Metaorders: Market Impact and Information

Market Microstructure – Confronting Many Viewpoints #3
2014

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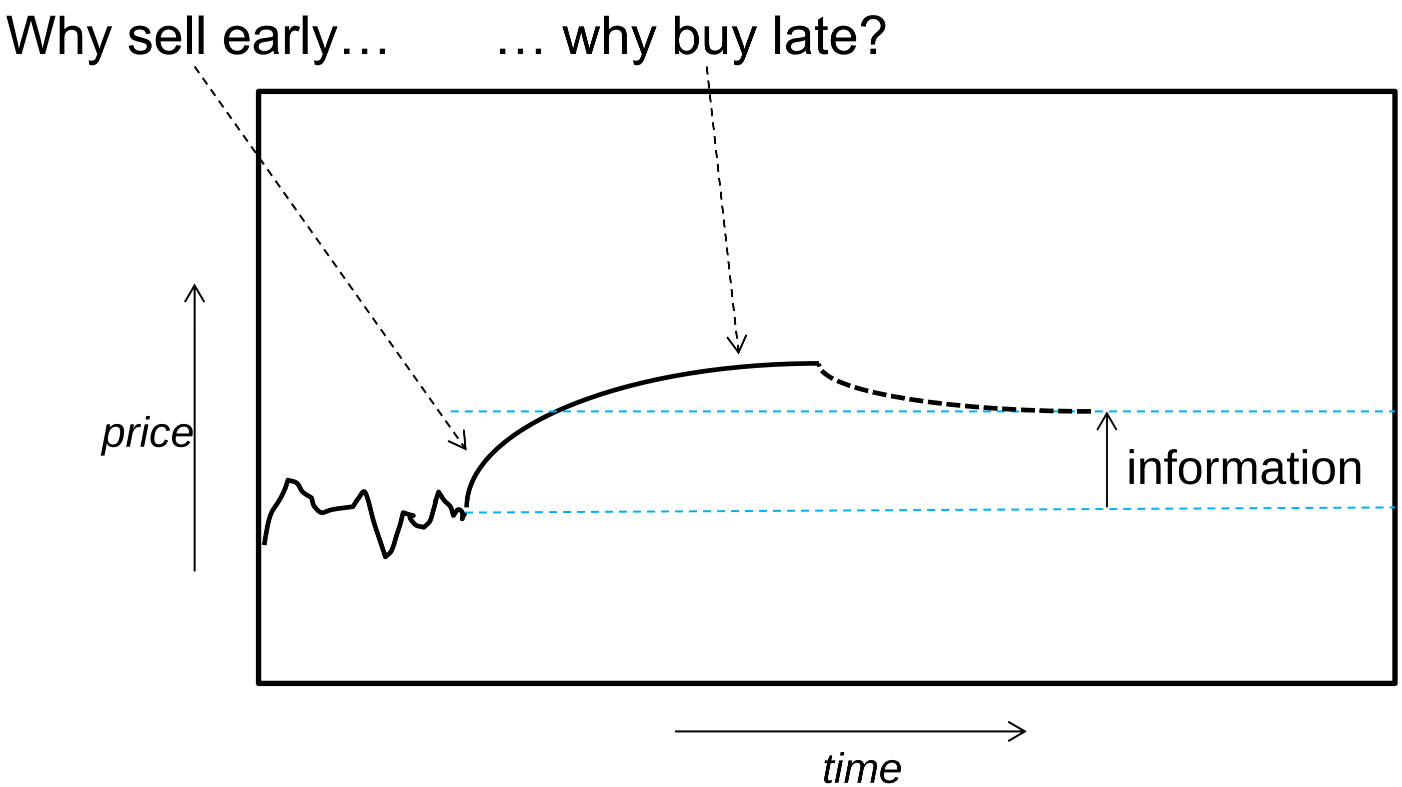
Collaborators

A. M. Criscuolo, J. D. Farmer, A. Gerig and F. Lillo (fair pricing: theory & numerics)
C. Gomes (fair pricing: empirical)

Related work:
N. Bershova and C. R. Stephens (order flow)
O. Missaoui (beating "fair pricing": machine learning)

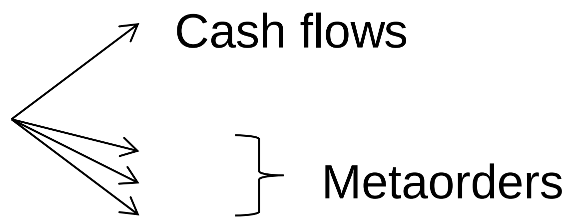
Rationality and institutional trades



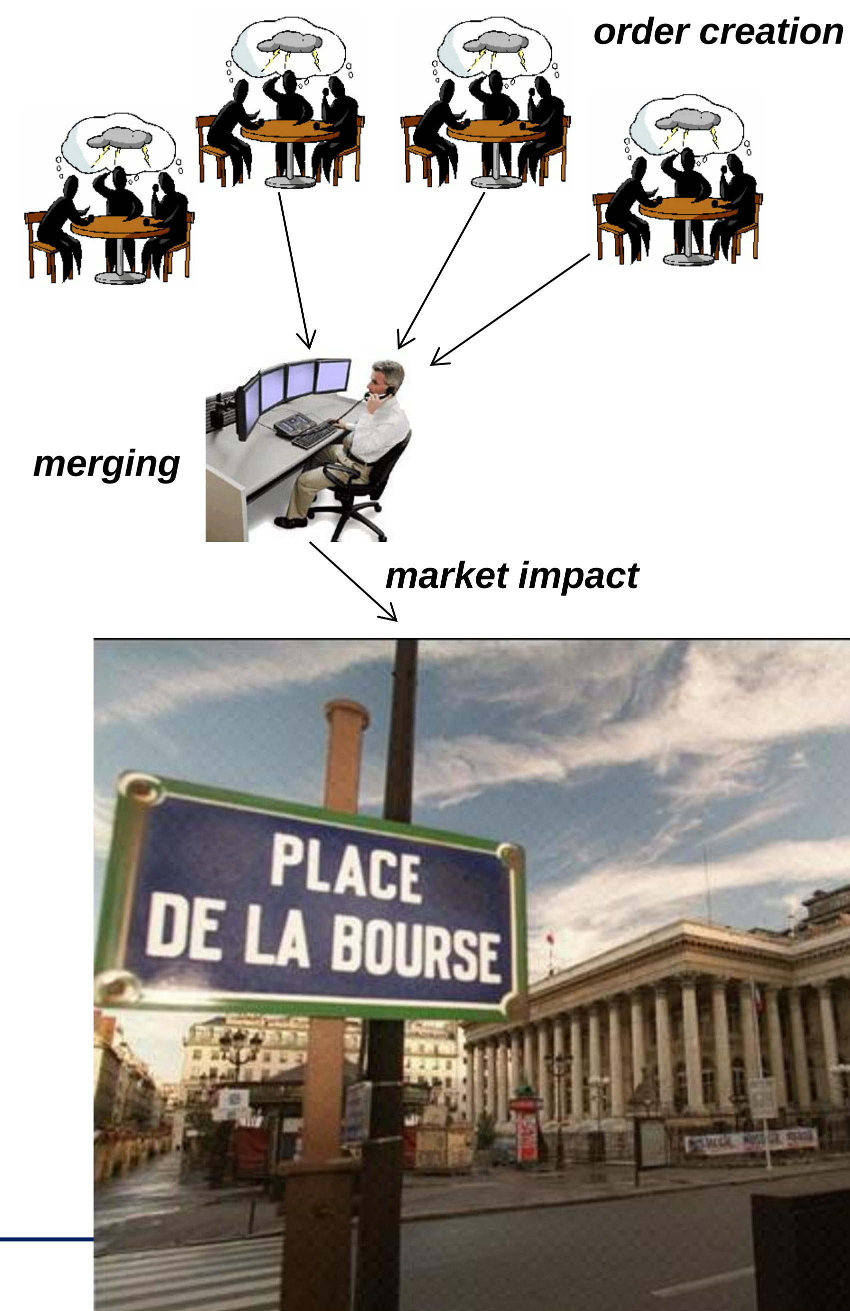
<u>Metaorders concept</u>… many traders react to same signal,
no-one knows the metaorder size

- portfolio managers create orders in response to signals (vote)
- orders are merged into a metaorder, market sets a new price (election)

Empirical study of institutional metaorders

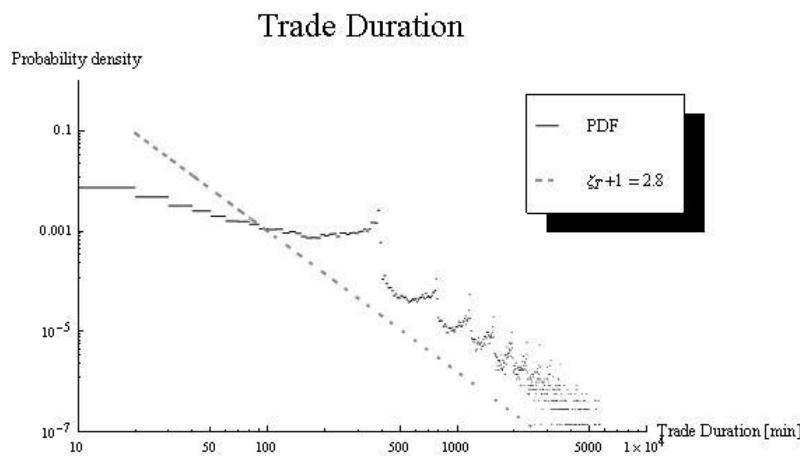


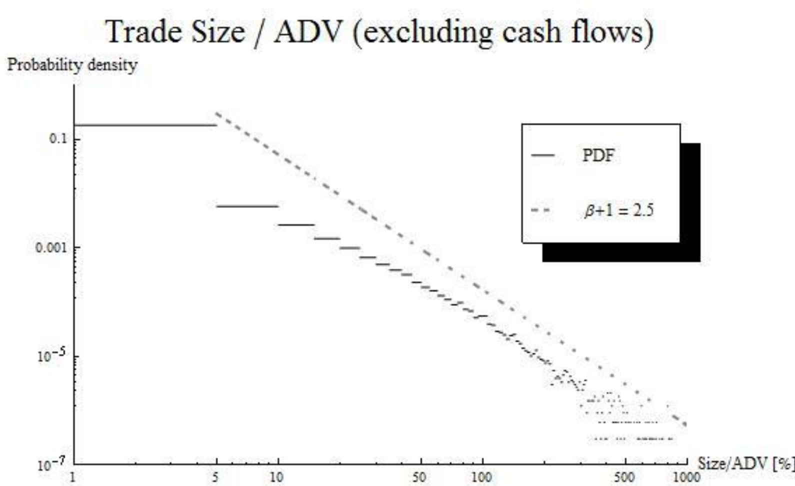
- 112 portfolio managers, 1.16m orders, 2009 – 3/2012
- <u>Metaorders: merge by symbol, side, firm, consecutive days</u>
- 129,944 filtered metaorders ($1.2tr)
  - <u>> 1% of daily volume</u>
  - > 5 minutes
  - participation rate < 50%
  - starting price > $1
  - volatility < 200%

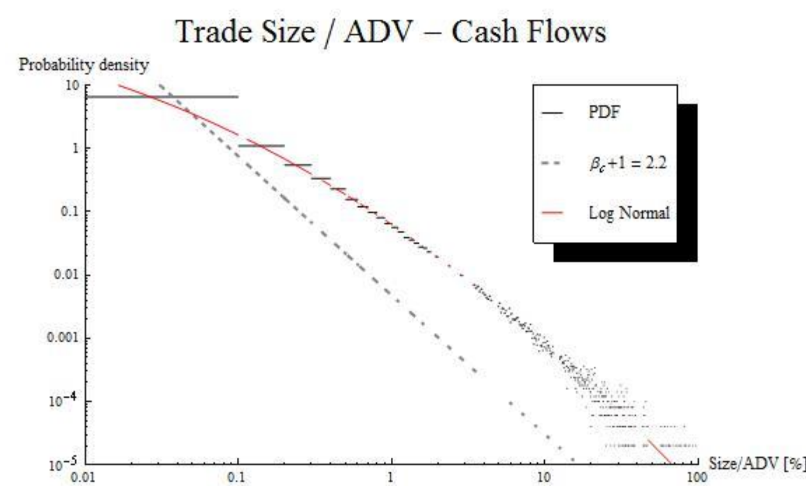


Metaorder size / duration distributions

(unfiltered)

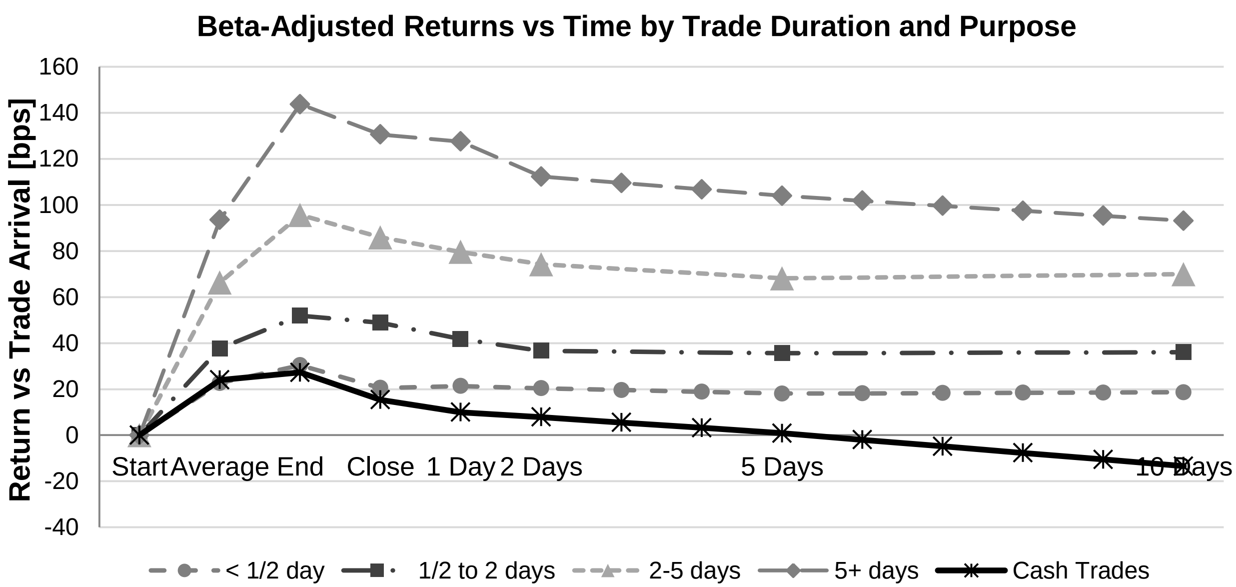






Price reversion and permanent impact

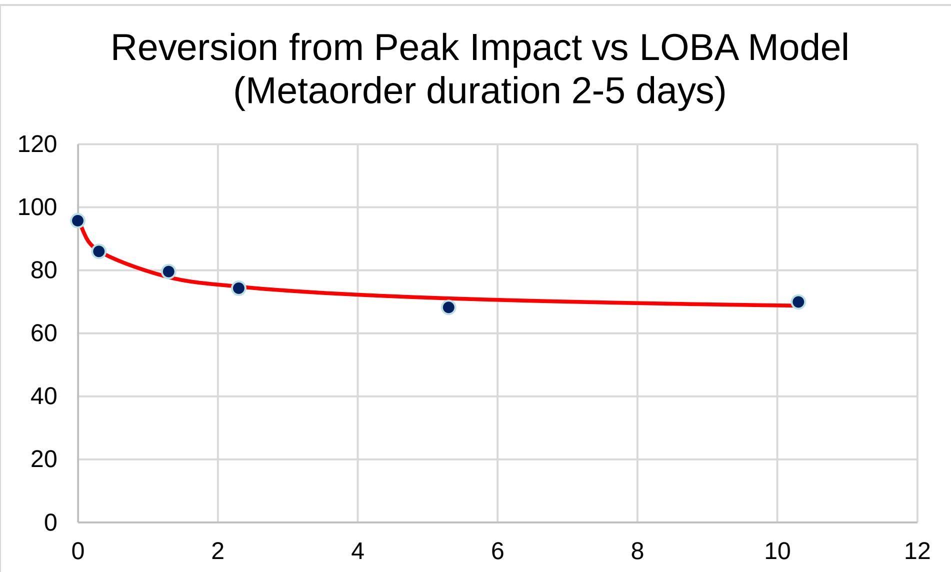
Controlling for continuation-trade bias: post-trade prices adjusted for impact of subsequent metaorders

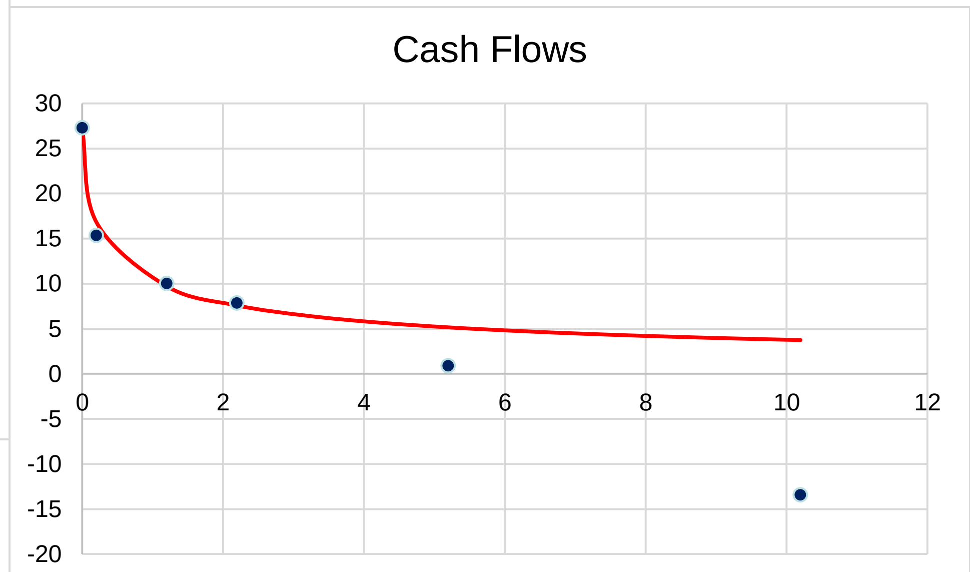


- ➢ Reversion time >= time to execute
- ➢ Cash flows revert completely… (continuing neg. trend is beta, not significant)
- ➢ Other trades revert to the average fill price (shortfall=permanent impact)

“Fair pricing”: Farmer, Gerig, Lillo Waelbroeck 2013; Bershova and Rakhlin 2013

Comparison with LOBA model





LOBA model (Donier, Bonart, Mastromatteo and Bouchaud): $I(Q, t > T) \sim \frac{\sqrt{t} - \sqrt{t-T}}{\sqrt{T}}$

Model (red)
left: T=1.7; Close = 2; permanent impact 0.66*I; t=x+2
right: T=0.8; Close=1;

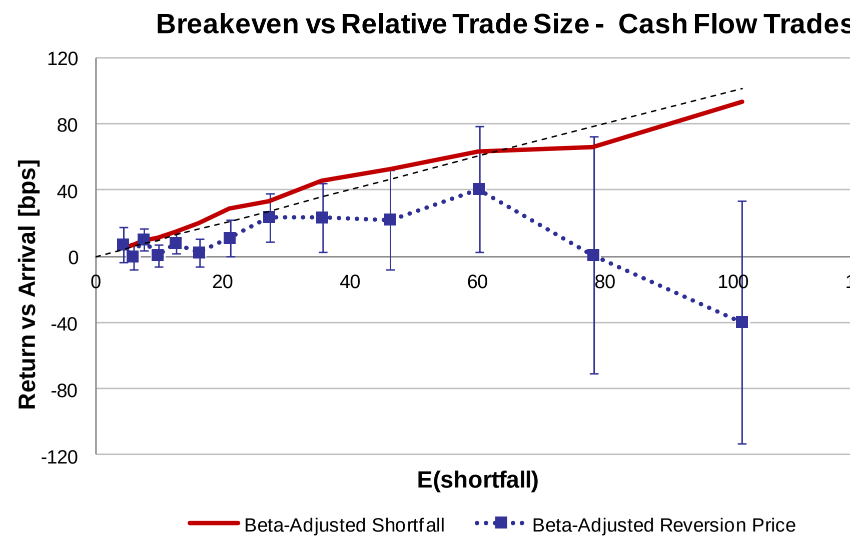
Uninformed trades -> no permanent impact

"No permanent impact if no information" is not a new concept

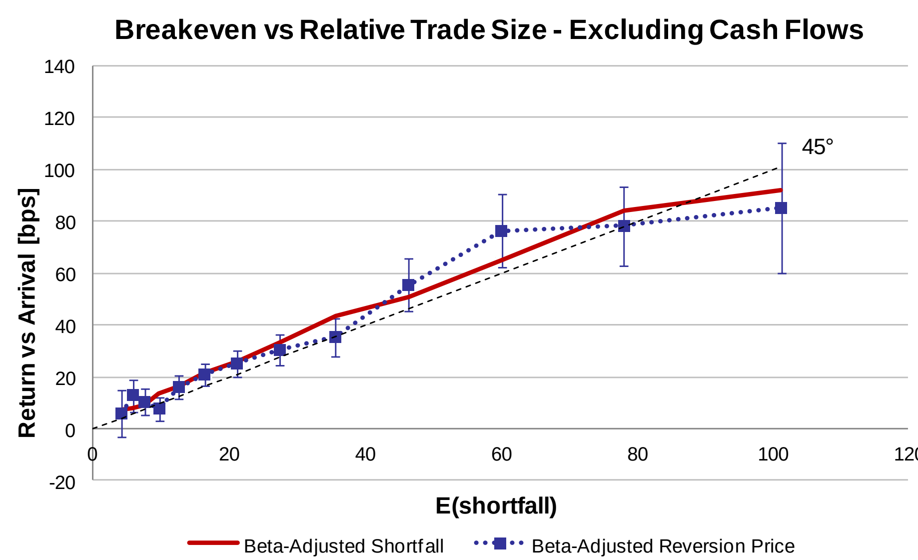
- Coval Stafford (2006): 100% reversion in flow-motivated sells. "Forced sales": positions sold w/outflows of at least 5%.
- Mitchel, Pulvino and Stafford (2004): price pressure from risk arbitrage (short acquirer, buy the target) causes -3.18% AR in the period followed by 2.53% reversion.
- Alexander, Cici and Gibson (2007): buys during outflows are profitable, buys during inflows are not.
- Chen, Noronha and Singal (2004, J Finance): S&P additions have permanent price rises, deletions don't cause any permanent price change. Awareness enhances stock values through reduced risk; is not lost when a company drops out of the S&P. Indirectly shows that the S&P effect is *not* a liquidity effect, which supports permanent_impact=information.
- Here (Gomes Waelbroeck 2014) no proxy required, use cash flow labels

Fair pricing: shortfall = "information"

Cash flows

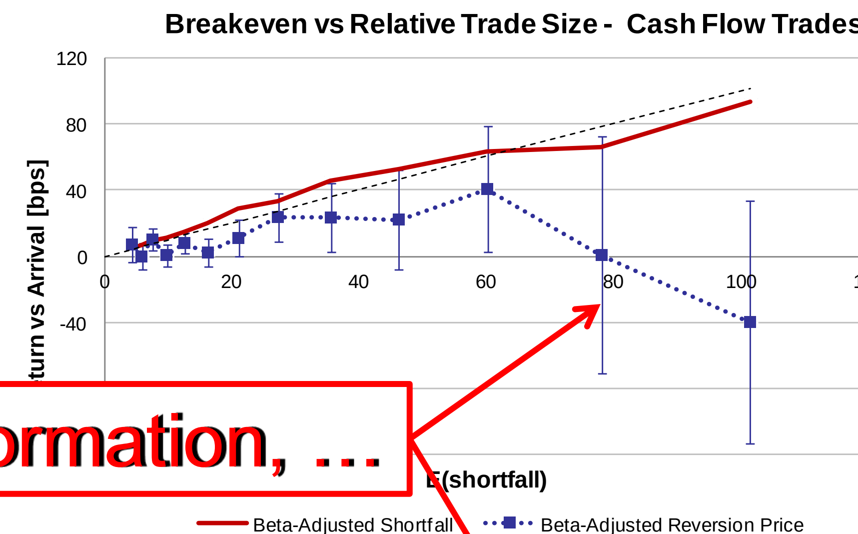


Other trades



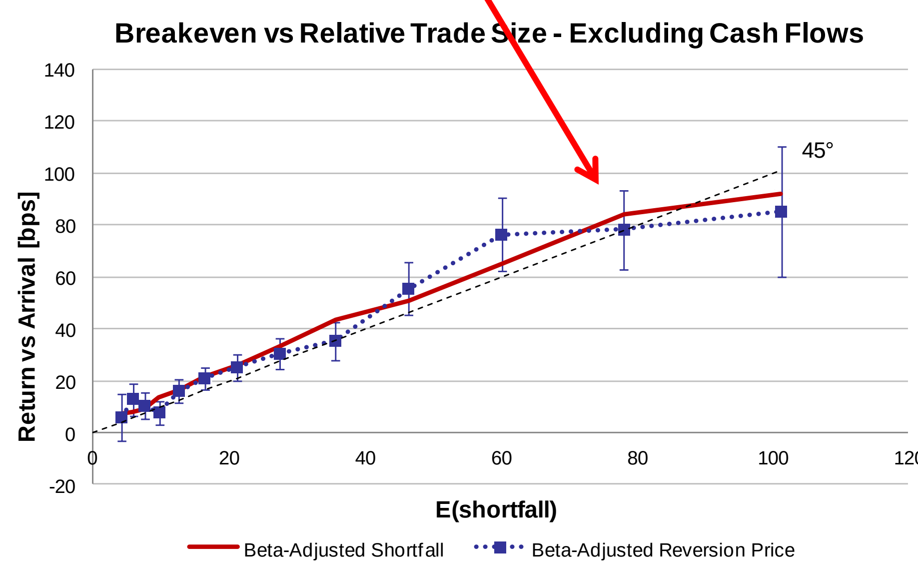
Fair pricing and “information”

Cash flows



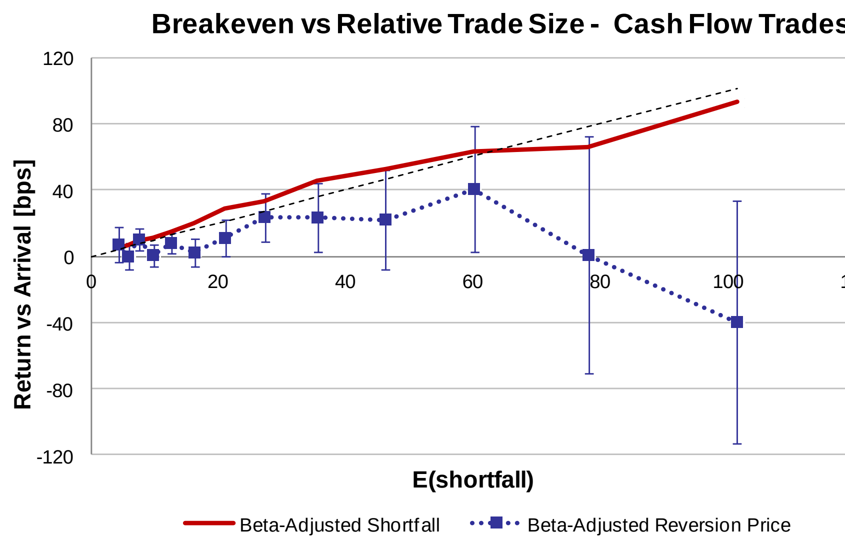
We can measure information, …

Other trades

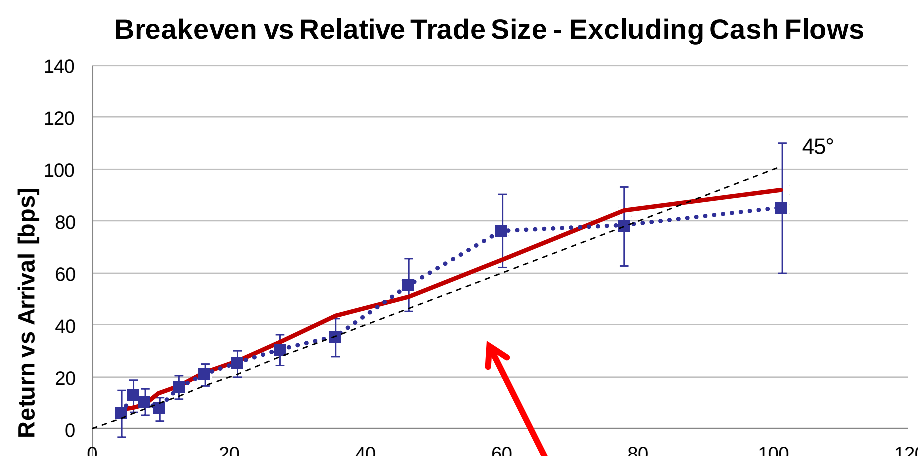


Fair pricing and “information”

Cash flows



Other trades



… and find that metaorder sizes predict information!!

… a far cry from prior studies of metaorders

(KAL, Baltimore Sun)

Excess volatility

- Rietz 1988, Barro 2006: rare disaster risk explains the equity premium

Problem: Barro model predicts stock volatility = dividend volatility. But…

- Shiller 1981, LeRoy and Porter 1981: dividend variance is far too small to explain market volatility

- Wachter 2013: time-varying disaster risk can explain excess volatility

- Roubini (NYU): We're in an asset bubble and it won't pop until 2016

  Ellis (Man Group): Machines have been outperforming people… computers are much better at putting up with more of the same

Shiller discounts k'th dividend by $\prod_{i=1}^{k} \frac{1}{1+r_i}$. use yield curve instead?

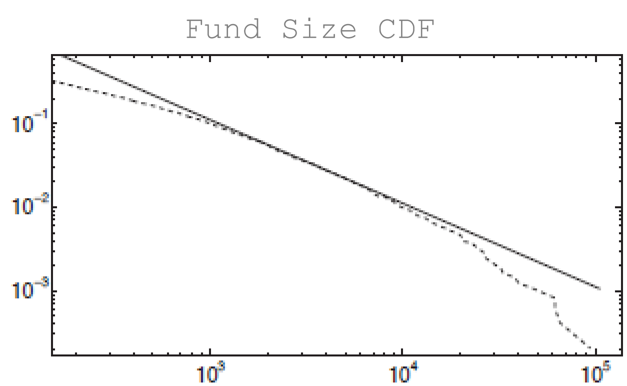
Fair pricing suggests that there is no excess volatility: every metaorder on each individual stock is sized ~ information^2

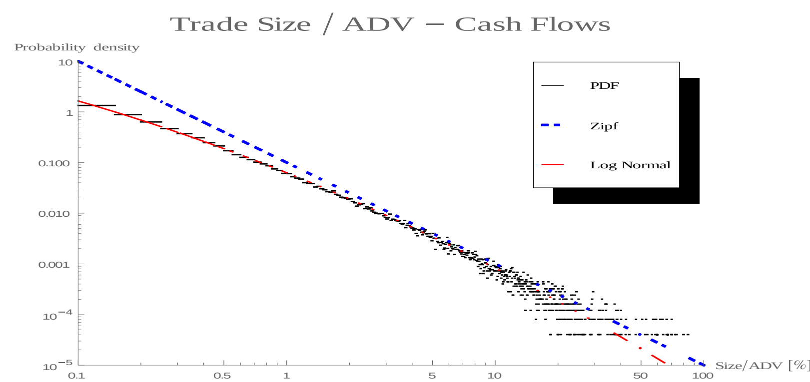
Relations between tail exponents

- Gabaix 2003: cap % losses if a signal M is useless $\rightarrow \varsigma_q = MAX(\frac{3}{2}\varsigma_s, \frac{1}{2}\varsigma_M)$

If fund sizes satisfy Zipf's law, $\varsigma_s = 1 \rightarrow \varsigma_q = 3/2$

But, Schwarzkopf&Farmer 2010: fund size distribution is Log Normal!





So, the ς_M term dominates … "fair pricing" tells us PM signals are informed, mispricings are realized through impact: $\varsigma_M = \varsigma_r = 3 \rightarrow \varsigma_q = 3/2$

Liquidity trades → Log Normal, no permanent impact

Informed trades → Pareto 3/2, implementation shortfall = information

Private information and Win-Lose models

Private information vs “semi-private”: win-lose vs fair pricing

- Kyle (1985): informed trader exacts profits from noise traders, specialist clears at expected final price given revealed orders

Private information → no competition w/other PMs, no Nash equilibrium

Most information signals are shared by several PMs. Market makers observe order flow, *will assume it is a metaorder -> efficient pricing leads to concave impact [FGLW 2013]!* Informed trader will expect this pricing and adopt a non-linear (front-loaded) execution plan.

- Easley, Kiefer, O’Hara and Paperman (1996): informed trader profits → losses for others → investors will price in private information risk → high PIN stocks have higher returns

Metaorders → no profits. So no need to compensate. BUT, high PIN → high volatility -> higher return by CAPM

Why fair pricing?

$Metaorder \sim Info^2 \rightarrow$ is fair pricing an example of collective intelligence?

A Nash equilibrium (Farmer, Gerig, Lillo and Waelbroeck 2014)

- Portfolio Managers (PM) place orders into a bin, orders get “merged”
- each PM receives the average price
- too small -> small trader will join; too big -> reduce size

Or, is price discovery endogenous (reflexive)?

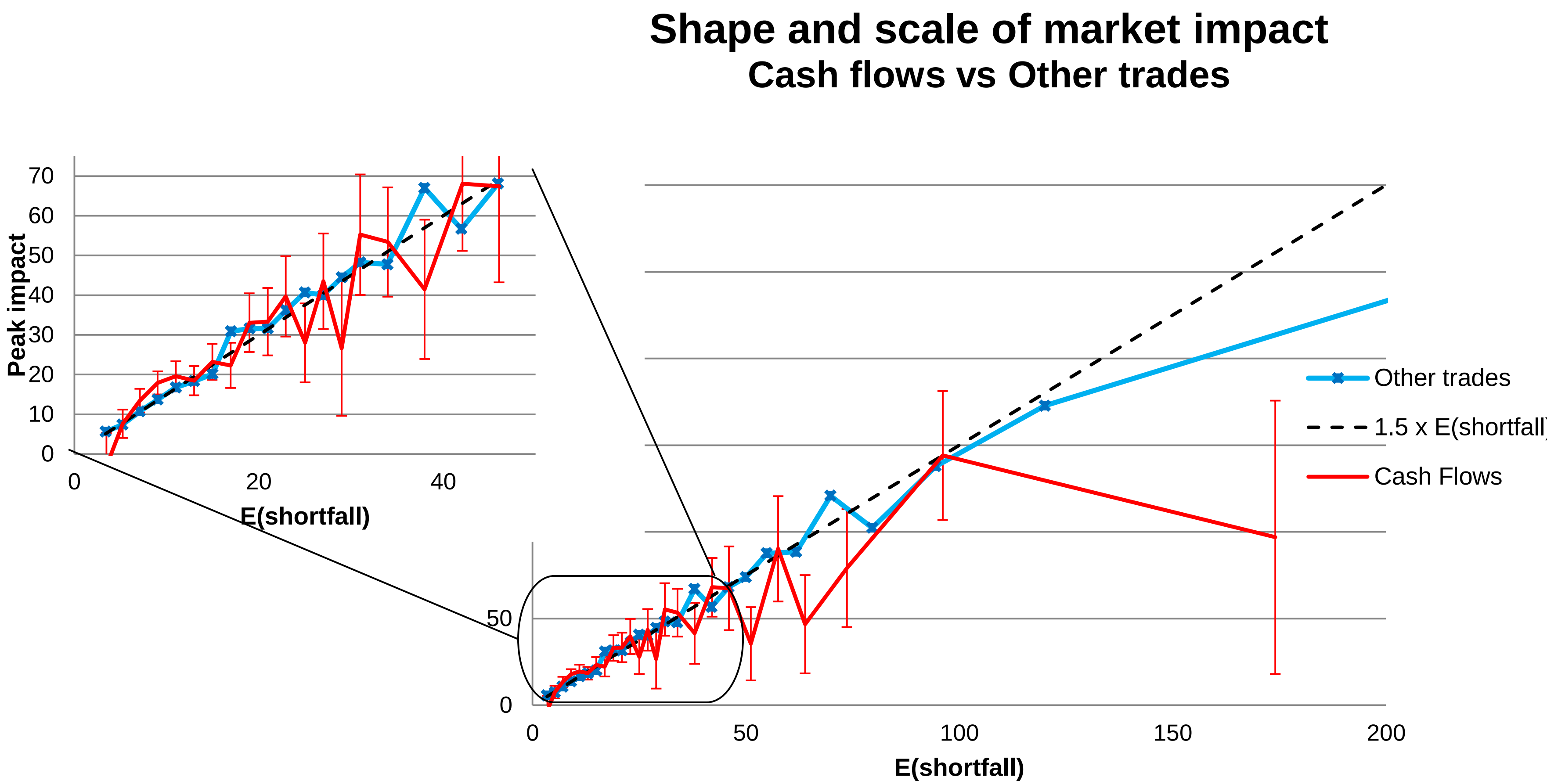
“Americans are apt to be unduly interested in discovering what average opinion believes average opinion to be; and this national weakness finds its nemesis in the stock market” – J. M. Keynes (1936)

If it was a big metaorder, surely portfolio managers must have been very confident in their information!

2 problems with reflexive viewpoint:

- Why fair pricing? Minimizing variance on Liquidity Provider P&L… but LPs can’t adjust their actions to minimize P&L variance
- If endogenous, why is the impact of cash flow trades the same *during* execution?

Does the market identify cash flow trades?



- Same scale of impact up to 50bps
- Impact of cash flows *may* become more concave (Log?) – more data is needed
- Data consistent with mechanical impact *during* execution followed by price discovery *after* execution

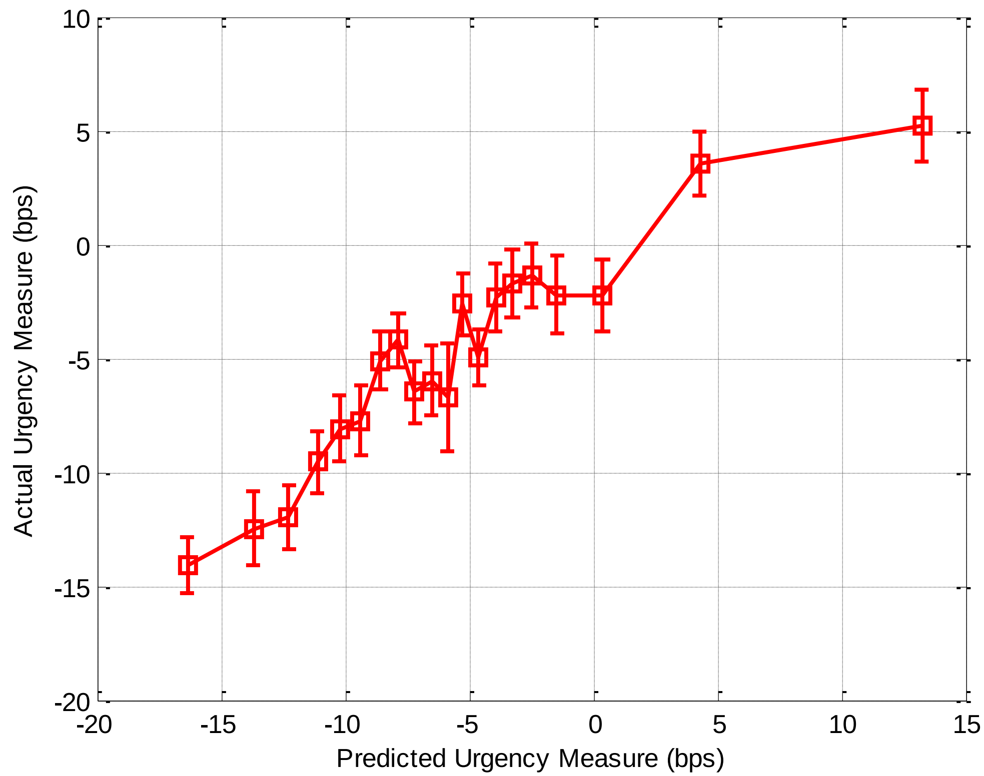
Beating fair pricing: mark-to-market P&L

Dependent Variable: Beta-adjusted P/(L) (Shortfall - Permanent Impact)				
	Cash		**Others**	
	Coefficient	S.E	Coefficient	S.E.
Sqrt(Size)	71.69*	(36.1)	4.47	(8.59)
Volatility	0.33	(0.17)	-0.03	(0.12)
Spread	-0.05	(0.06)	0.00	(0.07)
Large Cap	-6.5	(5.88)	8.57*	(3.77)
Mid Cap	-7.19	(4.38)	4.89	(3.27)
Buy	-3.24	(3.46)	-2.75	(2.18)
Multiple PM	-2.81	(5.05)	-12.98*	(2.61)
Nasdaq	0.3	(4.08)	-9.98*	(2.97)
New Trade	-7.08	(5.04)	-8.18*	(3.09)
Price Improve	1.75	(5.11)	7.43*	(2.99)
Take Profit	-14.89*	(6.52)	-4.51	(3.8)
Stop Loss	-12.37*	(6.1)	0.93	(4.17)
Momentum	-0.00	(0.02)	.15*	(0.02)
Constant	-0.73	(10.5)	5.61	(6.21)
R2	0.002		0.009	
N	27,591		87,658	

Alpha profiling

Urgency: E(shortfall | slow) – E(shortfall | fast)

- Small trades: “fast”=10%VP, “slow”=VWAP
- Medium trades: “fast” = finish today, “slow” = multiday
- Large trades: “fast” = 20%, “slow” = 5%



- Model: consensus of trees classifying NB scoring agents for scenario probabilities
- Training : Q4 2009 - 2012
- Testing : 2013 – Q1 2014

Optimal trade scheduling

Schedule-dependent Impact Model

Alpha Profiling

Volatility / Volume Prediction

Optimal Trade Schedule (minimize cost or risk-adjusted cost)

Hidden order detection time $\tau \equiv 1/\pi^2$.

Price = arithmetic random walk + α(t) + E(impact)

Fair pricing $\langle S_k(\{\pi_i\}_{i=1}^k)\rangle_G = \frac{\sum_{i=1}^k \pi_i^{-1} \langle \tilde{S}_i \rangle_G}{\sum_{i=1}^k \pi_i^{-1}}, k > 1.$

First interval impact ($\gamma = -0.2$) $\langle \tilde{S}_1 \rangle_G - S_0 = \hat{\mu}(\sigma)\pi_1^\gamma.$

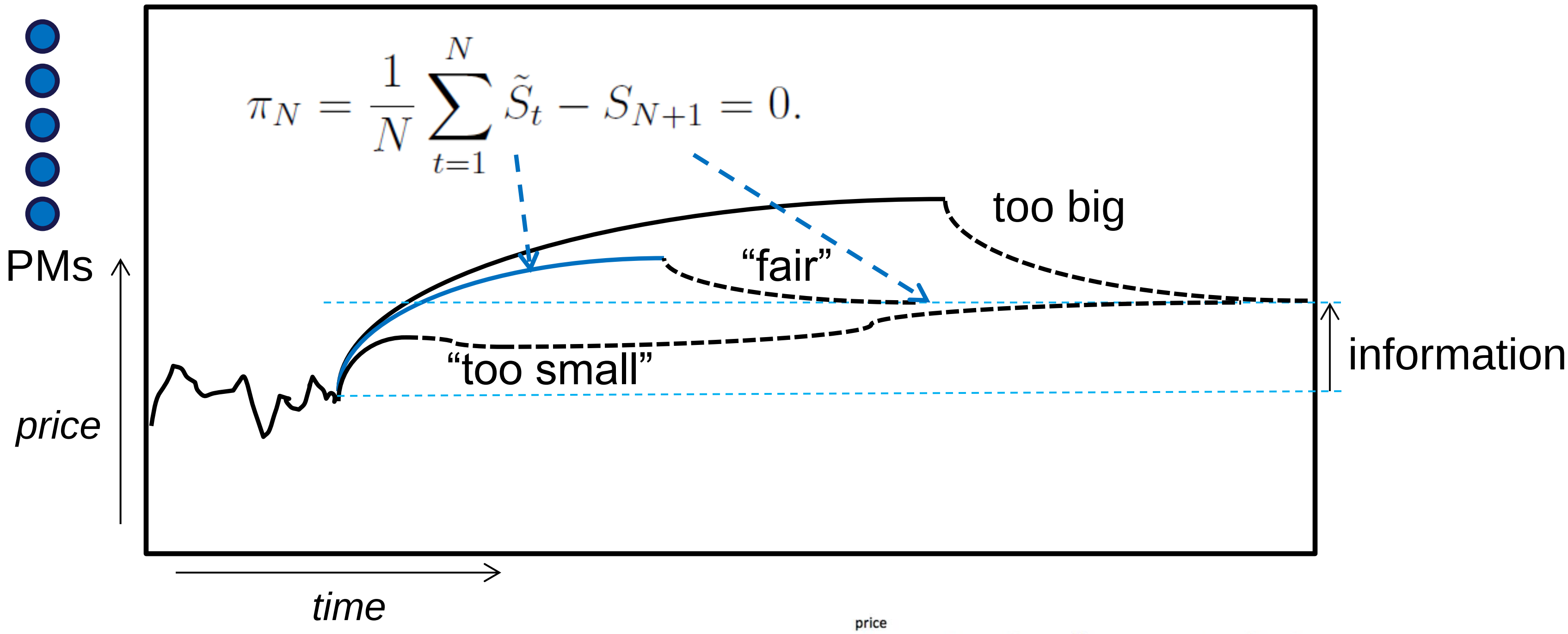
Temporary impact = f(current π, $\sum_{i=1}^k \pi_i^{-1}$)

In continuum limit, for a 3-stage schedule,

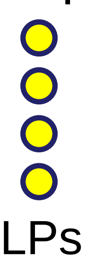
$$Cost = b\sigma\left(\pi_1^\beta x_1^{\alpha-1} + \pi_2^\beta (x_2^{\alpha-1} - x_1^{\alpha-1}) + \pi_3^\beta (x_3^{\alpha-1} - x_2^{\alpha-1})\right) + \alpha Cost$$

The market is solving 2N equations…

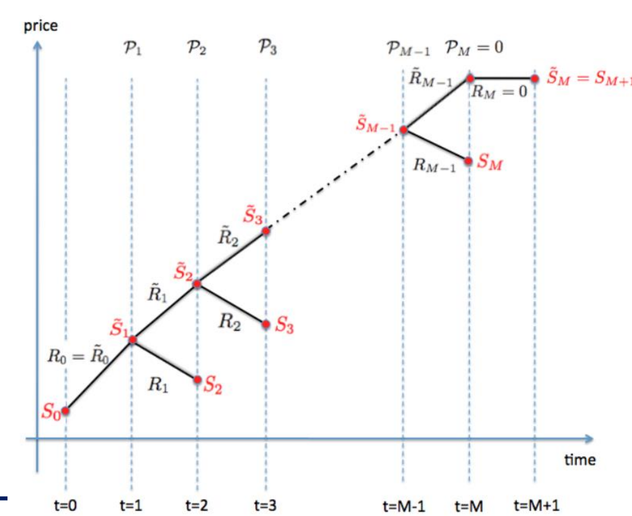
- Portfolio managers enforce fair pricing



- Liquidity providers enforce Martingale



$$\mathcal{P}_t\tilde{R}'_t - (1-\mathcal{P}_t)R'_t = 0.$$



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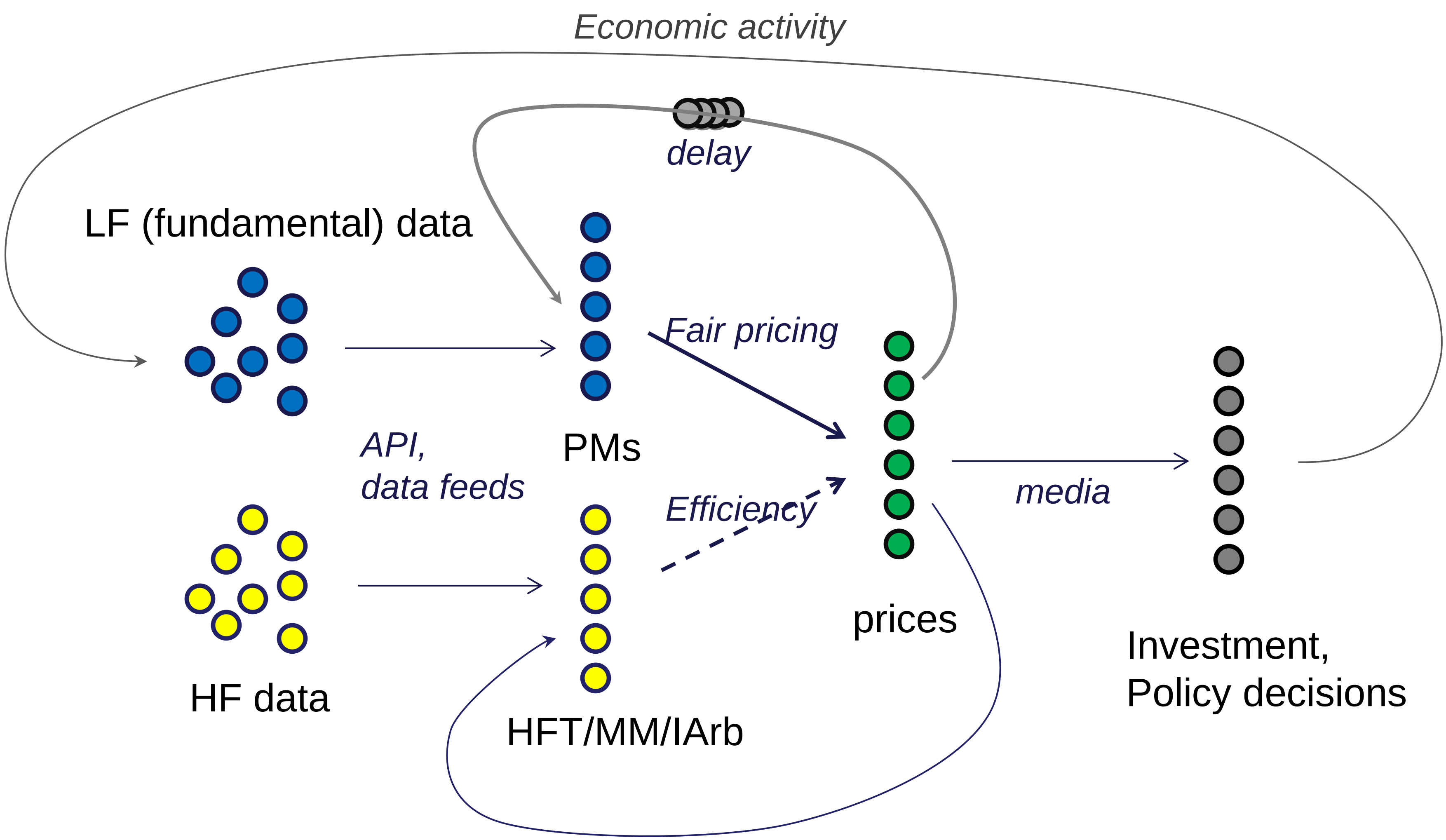
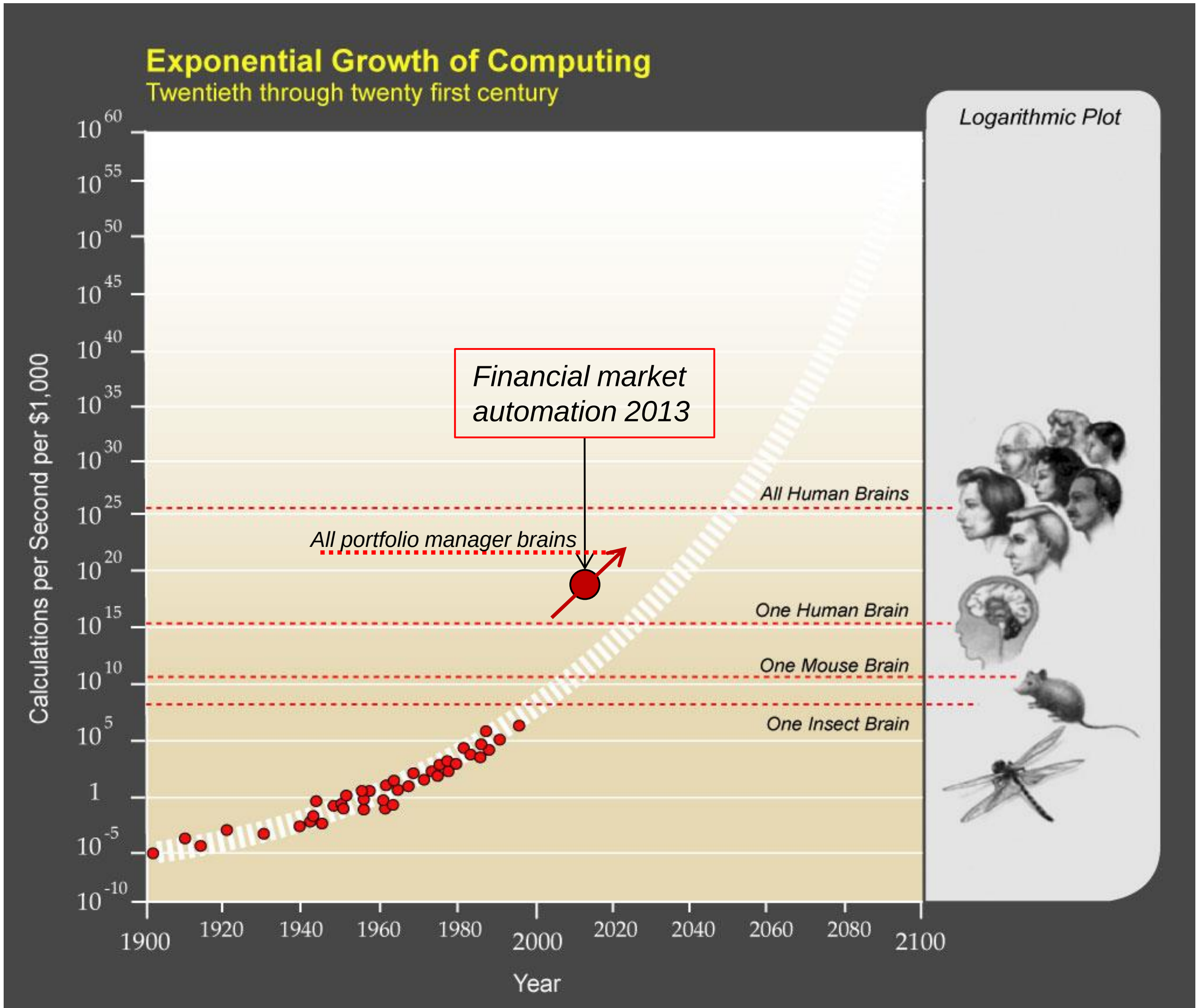
Do market expectations influence policy?



- Affordable Care Act: benefits insurance & pharma stocks, less so providers…
- Quantitative Easing: asset values -> asset-backed credit + wealth effect
- Deep Knowledge Ventures: VITAL named to the Board of Directors

Singularity?



Modified from original image courtesy of Ray Kurtzweil and Kurtweil Technologies, Inc.
"The Singularity is Near, When Humans Transcend Biology", pub. Viking Penguin (2005)

Financial market automation and "All portfolio managers" estimated using Big Dough data and public sources