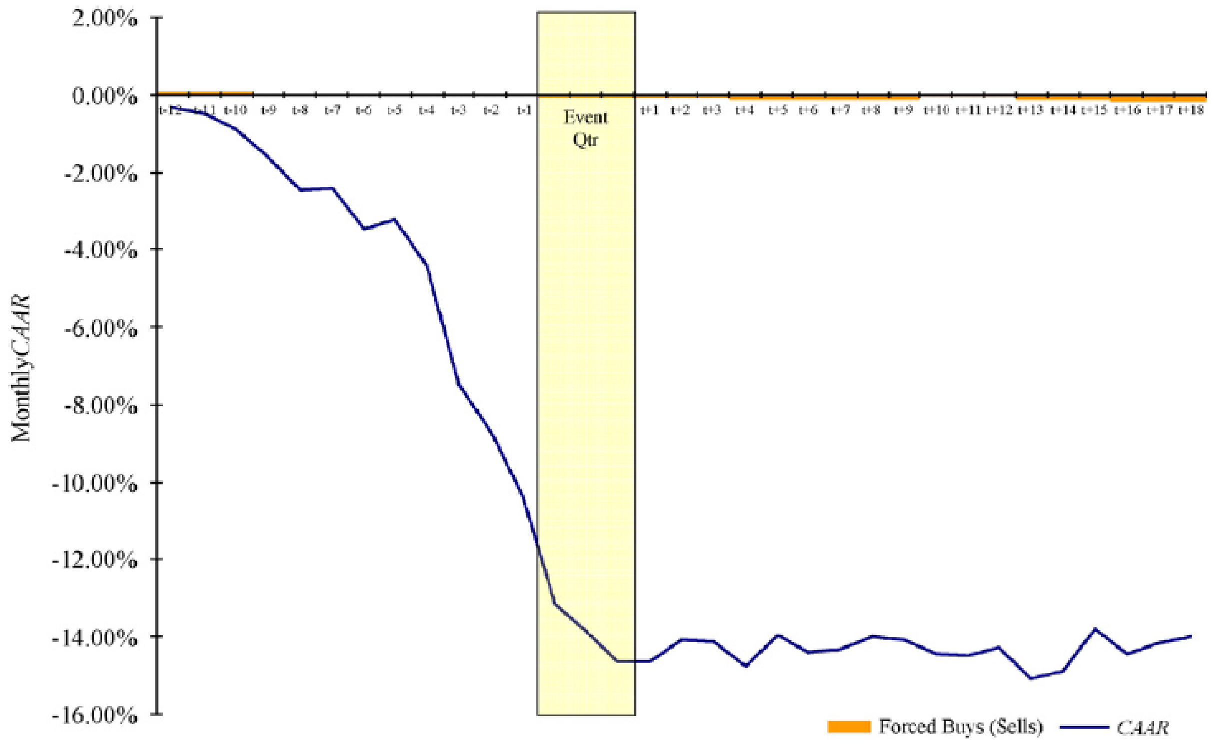


- You see that the price eventually reverts, consistent with price pressure and lack of liquidity

- Magnitude: over the two quarters through month t the abnormal stock returns is -7.9% (t-stat=-3.45)

- Prices revert over the following 18 months

- Instead, for stocks that are subject to voluntary sales (that is, construct Pressure variable without conditioning on flows) the price pattern is



- Consistent with information driven sales

- Notice that also in the case of flow driven sales the price starts declining before the quarter of the fire sale

- Possible explanations:
  - Outflows are persistent. So mutual funds were already selling that stock because of prior outflows
  - The prior price declines cause the negative performance of the fund which receives redemptions and is ultimately obliged to sell

Two profitable trading strategies

- Liquidity provision:
  - Buy the stocks that have been subject to a fire sale in the past year (skipping last quarter for informational reason) and short the stocks that are subject to positive price pressure
  - They show that alpha is 0.45% (monthly) from four-factor model (t-stat=2)
- Front running:
  - Based on past fund performance, predict future fund flows in a regression framework
  - Short the stocks that are mostly held by funds with high expected outflows and go long the stocks by funds with high expected inflows
  - That is, trade before and in the same direction as the funds that receive high out/inflows
  - The alpha of this strategy from four-factor model is 0.65% (monthly) with t-stat=2.51%
- Barbon, Di Maggio, Franzoni, Landier (2019) find that brokers foster front running of fire sales, more than liquidity

Possible explanations

- Duffie (2010) suggests two potential explanations, both of which prevent prices from adjusting immediately
  1. Investor inattention
  2. Imperfectly informed investors
- A model with **inattentive investors** (Duffie, 2010) is one in which a group of traders is only present in the market at infrequent dates, because continuous attention is costly
- In the same model, there are also investors that are present at all times, but have limited risk bearing capacity
- These investors require a compensation for absorbing the extra-supply of shares that originates from the fire sale. Therefore a price concession is necessary for them to buy the fire-sale stocks
- They will gradually sell the shares to the inattentive investors as they return to the market at higher prices

- This story generates the price drop in the fire-sale period and the subsequent reversal
- Similar predictions arise from an alternative model in which investors are **imperfectly informed** about the cause of the price drop, following the fire sale
- The market does not know whether the price drop is due to bad news or to exogenous events (such as a mutual fund in distress). In other words, the market assigns positive probability to negative information causing the price drop
- Over time, the market updates the conditional probability of adverse information downwards, and the price moves back up
- The two stories are to a large extent observationally equivalent. It is an open empirical challenge to disentangle them

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A 'more exogenous' measure of price pressure

- Edmans, Goldstein, and Jiang (2012, JF) require an exogenous source of price pressure in their study of the effect of underpricing on the takeover probability

- Coval and Stafford (2007) investigate actual trades executed by mutual funds

- These trades may not be a valid source of price variation if funds are trading deliberately based on private information on a firm's fundamentals

- These authors, instead, use mutual funds' hypothetical trades mechanically induced by flows by their own investors

- That is, they replace $Pressure$, with

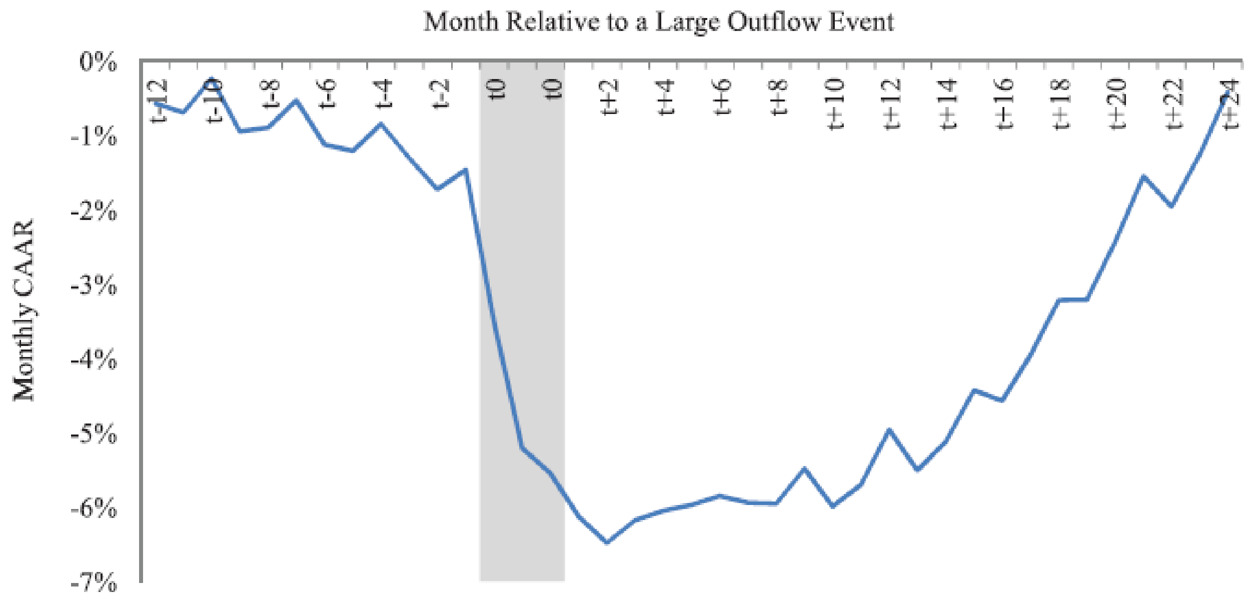
$$MFFlow_{i,t} = \sum_{j=1}^{m} \frac{F_{j,t} \times weight_{i,t-1,j}}{VOL_{i,t}},$$

where $F_{j,t}$ are the flows into fund j, $weight_{i,t-1,j}$ is the weight of stock i in fund j's portfolio in the prior period, $VOL_{i,t}$ is the stock trading volume

- They argue that fund investors' decisions to accumulate or divest from mutual funds are unlikely to be directly correlated with the takeover prospects of individual firms held by the fund

- Hence, investor flows lead to price pressure that may affect the probability of a takeover but are not directly motivated by this probability

- They find that their measure causes significant price changes followed by slow reversal that ends with full correction only after about 2 years



Lou (2012, RFS)

- He provides a mutual-fund-flow based explanation for three asset pricing regularities:
  1. Short-term persistence in mutual fund performance
  2. The 'smart money' money effect: mutual fund flows predict future fund performance
  3. Price momentum
- The explanation rests on two results from prior research:
  1. Mutual fund flows can cause price pressure (Coval and Stafford, 2007)
  2. Mutual fund flows are predictable based on past performance (e.g. Chevalier and Ellison, 1997)

Intuition for the result

- Past winning funds attract flows. The losing funds suffer outflows
- The funds scale up (or down if losers) their portfolios, trading in the stocks that they already hold
- Hence, inflows cause positive price pressure on past winners. Outflows cause negative price pressure on past losers
- This price pressure brings about continuation in prior stock returns
- As a result, winning (losing) funds/stocks contintue to be winners (losers) in the short run
- Also, flows predict future performance
- On a longer horizon, the price pressure vanishes and prices revert back

Empirical strategy

- Construct a stock level measure of flow-induced price pressure by aggregating the trading activity in a given stock by different mutual funds

$$FIT_j = \frac{\sum_i shares_{i,j,t-1} * flow_{i,t} * PSF_{i,t-1}}{\sum_i shares_{i,j,t-1}}$$

  where, $shares_{i,j,t-1}$ is the shares of stock j held by fund i in quarter $t-1$. $flow_{i,t}$ is the flows in the quarter t to the mutual fund i. $PSF_{i,t-1}$ a previously estimated partial scaling factor that translates flows into percentage of shares traded

- FIT_j gives the trading activity of the entire mutual fund industry in a given share and quarter

- FIT_j measures price pressure

- The author wants to show that FIT drives out:

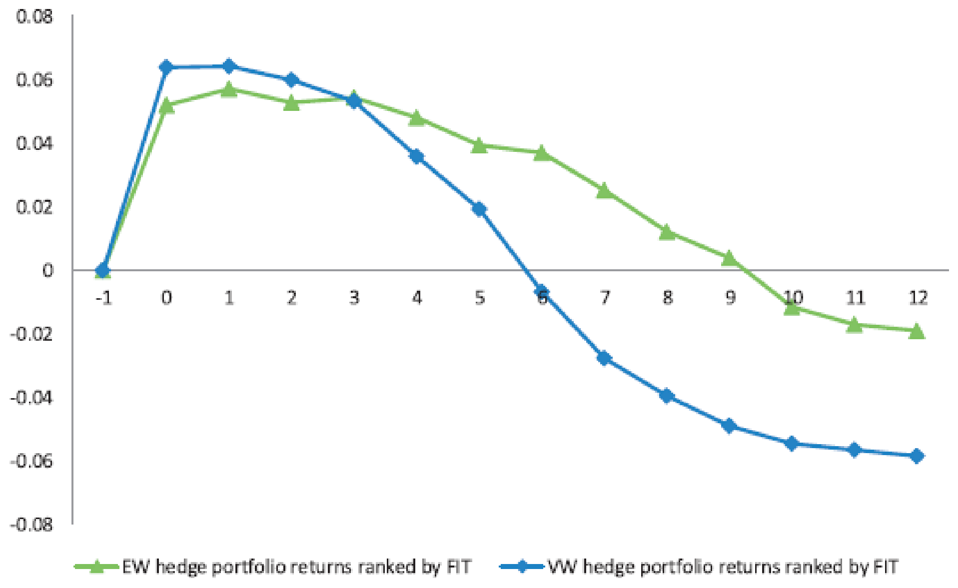
  1. Past fund returns as explanatory variable for future fund returns (mutual fund return persistence)

2. Past flows as explanatory variable for future fund returns (smart money effect)

3. Past stock returns as explanatory variable for future stock returns (momentum)

Flow-induced price pressure

- In the quarter in which flows occur, they cause pressure
- Then, reversal
- Long-short portfolio in deciles 10 - 1 of FIT:



- Similar pattern to Coval and Stafford (2007), but reversal does not occur immediately, it occurs after a year

- Two countervailing forces for delayed reversal:

  1. Price pressure which should be immediately reversed

  2. Fund flows are positively autocorrelated. So, they cause the price pressure to continue

- In Lou (2012), the second effect prevails. In Coval and Stafford (2007), the first effect prevails, possibly because they are looking at more extreme flows, which cause larger reversals, and are less likely to persist

Predicting flows

- In the previous figure, the price pressure is contemporaneous to FIT
- The author would like to be able to predict future price pressure
- For this reason, it is necesary to predict mutual fund flows
- Flows are highly predictable using past performance and past flows

$$\begin{aligned} flow_{i,t+1} = & \beta_0 + \beta_1\, alpha_{i,t} + \beta_2\, adjret_{i,t} + \beta_3\, flow_{i,t} + \beta_4\, flow_{i,t-1} \\ & + \beta_5\, flow_{i,t-2} + \beta_6\, flow_{i,t-3} + \varepsilon_{i,t+1}, \end{aligned}$$

Table 4
Predicting future flows

	Fama-MacBeth			Pooled OLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.028**	**0.028**	**0.010**	**0.016**	**0.014**	**0.007**
	(5.38)	(5.77)	(3.65)	(25.89)	(18.77)	(7.72)
$alpha_{i,t}$	**4.827**	**1.766**	**0.953**	**4.232**	**2.453**	**1.330**
	(9.67)	(4.38)	(4.47)	(9.02)	(9.15)	(5.43)
$adjret_{i,t}$		**0.396**	**0.229**		**0.202**	**0.089**
		(7.34)	(6.72)		(5.17)	(2.74)
$flow_{i,t}$			**0.194**			**0.228**
			(8.78)			(17.21)
$flow_{i,t-1}$			**0.102**			**0.109**
			(5.28)			(7.55)
$flow_{i,t-2}$			**0.122**			**0.090**
			(6.29)			(6.03)
$flow_{i,t-3}$			**0.033**			**0.029**
			(5.47)			(3.67)
Adjusted R^2	4.53%	7.70%	24.79%	5.25%	7.14%	19.83%
No. observations	98,264	98,264	95,285	98,264	98,264	95,285

- The next step is to obtain fitted values from these regressions $\widehat{flow}_{i,t+1}$
- The fitted values are used to compute expected flow-induced price pressure

$$E_t\left[FIT_j\right] = \frac{\sum_i shares_{i,j,t} * E_t\left[flow_{i,t+1}\right] * PSF_{i,t}}{\sum_i shares_{i,j,t}}$$

- One can also compute expected FIT at the fund level, as the weighted average of the FIT of all the stocks in a fund portfolio

$$E_t\left[FIT_i^*\right] = \sum_j \left(E_t\left[FIT_j\right] * \omega_{i,j,t}\right)$$

where $\omega_{i,j,t}$ is the weight of stock j in fund i's portfolio

- This quantity measures the price pressure on the portfolio holdings of a given fund from the trading activity of the entire mutual fund sector

Performance Persistence and Smart Money Effect

- Prior literature shows that funds with high (low) performance in the past continue to have high (low) peformance in the next year (Carhart, 1997; Cohen, Coval, and Pastor, 2005)
- This could result from the skill of the managers, or from the price pressure of flows
- Similarly, prior literature shows that flows predict performance (smart money, Gruber, 1996)
- This could result from investors' ability to spot the good managers, or from the price pressure of the flows
- Run a horse race for these alternative explanations:

$$RET_{i,t+1} = \beta_0 + \beta_1 \; E_t[FIT_i^*] + \beta_2 \; alpha_{i,t} + \beta_3 \; flow_{i,t} + \gamma \; Control_t + \varepsilon_{i,t+1}$$

where the dependent variable is the fund return in quarter t+1, and the explanatory variables include the fund level predicted FIT, the alpha from a four-factor model (to test for performance persistence), and the flows (to test for the smart money effect)

Table 8
Mutual fund performance regressions

	Fama-MacBeth Regressions of Quarterly Fund Returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Intercept	**0.050**	**0.053**	**0.053**	**0.054**	**0.049**	**0.051**	**0.051**
	(5.47)	(5.85)	(5.69)	(5.82)	(5.20)	(5.48)	(5.30)
$E[FIT^*]$	**3.081**				**2.602**	**2.952**	**2.687**
	(3.06)				(2.35)	(2.93)	(2.43)
$aplha_{i,t}$		**0.581**		**0.548**	0.042		0.005
		(3.82)		(3.64)	(0.24)		(0.03)
$flow_{i,t}$			**0.012**	**0.010**		0.004	0.004
			(2.28)	(2.08)		(0.82)	(0.93)
$expenses_{i,t}$	−0.351	−0.830	−0.765	−1.138	−0.319	−0.657	−0.653
	(−0.27)	(−0.55)	(−0.48)	(−0.75)	(−0.26)	(−0.51)	(−0.52)
$\log(age_{i,t})$	0.000	0.000	0.001	0.001	0.000	0.000	0.001
	(0.17)	(0.47)	(0.63)	(0.90)	(0.37)	(0.65)	(0.84)
$\log(numStocks_{i,t})$	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**	**0.002**
	(3.58)	(3.95)	(3.72)	(3.78)	(3.27)	(3.44)	(3.02)
$\log(TNA_{i,t})$	−0.001	**−0.001**	**−0.001**	**−0.001**	−0.001	**−0.001**	**−0.001**
	(−1.91)	(−2.18)	(−2.18)	(−2.30)	(−1.82)	(−2.08)	(−2.00)
$turnover_{i,t}$	**0.002**	0.002	0.002	0.002	**0.001**	**0.002**	**0.001**
	(2.05)	(1.76)	(1.56)	(1.74)	(1.96)	(2.06)	(1.96)
Adjusted R^2	15.77%	11.03%	8.06%	11.91%	17.46%	16.53%	18.24%
No. observations	93,805	93,805	93,805	93,805	93,805	93,805	93,805

- The predicted FIT always wins the horse races (columns (5)-(7))
- Conclusion: flow-induced pressure seems to explain both performance peristence and the smart money effect

Momentum

- Jagadeesh and Titman (1993, 2001) find that past winners continue to outperform past losers in the next 3 to 12 months

- Can flow-induced price pressure explain this effect?

- Run a horse race, using stock-level FIT as competing variable:

$$ret_{j,t+1:t+3} = \beta_0 + \beta_1\ E_t[FIT_j^k] + \beta_2\ ret_{j,t-k:t-1} + \gamma\ Control_t + \varepsilon_{j,t+1:t+3}$$

where the dependent variable is the stock return in the next quarter, while k ranges from 3 to 12

Table 9
Stock price momentum

Panel A: The full sample

	$k=12$		$k=6$		$k=3$	
	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**0.103**	**0.092**	**0.096**	**0.077**	**0.094**	**0.084**
	(2.81)	(2.36)	(2.63)	(2.01)	(2.58)	(2.34)
$E_t[FIT_j^k]$		**0.085**		**0.145**		**0.250**
		(3.07)		(2.93)		(3.32)
$ret_{j,t-k:t-1}$	**0.020**	**0.015**	**0.027**	**0.020**	**0.024**	0.014
	(4.06)	(3.31)	(3.59)	(2.82)	(2.29)	(1.40)
$ret_{j,t}$	−0.024	**−0.029**	−0.024	**−0.030**	−0.020	**−0.029**
	(−1.67)	(−2.16)	(−1.63)	(−2.26)	(−1.35)	(−2.18)
$ret_{j,t-36,t-k-1}$	**−0.005**	**−0.004**	**−0.004**	**−0.004**	**−0.004**	**−0.004**
	(−3.19)	(−3.05)	(−2.64)	(−2.56)	(−2.54)	(−2.54)
$bm_{j,t}$	0.005	0.005	0.005	0.005	0.006	0.006
	(1.33)	(1.37)	(1.25)	(1.42)	(1.40)	(1.78)
$\log(mktcap_{j,t})$	**−0.003**	−0.003	**−0.003**	−0.002	−0.003	−0.002
	(−2.16)	(−1.73)	(−1.96)	(−1.33)	(−1.88)	(−1.59)
$turnover_{j,t}$	**−0.004**	**−0.005**	−0.004	**−0.004**	−0.004	**−0.004**
	(−2.02)	(−2.26)	(−1.87)	(−2.06)	(−1.63)	(−2.05)
Adjusted R^2	7.08%	7.85%	6.75%	7.85%	6.38%	7.88%
No. observations	198,692	198,692	198,692	198,692	198,692	198,692

- You note that predicted FIT explains 25%, 31%, and 42% of the momentum effect, respectively (these numbers measure the decline of the slope on lagged returns)

- The explanatory power of FIT is relatively stronger in the context of shorter formation periods because on longer formation periods it is more likely that winning mutual funds end up holding portfolios of losers (given the reversal that occurs at some point)

- Also, this analysis only looks at price pressure from trading by mutual funds. If the analysis is extended to other institutional investors the explanatory power could increase

Effects of institutional trading on second moments

- Greenwood and Thesmar (2011) study the relationship between the ownership structure of assets and non-fundamental risk:
  - Limits of arbitrage allow liquidity shocks to have price impact
  - Stocks that are held by investors with more volatile trading (e.g. because of more volatile flows) are going to experience more non-fundamental volatility as a result of price-pressure
  - For stocks with a more diversified investor base the liquidity shocks are more likely to cancel out
  - Construct a measure of stock level **fragility** as a positive function of the volatility and correlation of the flows of the mutual funds owning the stock, and negative function of the number of mutual funds owning the stock
  - They show that fragility explains 8% of future stock-level volatility
  - They also construct a measure of co-fragility using the correlation of flows of mutual funds that own the stock

- Co-fragility explains covariance beyond standard factors
- Issue: endogeneity. Flows could be correlated because of correlated preference shocks to owners. Not really a liquidity effect, but an expected return effect

- Anton and Polk (2014) relate stock-level commonality in mutual fund ownership (‘**connectedness**’) to excess comovement of stock returns
  - Motivation: mutual fund ownership causes price pressure (Coval and Stafford, 2007, Lou, 2012). Ownership by the same mutual funds causes price pressure in the same direction (i.e. comovement)
  - For each pair of stocks, they compute connectedness as the share of the total market capitalization of the two stocks that is held by the same mutual funds
  - They show that connectedness predicts excess correlation, which is the correlation of the residuals from a four-factor regression on daily data, within a month
  - This predictive power is stronger when connected funds experience large flows
  - They solve the endogeneity issue by exploiting exogenous variation in mutual fund ownership resulting from outflows from funds involved in the late-trading scandal in 2003

- They construct a trading strategy: go long stocks whose return is low when the return on the connected stocks is also low, short stocks whose return is high when return on connected stocks is also high (that is, isolate stocks whose prices are more likely to move because of price pressure by mutual funds). The strategy earns 9% per year
- Show that hedge funds on average have negative loadings on the returns from this strategy. It means that hedge funds are causing the price pressure, rather correcting it

- Ben-David, Franzoni, and Moussawi (2018) focus on the price pressure in the **ETF** market which propagates to the underlying securities via arbitrage
  - They show that stocks with higher ETF ownership have higher total volatility and have a higher mean-reverting component in stock prices (i.e. more noise)
  - Channel: noise traders cause price pressure in ETFs; arbitrageurs trade the underlying securities to profit from the price pressure; the arbitrage activity propagates the initial shock to the underlying securities
  - Identification: exploit exogenous variation in ETF ownership occuring when Russell indexes are reconstituted annually, in a Regression Discontinuity Design (as in Chang, Hong, Liskovich, 2015)

- Argument: ETFs are more liquid vehicles. Then, they attract investors who wish to trade at higher frequency (as in Amihud and Mendelson, 1986). Among these investors there are noise traders. So, liquidity shocks are impounded at higher frequency because of ETFs

- Punchline: Even passive institutional investors such as ETFs can cause price dislocations

- Ben-David, Franzoni, Moussawi, and Sedunov (2016) study the effect of stock ownership by **large institutional investors** on stock volatility

  - They find that large institutional investors increase stock volatility, controlling for ownership by all institutions

  - Identification: Merger between BlackRock and BGI in 2009. The merger was an exogenous event that increased the amount of institutional ownership by large firms

  - Channel: trades by large institutions have a larger price impact

  - Story: A large insitution cannot be considered as a collection of smaller independent entities. There is a correlated beahavior within the institution. E.g., common research or risk management functions cause the different entities to trade in a correlated way. Therefore the trades of large institutions are less diversifies and cause larger price impact

- The authors show that large institutional ownership is correlated with less efficient pricing (more price reversal)

- Vayanos and Woolley (2013) develop a theory that generates many of the price pressure effects of institutional investors that are found in the data
  - Investors chase performance because they infer manager ability from returns
  - Flows put pressure on prices, in a context with limited arbitrage
  - This fact generates momentum in the short run and reversal in the long run
  - Also, price pressure generates excess comovement