ETFs, Learning, and Information in Stock Prices

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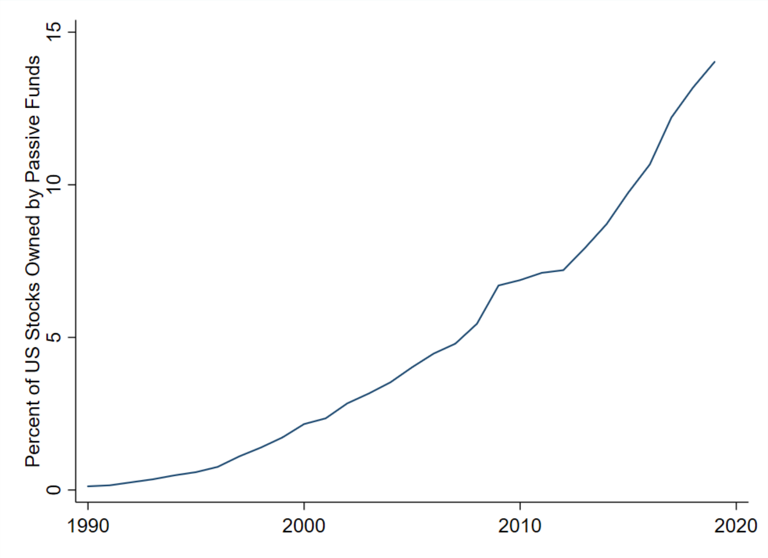
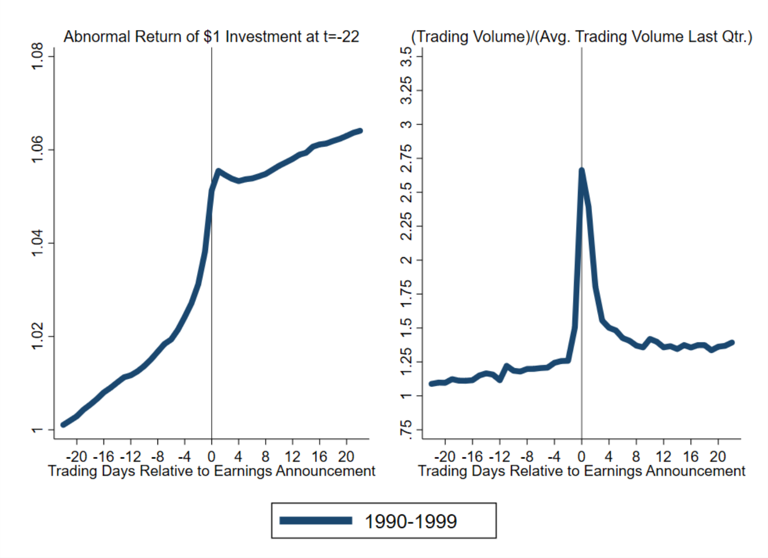
May 25, 2020

Passive Funds Grew from Nothing to Owning 15% of the Market Over the Last 30 Years



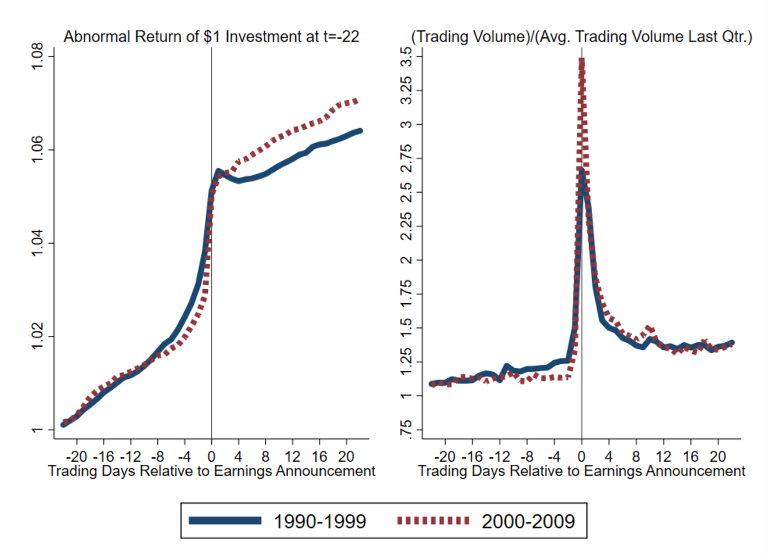
Notes: Passive is defined as all index mutual funds and ETFs in the CRSP mutual fund database.

Good News Gets into Prices Before Announcements



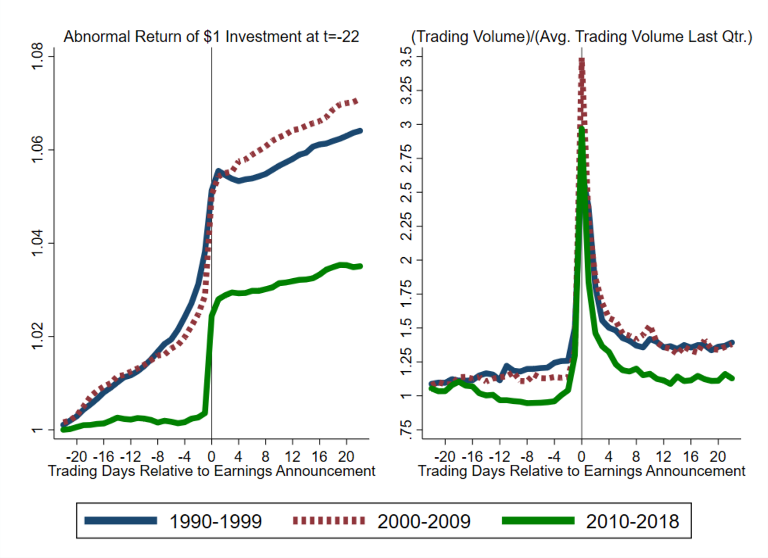
- 1990-1999: 3.6% of total annual volatility occurs on earnings days.

Prices Became Less Informative in the 2000's



- 2000-2009: 8.2% of total annual volatility occurs on earnings days.

And Even Less Informative in the 2010's



- 2010-2018: 13.9% of total annual volatility occurs on earnings days.

Motivation

Prices became less informative over the past 30 years

- Pre-earnings trading volume dropped
  - Admati and Pfleiderer (1988), Wang (1994)
- Pre-earnings drift declined, and earnings-day volatility increased
  - Ball and Brown (1968), Foster et. al. (1984), Weller (2017)

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Why do we care? Purpose of financial markets is aggregating information. Stock prices matter for:

- Firms' investment decisions: Dow and Rahi (2003), Chen, Goldstein and Jiang (2006), Dow, Goldstein, Guembel (2017)
- Disciplining management: Edmans et. al. (2012)
- Capital allocation: Dow and Gorton(1997), Goldstein and Guembel (2007), Berk, van Binsbergen and Liu (2017)

This Paper

- Taking the increase in passive ownership as exogenous, develop a model to jointly explain:
  - Decline in pre-earnings trading volume
  - Decline in the pre-earnings drift
  - Increase in volatility on earnings days
- Test the model's qualitative predictions in the data
  - Correlation between price informativeness and passive ownership
  - Causal evidence with index additions/deletions
  - Decreased information gathering for stocks with high passive ownership

Roadmap

1. Model
2. Cross-Sectional Results
3. Index Additions/Deletions
4. Information Gathering

Model

Key Model Ingredients

- Assets are exposed to both idiosyncratic and systematic risk
  - Interpretation: Systematic risk can be thought of as economy-wide risk, or sector-specific risk
- Imperfectly informed agents
- Endogenous information acquisition
- Today, I am presenting a 3-period version of the model
- Experiment: Introduce an ETF only exposed to the systematic risk-factor
  - Assumption: Without the ETF, agents cannot perfectly replicate the systematic risk-factor

Model Timeline

Agents make decisions at $t = 0$ and $t = 1$ to maximize utility over $t = 2$ wealth.

$t = 0$

- Agents make binary decision to pay c and become informed or stay uninformed.
- If informed, decide how to allocate one unit of attention to the underlying risks

$t = 1$

Informed agents receive private signals. All agents submit demands

$t = 2$

Payoffs realized, agents consume

Asset Payoffs

The time 2 payoff of asset i is defined as:

$$\text{Stock:} \quad z_i = \mu + f + \eta_i \text{ for } i = 1, \ldots, n$$
$$\text{ETF:} \quad z_{n+1} = \mu + f$$

- f is the common factor in asset payoffs
- $\eta_i \overset{\text{iid}}{\sim} N(0, \sigma^2)$, $f \sim N(0, \sigma_f^2)$
- For assets 1 to n:
  - Average endowment of each asset is $\overline{x}$
  - Exogenous supply shocks $x_i \overset{\text{iid}}{\sim} N(0, \sigma_x^2)$
- For the ETF:
  - Agents receive no endowment
  - Supply shocks $x_{i,n+1} \sim N(0, \sigma_{n+1,x}^2)$

ETF vs. Futures Contract

Signals and Learning Technology

If agent j decides to become informed, they receive signals at time 1 about the payoffs of the underlying **assets**:

$$\text{Stock:} \quad s_{i,j} = \mu + (f + \epsilon_{f,j}) + (\eta_i + \epsilon_{i,j}) \quad i = 1, \ldots, n$$
$$\text{ETF:} \quad s_{n+1,j} = \mu + (f + \epsilon_{f,j})$$

where $\epsilon_{i,j} \overset{\text{iid}}{\sim} N(0, \sigma^2_{\epsilon_{i,j}})$ is the signal noise for risk-factor i.

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where $\epsilon_{i,j} \overset{\text{iid}}{\sim} N(0, \sigma^2_{\epsilon_{i,j}})$ is the signal noise for risk-factor i.

If agent j allocates attention $K_{i,j}$ to risk-factor η_i or f:

$$\sigma^2_{\epsilon_{i,j}} = \frac{1}{\alpha + K_{i,j}}, \quad \sigma^2_{\epsilon_{f,j}} = \frac{1}{\alpha + K_{n+1,j}}$$

Total attention constraint: $\sum_i K_i \leq 1$
No-forgetting constraint $K_{i,j} \geq 0$ for all i and j. details

Agents' Problems

Define terminal wealth as:

$$w_{2,j} = (w_{0,j} - \mathbb{1}_{informed,j} c) + \mathbf{q}_j'(\mathbf{z} - \mathbf{p})$$

At time 1, agent j submits demand $\mathbf{q}_j$ to maximize expected utility over time two wealth:

$$U_{1,j} = E_{1,j}[-exp(-\rho w_{2,j})]$$

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At time 1, agent j submits demand $\mathbf{q}_j$ to maximize expected utility over time two wealth:

$$U_{1,j} = E_{1,j}[-exp(-\rho w_{2,j})]$$

At time 0, agent j decides whether or not to pay c and become informed. If informed, allocates attention $K_{i,j}$'s to maximize time 0 expected utility. Follow Veldkamp (2011) and Kacperczyk et. al. (2016) and define time 0 objective function as:

$$-E_0[ln(-U_{1,j})]/\rho$$

which simplifies to:

$$U_0 = E_0\left[E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}]\right]$$

formulation as recursive utility with infinite EIS | expected utility | does initial wealth matter?

Equilibrium Conditions and Trade-Offs

- Share of informed agents is pinned down by indifference condition: $U_{0,informed} = U_{0,uninformed}$
- Beliefs: Rational expectations equilibrium
- Market clearing
- Attention is allocated optimally
  - I restrict to symmetric equilibria: all informed agents have the same $K_{i,j}=\overline{K}_i$

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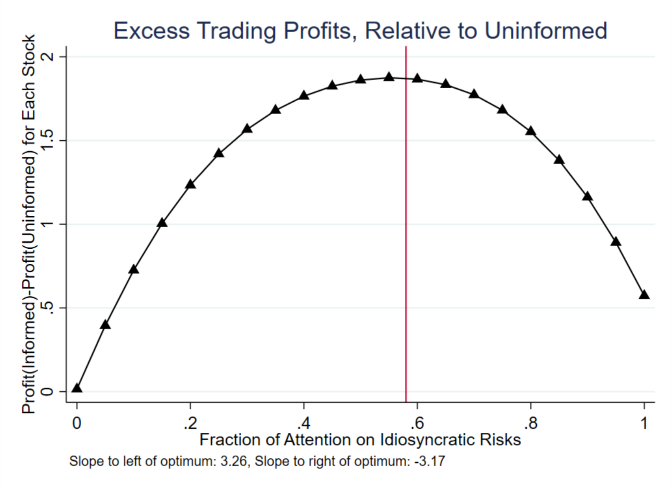
Learning trade-offs:

1. When an investor learns about systematic risk, they get more precise signals about every asset
2. But, volatility of systematic risk-factor (σ_f^2) is low, relative to idiosyncratic risk-factors (σ^2)

How does introducing the ETF affect this trade-off? If ETF is not present, agents cannot take a bet purely on systematic risk, or idiosyncratic risks.

rotated version of the model

Example of Learning Tradeoffs, No ETF



Notes: Two assets, systematic risk, no ETF. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Attention on stock-specific risks is equal. Residual attention is on systematic risk-factor. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$ no systematic risk higher σ_f^2

with ETF

Effects of Introducing the ETF

1. How agents allocate their attention (Intensive Margin)
2. How many agents become informed (Extensive Margin)
3. Risk premia

- To walk through the intuition of the model, I need to choose some parameters
  - Not a calibration, just an example to understand intuition behind the model
  - $n = 8$ i.e. there are 8 stocks

parameters

Introducing the ETF has an ambiguous effect on attention to systematic risk (Intensive Margin)

			Attention Allocation			
		Share	No ETF		ETF	
ρ	σ_f^2	Informed	Idio.	Sys.	Idio.	Sys.
0.1	0.2	0.5	86.0%	14.0%	100.0%	0.0%
0.1	0.5	0.5	66.0%	34.0%	80.0%	20.0%
0.35	0.2	0.5	56.0%	44.0%	12.0%	88.0%
0.35	0.5	0.5	52.0%	48.0%	0.0%	100.0%

Notes: *Idio.* is total attention on all idiosyncratic risk-factors, *Sys.* is attention on the systematic risk-factor.

increasing σ_f^2 increasing ρ all permutations

Introducing the ETF has an ambiguous effect on the share of agents who become informed (Extensive Margin)

		Share Informed		Attention Allocation			
				No ETF		ETF	
ρ	σ_f^2	No ETF	ETF	Idio.	Sys.	Idio.	Sys.
0.1	0.2	0.5	0.55	78.0%	22.0%	100.0%	0.0%
0.1	0.5	0.5	0.2	58.0%	42.0%	56.0%	44.0%
0.35	0.2	0.5	0.3	44.0%	56.0%	0.0%	100.0%
0.35	0.5	0.5	0.3	36.0%	64.0%	0.0%	100.0%

Notes: Cost of becoming informed is set so 50% learn in equilibrium when the ETF not is present. *Idio.* is total attention on all idiosyncratic risk-factors, *Sys.* is attention on the systematic risk-factor.

increasing σ_f^2 increasing ρ all permutations how big is this cost?

Recap

Model revealed a problem with standard story on the effect of introducing an ETF:

- If risk aversion ρ is high, or the volatility of the systematic risk-factor σ_f^2 is high, agents learn more about systematic risk when the ETF is present
  - If agents are risk averse, they generally care more about systematic risk because idiosyncratic risk can be diversified away. When we give them the ETF to trade on systematic risk directly, they want to learn even more about it.
- If risk aversion is low, or the volatility of the systematic risk-factor σ_f^2 is low, the opposite happens
  - If agents are closer to risk neutral they care more about profits than risk. When you give them the ETF, it lets them take more targeted bets on volatile individual securities, and they do more of that.

Mapping the Model to the Data

The extensive and intensive margin effects of introducing the ETF are ambiguous.

In either case, the model has predictions for following objects, which are going to be the outcome variables in my empirical work:

- Pre-earnings volume: $\sum_j |\mathbf{q}_j - (\overline{\mathbf{x}} + \mathbf{x})/(J)|$
- Pre-earnings drift $DM = \begin{cases} \frac{1+r_{(0,1)}}{1+r_{(0,2)}} & \text{if } r_2 \geq 0 \\ \frac{1+r_{(0,2)}}{1+r_{(0,1)}} & \text{if } r_2 < 0 \end{cases}$
- Share of volatility on earnings days: $r_2^2/\left(r_1^2 + r_2^2\right)$

Only defined using stocks i.e. assets 1 to n. Work with *market-adjusted* returns to take out effect of ETF on risk premia

risk premia 1 risk premia 2 drift examples

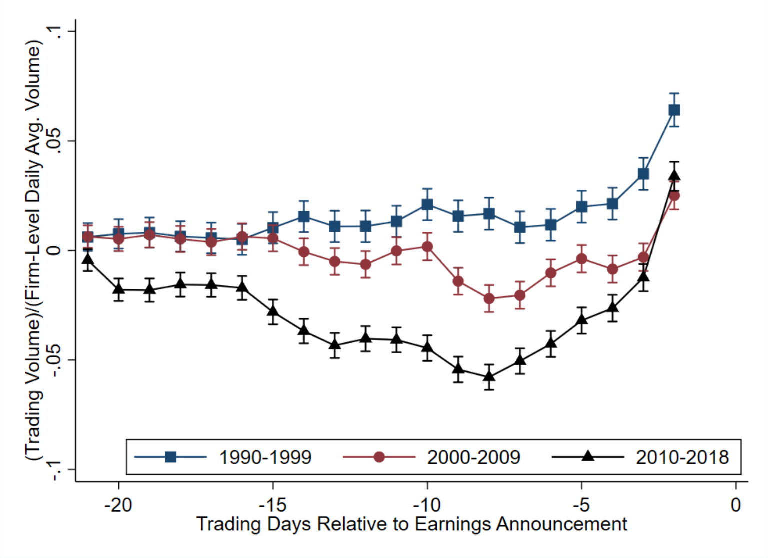
Predicted Effect of ETF on Price Informativeness

	ρ	σ_f^2	No ETF	ETF	Change
Volume	0.1	0.2	1.4377	1.7168	0.2791
	0.1	0.5	1.4387	0.6964	-0.7423
	0.35	0.2	0.4192	0.3026	-0.1166
	0.35	0.5	0.4216	0.3026	-0.1191
Drift	0.1	0.2	96.82%	96.98%	0.16%
	0.1	0.5	96.70%	96.24%	-0.45%
	0.35	0.2	95.92%	95.88%	-0.04%
	0.35	0.5	95.22%	95.14%	-0.08%
Volatility	0.1	0.2	60.38%	56.89%	-3.48%
	0.1	0.5	60.46%	76.18%	15.72%
	0.35	0.2	74.70%	78.01%	3.32%
	0.35	0.5	75.24%	78.43%	3.19%

Notes: Cost of becoming informed is set so 50% learn in equilibrium when the ETF is not present.

Cross-Sectional Results

Quantifying the Drop in Pre-Earnings Trading Volume



Notes: Bars represent 95% confidence intervals with standard errors clustered at the firm level. Regression includes firm fixed-effects. Firm-level daily average is computed over the past 66 trading days. Cumulative decline from 1990's to 2010's was 2.17 days worth of trading volume, or about 10% of average trading volume.

Passive Correlated with Decreased Pre-Earnings Volume

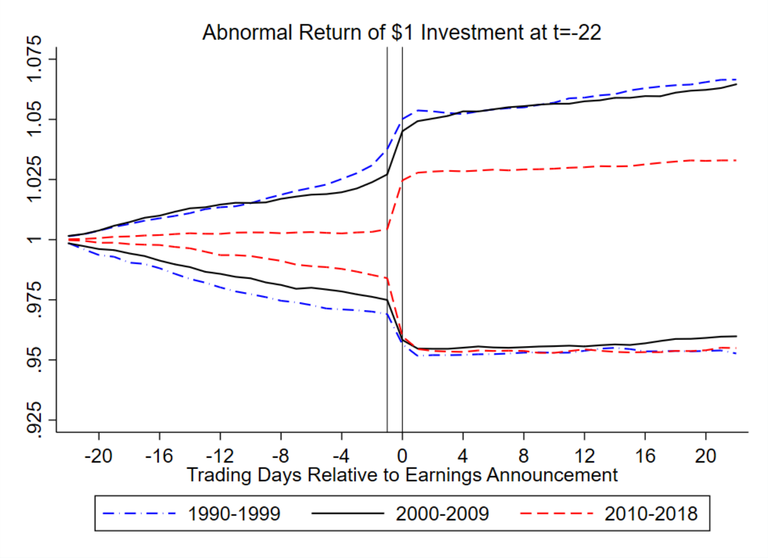
$$\Delta AbnormalVolume_{i,t} = \alpha + \beta \times \Delta Passive_{i,t} + controls + \epsilon_{i,t}$$

	(1)	(2)	(3)
Inc. Passive	-12.81***	-16.09***	-23.96***
	(1.977)	(2.441)	(5.615)
Observations	239,859	239,859	239,859
R-squared	0.022	0.04	0.112
Controls	No	Yes	Yes
Firm FE	No	Yes	Yes
Weight	Eq.	Eq.	Val.

10% increase in passive ownership $\Rightarrow$ 50% of the average decline in pre-earnings trading volume.

Notes: $AbnormalVolume$ is the sum of daily abnormal volume from $t = -22$ to $t = -1$. Panel Newey-West SE with 4 lags. Firm-level controls: lagged passive ownership, lagged market cap., lagged idiosyncratic volatility, lagged institutional ownership, growth of market capitalization. All specifications include year/quarter fixed effects. $AbnormalVolume$ (level) has a value-weighted mean of 22.6 and a standard deviation of 10.4.

Pre-Earnings Drift has Declined



Notes: Black line is the top decile of SUE, blue line is bottom decile of SUE. Abnormal returns are defined as returns minus the return on the CRSP value-weighted index. Black vertical lines denote $t = -1$ and $t = 0$.

Quantifying the Pre-Earnings Drift

$$Drift_{it} = \begin{cases} \frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} & \text{if } r_t > 0 \\ \\ \frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} & \text{if } r_t < 0 \end{cases}$$

Asymmetry is needed so larger values of drift always mean prices were more informative before the earnings announcement

Example: $r_{(t-22,t-1)} = -1\%$ and $r_{(t-22,t)} = -5\%$

$\frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} = 0.99/0.95 > 1$ (wrong way)

$\frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} = 0.95/0.99 < 1$ (right way)

trends examples

Passive Correlated with Decreased Pre-Earnings Drift

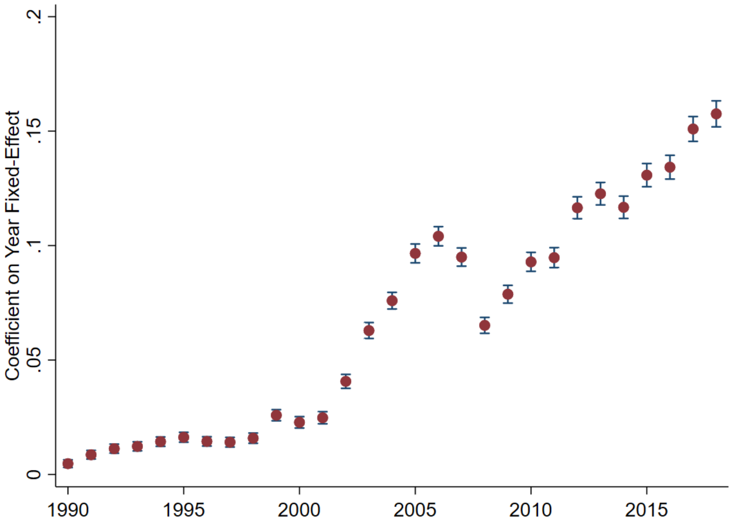
$$\Delta Drift_{i,t} = \alpha + \beta \times \Delta Passive_{i,t} + controls + \epsilon_{i,t}$$

	(1)	(2)	(3)
Inc. Passive	-0.0298**	-0.0322**	-0.0965***
	(0.012)	(0.013)	(0.028)
Observations	239,689	239,689	239,689
R-squared	0.02	0.045	0.063
Controls	No	Yes	Yes
Firm FE	No	Yes	Yes
Weight	Eq.	Eq.	Val.

10% increase in passive ownership ⇒ 15% of the average decline in pre-earnings trading volume.

Notes: Panel Newey-West standard errors with 4 lags. Firm-level controls: lagged passive ownership, lagged market capitalization, lagged idiosyncratic volatility, lagged institutional ownership, growth of market capitalization. All specifications include year/quarter fixed effects. $Drift$ (level) has a value-weighted mean of 0.971 and a standard deviation of 0.033.

Earnings-Day Volatility, $\frac{\Sigma_{\tau=1}^{4} r_{i,\tau,t}^2}{\Sigma_{\tau=1}^{252} r_{i,\tau,t}^2}$, Has Increased



Notes: Each dot represents the coefficient on a year fixed-effect in a pooled regression across all years. Bars represent 95% confidence intervals with standard errors clustered at the firm level. Regression includes firm fixed-effects.

Passive Correlated with Increased Earnings-Day Volatility

$$\Delta \frac{\Sigma_{\tau=1}^{4} r_{i,\tau,t}^2}{\Sigma_{\tau=1}^{252} r_{i,\tau,t}^2} = \alpha + \beta \times \Delta Passive_{i,t} + controls + \epsilon_{i,t}$$

	(1)	(2)	(3)
Inc. Passive	0.200***	0.106***	0.381**
	(0.030)	(0.035)	(0.171)
Observations	127,951	126,319	126,319
R-squared	0.011	0.03	0.035
Controls	No	Yes	Yes
Firm FE	No	Yes	Yes
Weight	Eq.	Eq.	Val.

10% increase in passive ownership ⇒ 10-20% of the average increase in earnings-day volatility

Notes: Panel Newey-West standard errors with 4 lags. Firm-level controls: lagged passive ownership, lagged market capitalization, lagged idiosyncratic volatility, lagged institutional ownership, growth of market capitalization. All specifications include year/quarter fixed effects.

$\frac{\Sigma_{\tau=1}^{4} r_{i,\tau,t}^2}{\Sigma_{\tau=1}^{252} r_{i,\tau,t}^2}$ (level) has a value-weighted mean of 0.085 and a standard deviation of 0.101. by announcement

Index Additions/Deletions

S&P 500 Index Additions

According to S&P: *"Stocks are added to make the index representative of the U.S. economy, and is not related to firm fundamentals."*

Two groups of control firms:

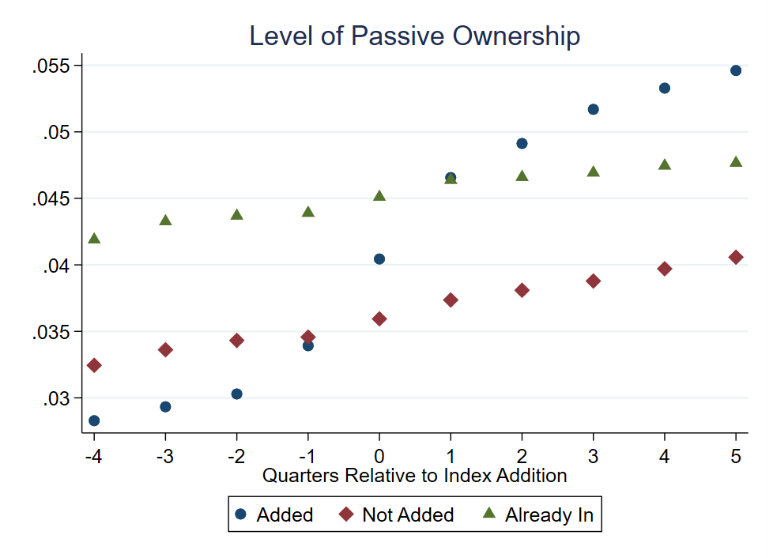
1. Same 2-digit SIC industry, similar market cap., not in the index
2. Same 2-digit SIC industry, similar market cap., already in the index

First stage: $\Delta Passive_{i,t} = \alpha + \beta \times Treated_{i,t} + \gamma_t + \epsilon_{i,t}$

Second Stage : $\Delta Outcome_{i,t} = \alpha + \beta \times \Delta \widehat{Passive}_{i,t} + \gamma_t + \epsilon_{i,t}$

Where γ_t is a month-of-index-addition fixed effect

S&P 500 Index Addition: First Stage



S&P 500 Index Addition Decreases Pre-Earnings Price Informativeness

	Treated vs. In/Out of Index		
	Volume	Drift	Volatility
$\widehat{Inc.Passive}$	-51.08**	-0.322**	1.924**
	(22.550)	(0.140)	(0.768)
R-squared	0.098	0.074	0.115
Reduced Form	-23.96***	-0.0965***	0.381**

Notes: All specifications include month of index addition fixed effects. There are 419 treated firms, 906 control firms out of the S&P 500 index and 508 control firms in the S&P 500 index.

Pre/Post Trends: volume drift volatility

Empirical Effect of being added to the S&P 500 vs. Model Effect of Introducing the ETF

$$\Delta Outcome_{i,t} = \alpha + \beta \times Treated_{i,t} + \gamma_t + \epsilon_{i,t}$$

	Treated vs. In/Out of Index		
	Volume	Drift	Volatility
Treated	-0.813**	-0.00534**	0.0179**
	(0.369)	(0.002)	(0.007)
Model	-0.1166	-0.0004	0.0332

Notes: In the model, cost of becoming informed is set so 50% learn in equilibrium when the ETF is not present. $\rho = 0.35$, σ_f^2=0.2. Regressions include month of index addition fixed effects.

Russell 1000/2000 Index Reconstitution

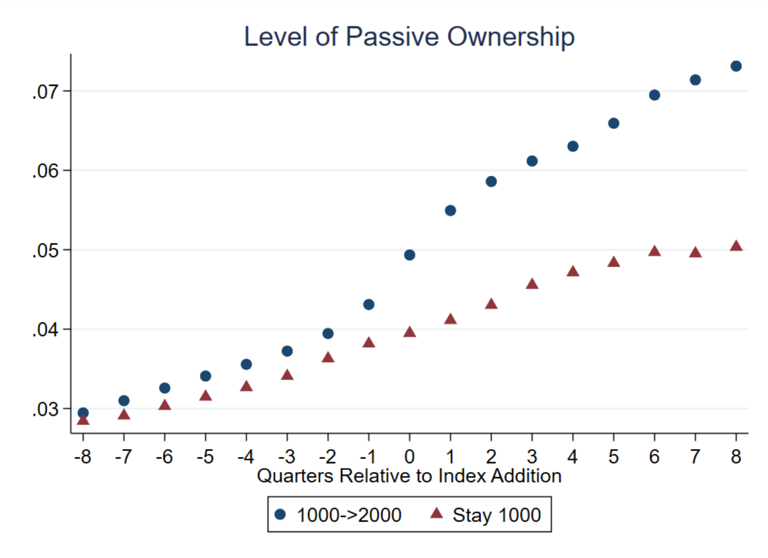
Treated Group: Firms moving from the Russell 1000 to the 2000
Control group: Firms with June ranks 900-1000 that stay in the Russell 1000

First stage: $\Delta Passive_{i,t} = \alpha + \beta \times Treated_{i,t} + \gamma_t + \epsilon_{i,t}$

Second Stage : $\Delta Outcome_{i,t} = \alpha + \beta \times \Delta \widehat{Passive}_{i,t} + \gamma_t + \epsilon_{i,t}$

Where γ_t is a month-of-index-rebalancing fixed effect

Russell 1000/2000 Rebalancing: First Stage



Index Re-Balancing Decreases Pre-Earnings Price Informativeness

	Volume	Drift	Volatility
Inc. Passive	-44.71**	-0.285**	0.0109
	(20.740)	(0.125)	(0.411)
R-squared	0.099	0.126	0.073
Reduced Form	-23.96***	-0.0965***	0.381**

Notes: All specifications include month of index reconstitution fixed effects. There are 216 treated firms and 158 control firms.

Information Gathering

Passive Decreases Information Gathering

$$Outcome_{i,t} = \alpha + \beta \times \Delta Passive_{i,t} + controls + e_{i,t}$$

	# Analysts	Distance	Time	Downloads
Inc. Passive	-8.935***	1.557***	14.93*	-3.756***
	(0.824)	(0.244)	(8.692)	(1.185)
Observations	99,004	96,365	79,131	96,380
R-squared	0.1	0.062	0.065	0.233
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Weight	Eq.	Eq.	Eq.	Eq.

Notes: Panel Newey-West standard errors with 4 lags. Firm-level controls: lagged market capitalization, lagged idiosyncratic volatility, lagged institutional ownership, growth of market capitalization. Distance is the absolute deviation of earnings from the last consensus estimate before the announcement date, divided by the earnings value, excluding observations where earnings is less than 1 cent in absolute value. Time is average days between each covering analyst's estimate updates. The *time* regression only includes stocks/years which have an analyst who updated their estimate at least once within the corresponding IBES statistical period. Downloads is total non-robot downloads from the SEC server log, and has a mean of 10.4.

Earnings Response Regression

Baseline:

$$r_{i,t} = \alpha + \beta \times SUE_{i,t} + controls + \epsilon_{i,t}$$

Allowing for asymmetry between positive and negative surprises:

$$r_{i,t} = \alpha + \beta_1 \times SUE_{i,t} \times \mathbf{1}_{SUE_{i,t}>0} +$$
$$\beta_2 \times |SUE_{i,t}| \times \mathbf{1}_{SUE_{i,t}<0} + controls + \epsilon_{i,t}$$

Passive Increases Earnings Response

$$r_{i,t} = \alpha + \beta_1 \times SUE_{i,t} + \beta_2 \left(SUE_{i,t} \times Passive_{i,t}\right) + controls + \epsilon_{i,t}$$

	(1)	(2)	(3)	(4)
SUE	0.00912***		0.00314***	
	(0.000)		(0.000)	
$SUE \times \mathbf{1}_{SUE>0}$		0.00745***		0.00369***
		(0.000)		(0.000)
$SUE \times \mathbf{1}_{SUE<0}$		-0.00394***		0.000128
		(0.000)		(0.001)
SUE x passive	0.0545***		0.0435***	
	(0.003)		(0.007)	
$SUE \times \mathbf{1}_{SUE>0}$ x passive		0.0217***		0.0246***
		(0.003)		(0.006)
$SUE \times \mathbf{1}_{SUE<0}$ x passive		-0.0411***		-0.0196*
		(0.004)		(0.011)
Observations	415,961	415,961	415,961	415,961
R-squared	0.068	0.069	0.039	0.041
Controls/Firm FE	Yes	Yes	Yes	Yes
Weight	Eq.	Eq.	Val.	Val.

Notes: Standard errors double clustered at the firm and year level. Firm-level controls: lagged market capitalization, lagged idiosyncratic volatility, lagged institutional ownership. trends

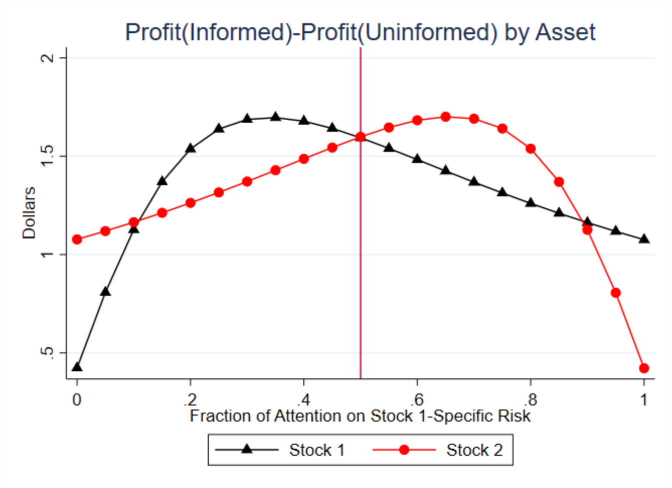
Conclusion

Conclusion

- Based on standard model, price informativeness could increase or decrease after introducing the ETF
- New evidence on the empirical effects of passive ownership on price informativeness
  1. Time-series decrease in average price informativeness
  2. Correlation between price informativeness and passive ownership
  3. Causal evidence with index additions/deletions
  4. Decreased information gathering for stocks with high passive ownership

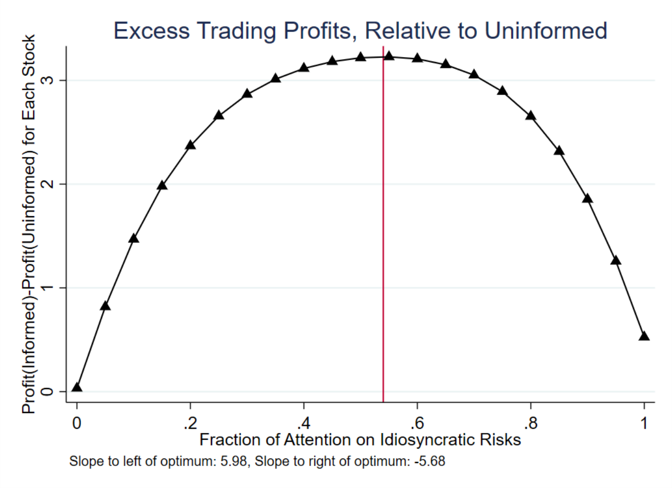
Appendix

Two Stocks, No Systematic Risk, No ETF



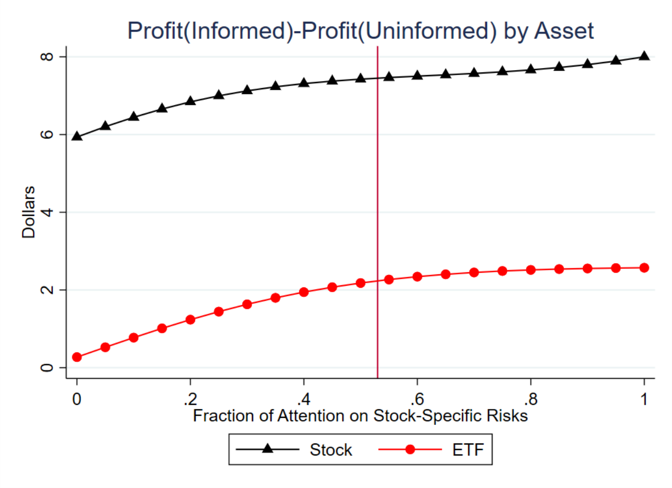
Notes: Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on Stock 2-specific risk. $\rho = 0.1$, $\sigma^2 = 0.55$ back

Two Assets, Systematic Risk, No ETF (higher σ_f^2)



Notes: Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Attention on stock-specific risks is equal. Residual attention is on systematic risk-factor. $\rho = 0.1$, σ_f^2=0.5, $\sigma^2 = 0.55$ back

Two Stocks, One ETF (higher σ_f^2)



Notes: Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on systematic risk-factor. ETF is in zero average supply. $\rho = 0.1$, $\sigma_f^2 = 0.5$, $\sigma^2 = 0.55$ back

Model Parameters

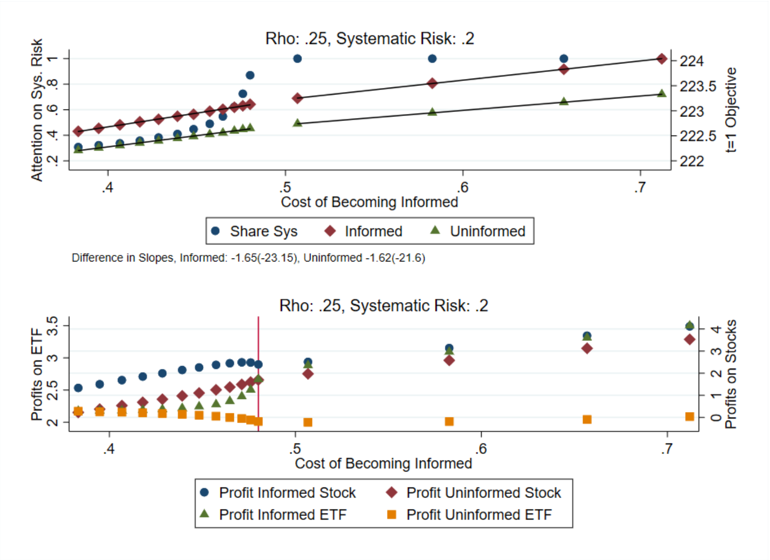
Mean asset payoff	μ	15
Volatility of idiosyncratic shocks	σ^2	0.55
Volatility of noise shocks	σ_x^2	0.5
Risk-free rate	r_f	1
Initial wealth	w_0	0
Baseline Learning	α	0.001
# idiosyncratic assets	n	8
Coef. of risk aversion (low)	ρ	0.1
Coef. of risk aversion (high)	ρ	0.35
Vol. of systematic shocks (low)	σ_f^2	0.2
Vol. of systematic shocks (high)	σ_f^2	0.5
Total supply of idiosyncratic assets	$\sum_{i=1}^{n-1} \overline{x}_i$	20

back

Understanding the Kink in c vs. Percent Informed

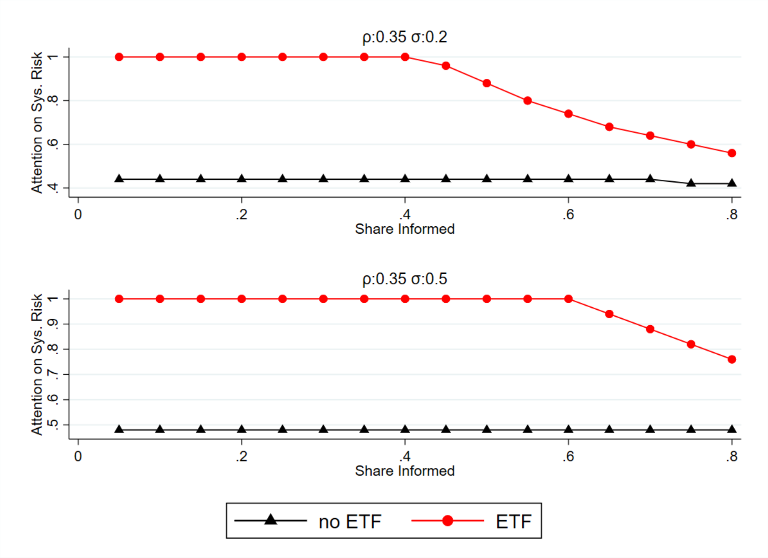
- To the right of the kink, informed agents only learn about systematic risk
- To the left of the kink, informed agents diversify their information
  - To the left of the kink, informed agents' profits on stocks diverges from the uninformed
  - This makes it relatively more attractive to become informed
  - Leads to a change in slopes to the right/left of the kink on the next slide

Understanding the Kink



back

Effect of increasing σ_f^2 on Intensive Learning Margin



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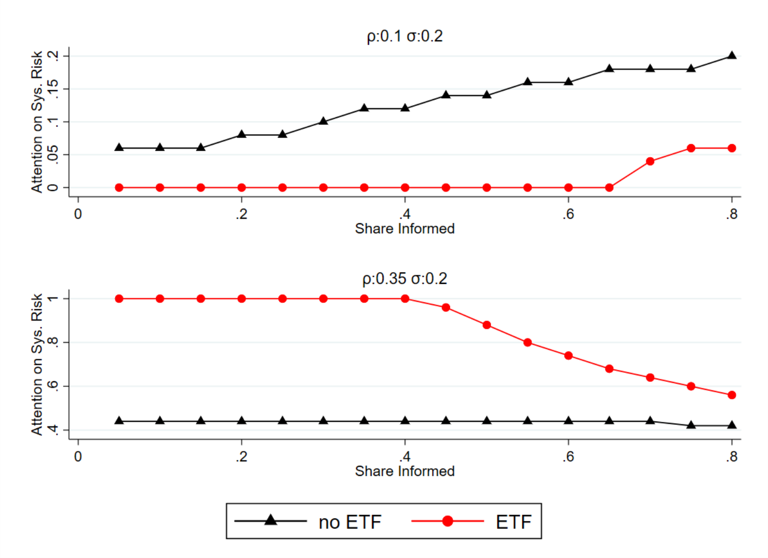
Effect of increasing ρ on Intensive Learning Margin



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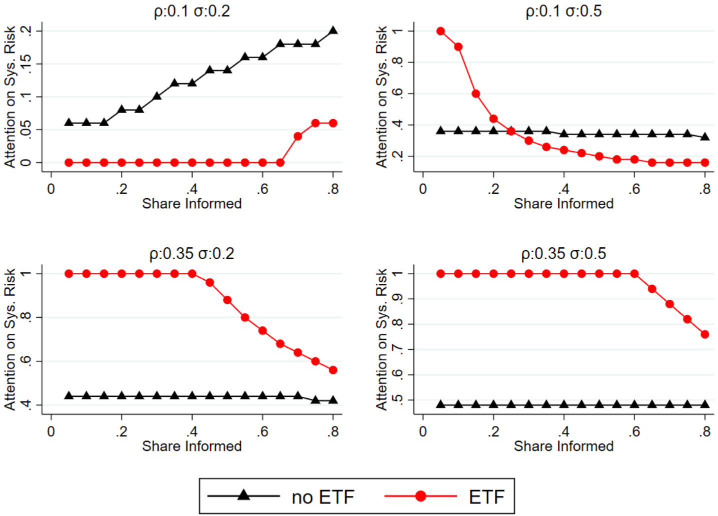
Effect of ETF on Intensive Learning Margin



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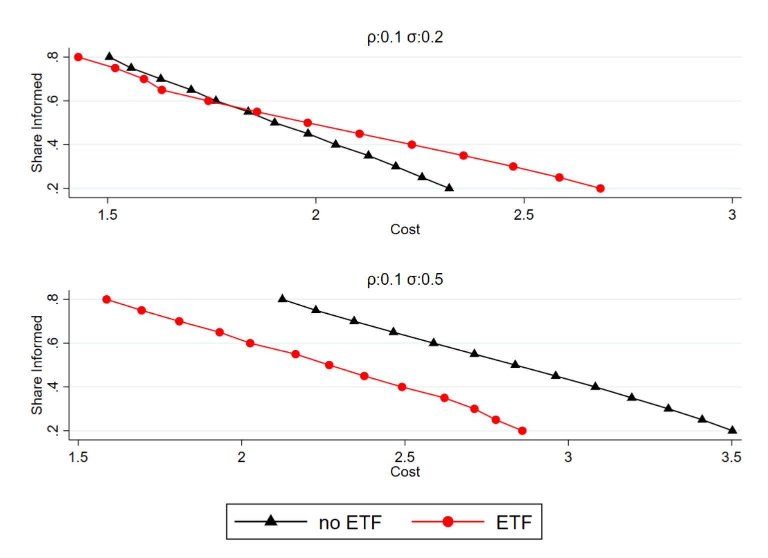
Effect of increasing σ_f^2 on Extensive Learning Margin



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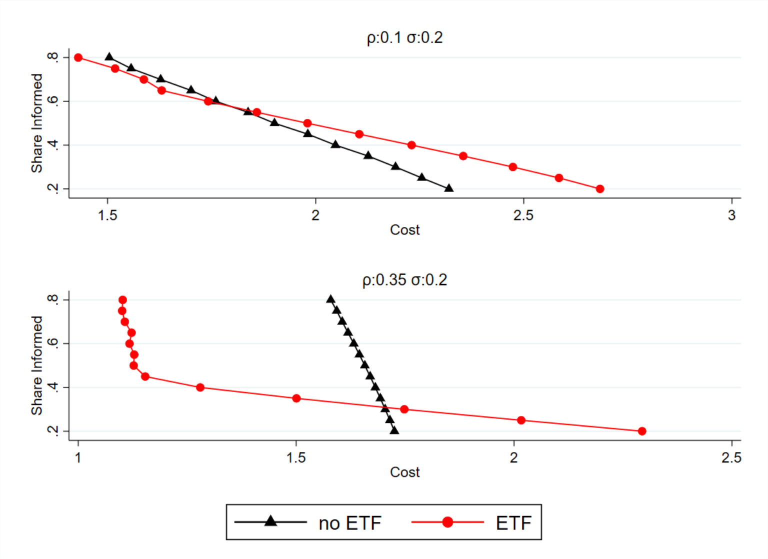
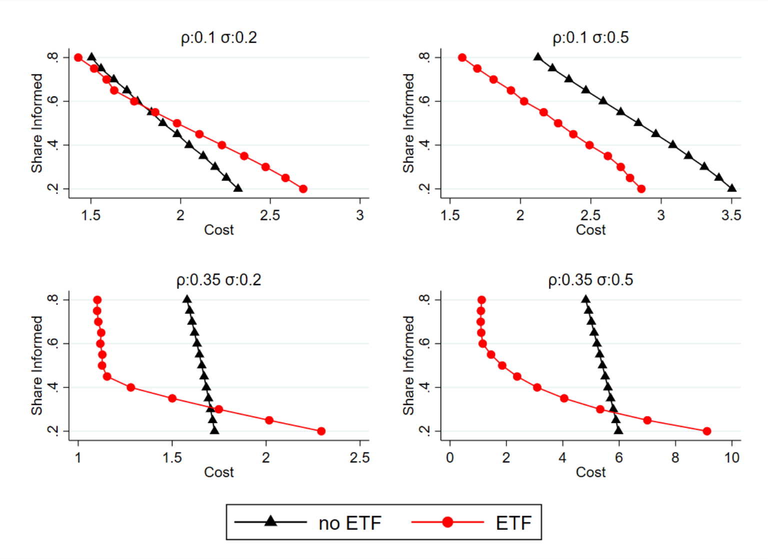
Effect of increasing ρ on Extensive Learning Margin



back understanding kink

Effect of ETF on Decision to Become Informed



back

Effect of the ETF on Risk Premia (Fixed Share Informed)

			Risk Premium		
ρ	σ_f^2	Shr. Inf.	No ETF	ETF	Change(PP)
0.1	0.2	0.1	3.73%	3.71%	-0.02%
0.1	0.2	0.3	3.71%	3.59%	-0.12%
0.1	0.5	0.1	8.18%	8.19%	0.01%
0.1	0.5	0.3	8.09%	8.05%	-0.04%
0.35	0.2	0.1	14.33%	14.32%	-0.01%
0.35	0.2	0.3	14.28%	14.23%	-0.05%
0.35	0.5	0.1	35.98%	36.09%	0.11%
0.35	0.5	0.3	35.65%	35.94%	0.30%

back

Effect of the ETF on Risk Premia (Fixed c)

		Risk Premium		
ρ	σ_f^2	No ETF	ETF	Change(PP)
0.1	0.2	3.68%	3.38%	-0.30%
0.1	0.5	7.98%	8.19%	0.21%
0.35	0.2	14.23%	14.23%	0.00%
0.35	0.5	35.32%	35.94%	0.63%

Note: c is set so 50% of agents become informed when the ETF is not present. back

Expected Utility

Suppose we have n independent assets (no systematic risk)

- $U_0 = E_0\left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]$ introduces a preference for the early resolution of uncertainty *and specialization* (Veldkamp, 2011).
  - Optimal demand: $q = \frac{1}{\rho}\hat{\Sigma}^{-1}\left(\hat{\mu} - p\right)$ where $\hat{\Sigma}^{-1}$ is the posterior covariance matrix and $\hat{\mu}$ is the posterior mean
  - Expected excess portfolio return achieved through learning depends on $cov(q, f-p){=}E_0\left[q'(f-p)\right] - E_0\left[q\right]' E_0\left[(f-p)\right]$.
  - Specializing in learning about one asset leads to a high covariance between payoffs and holdings of that asset. Realized portfolio can, however, deviate substantially from the time 0 expected portfolio.
  - Learning a little about every risk leads to smaller deviations between the realized and time 0 expected portfolio, but also lowers $cov(q, f-p)$.
- Expected utility, $U_{0,j} = E_{0,j}\left[E_{1,j}[-exp(-\rho w_{2,j})]\right]$

back risk aversion vs. 1/EIS

Expected Utility

Suppose we have n independent assets (no systematic risk)

- $U_0 = E_0\left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]$ introduces a preference for the early resolution of uncertainty *and specialization* (Veldkamp, 2011).
- Expected utility, $U_{0,j} = E_{0,j}\left[E_{1,j}[-exp(-\rho w_{2,j})]\right]$
  - $U_{0,j} = E_{0,j}\left[-exp\left(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}]\right)\right]$
  - Agents are averse to time 1 portfolio uncertainty (i.e. risk that signals will lead them to take aggressive bets), so do not like portfolios that deviate substantially from $E_0[q]$
    - Why? Utility is a concave function of mean and variance
  - The utility cost of higher uncertainty from specialization just offsets the utility benefit of higher portfolio returns, removing the "planning benefit" experienced by the mean-variance specification
  - Recursive utility investors are not averse to risks resolved before time 2, so specialization is a low-risk strategy. Lowers time 2 portfolio risk by loading portfolio heavily on an asset whose payoff risk will be reduced by learning.

back risk aversion vs. 1/EIS

Expected Utility

Suppose we have n independent assets (no systematic risk)

- $U_0 = E_0\left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]$ introduces a preference for the early resolution of uncertainty *and specialization* (Veldkamp, 2011).
- Expected utility, $U_{0,j} = E_{0,j}\left[E_{1,j}[-exp(-\rho w_{2,j})]\right]$

When solving the model, I don't find any qualitative differences using expected utility. Not surprising given the results in the appendix of Kacperczyk et. al. (2016). back risk aversion vs. 1/EIS

Another Way to View the Recursive Formulation

$$V_t = \left((1-\beta)c_t^{1-\rho} + \beta[E_t(V_{t+1}^{1-\alpha})]^{(1-\rho)/(1-\alpha)}\right)^{1/(1-\rho)}$$

Set t=0, c_0=0, $\beta = 1$: $\quad V_0 = \left([E_0(V_1^{1-\alpha})]^{(1-\rho)/(1-\alpha)}\right)^{1/(1-\rho)}$

Set $\alpha = 1$: $\quad V_0 = \left(exp[E_0(ln[V_1])]^{(1-\rho)}\right)^{1/(1-\rho)}$

Set $\rho = 0$: $\quad V_0 = exp[E_0(ln[V_1])]$

This is equivilent to maximizing: $\quad V_0 = E_0(ln[V_1])$

In my setting: $\quad V_1 = E_1[-exp(-\rho w)]$ i.e. utility times -1

So the final maximization problem is: $\quad V_0 = -E_0(ln[-V_1])$

$\alpha > \rho$ so agents have a preference for early resolution of uncertainty. For expected utility, would set $\alpha = 0$, and then there would be no preference for early resolution of uncertainty. back

ETF allows informed investors to be more aggressively on private signals

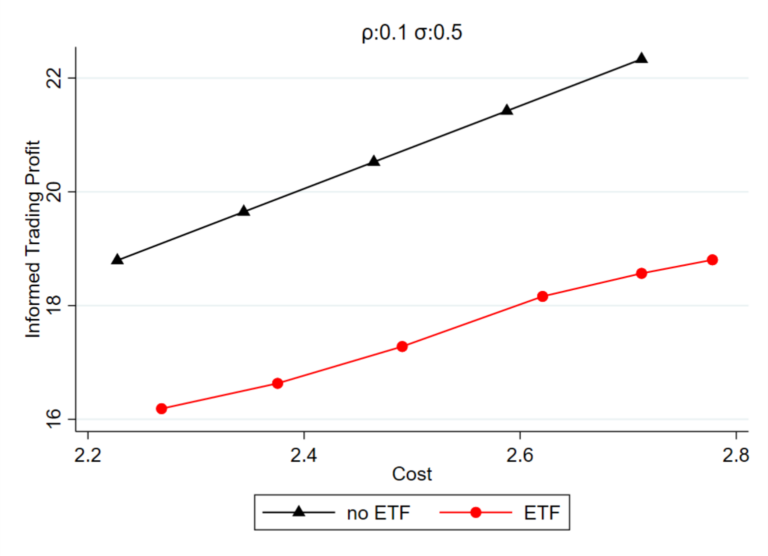
- Investors hedge out all systematic risk when ETF is present

Demand function: $G_0 + G_1 \mathbf{s}_j + G_2 \mathbf{p}$

			No ETF			ETF	
ρ	σ_f^2	Shr. Inf.	$G_{i,i}$	$G_{i,j}$	$7 \times G_{i,j}$	$G_{i,i}$	$G_{i,j}$
0.1	0.2	0.5	0.968	-0.117	-0.817	1.260	-1.260
0.1	0.5	0.5	0.766	-0.069	-0.484	1.010	-1.010
0.25	0.2	0.5	0.290	-0.024	-0.171	0.274	-0.274
0.25	0.5	0.5	0.255	-0.019	-0.130	0.124	-0.124
0.35	0.2	0.5	0.189	-0.014	-0.100	0.046	-0.046
0.35	0.5	0.5	0.176	-0.012	-0.086	0.003	-0.003

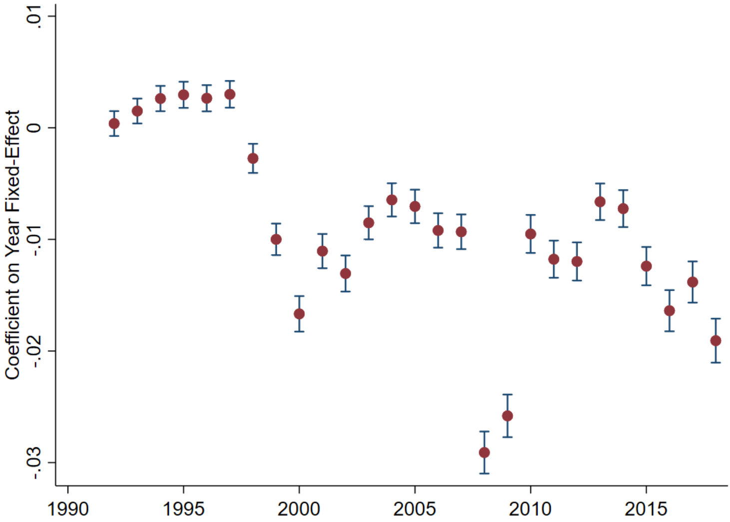
Notes: For $j \neq i$ and $i \neq n + 1$. 8 stocks. back

How Big is the Cost of Becoming Informed?



back

Pre-Earnings Drift Has Declined



Notes: Each dot represents the coefficient on a year fixed-effect in a pooled regression across all years. Bars represent 95% confidence intervals with standard errors clustered at the firm level. Regression includes firm fixed-effects. back

Does Initial Wealth Matter?

Define trading profits as $\pi_{2,j}$. With recursive utility:

$$U_0 = w_{0,j} + E_0\left[(E_{1,j}[\pi_{2,j}] - 0.5\rho Var_{1,j}[\pi_{2,j}])\right]$$

With expected utility:

$$U_{0,j} = -exp(-\rho w_{0,j})E_{0,j}\left[E_{1,j}[-exp(-\rho\pi_{2,j})]\right]$$

So w_0 will not affect the optimization in either case.

back

Learning Technology Details

- Why $\sigma_{\epsilon_{i,j}} = \frac{1}{\alpha+K_{i,j}}$ vs. a linear learning technology e.g. $\sigma_{\epsilon_{i,j}} = 1 + \alpha - K_{i,j}$?
  - Decreasing returns to specialized information
  - Allows me to check numerical method when the ETF is present against the closed form solution in Kacperczyk et. al. (2016)
- Need $\alpha > 0$ so $var(\epsilon_i)$ is well defined even if agents devote no attention to asset i.
- Matters for matching a rotated version of the economy with independent assets/signals to any possible unrotated version of the economy with correlated assets/signals
- Interpretation with $\alpha = 0$ and independent assets/signals: The manager j can observe N signal draws, each with precision $K_{i,j}/N$, for large N. The investment manager then chooses how many of those N signals will be about each shock.

back

Recursive Utility Formulation (1)

Start with Epstein-Zin preferences:

$$U_t = \left[(1-\beta)c_t^\alpha + \beta\mu_t\left(U_{t+1}\right)^\alpha\right]^{1/\alpha}$$

where EIS$=1/(1-\alpha)$ and μ_t is certainty equivalent operator.

- In my setting, all consumption happens at time 2, so set $t=0$. The risk-free rate is zero, so set $\beta=1$.
- Choose the von Neumann-Morgenstern utility index $u(w) = -exp(-\rho w)$.
- Following Veldkamp (2011), define the certainty equivalent operator $\mu_t(U_{t+1}) = E_t\left[-ln(-U_{t+1})/\rho\right]$.
- Recall: $U_{1,j} = E_{1,j}[-exp(-\rho w_{2,j})]$. Wealth is normally distributed so $U_{1,j} = -exp(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}])$

Recursive Utility Formulation (2)

Substitute in expression for CE operator:

$$U_0 = \left[\mu_0 \left(U_1\right)^{\alpha}\right]^{1/\alpha}$$

$$U_0 = \left[E_0 \left[-ln(-U_1)/\rho\right]^{\alpha}\right]^{1/\alpha}$$

$$U_0 = \left[E_0 \left[-ln(exp(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}]))/\rho\right]^{\alpha}\right]^{1/\alpha}$$

$$U_0 = \left[E_0 \left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]^{\alpha}\right]^{1/\alpha}$$

Setting $\alpha = 1$ i.e. infinite EIS:

$$U_0 = E_0 \left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]$$

Which matches Equation 6 in Kacperczyk et. al. (2016). back

Recursive Utility Formulation (3)

When solving for optimal information choice, need to compute:

$$U_0 = E_0\left[(E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}])\right]$$

We have closed form expressions for $E_{1,j}[w_{2,j}]$ and $Var_{1,j}[w_{2,j}]$:

$$\text{Posterior mean}: \quad E[z] = B_0 + B_1 s_j + B_2 p$$

$$\text{Posterior Variance}: \quad \hat{\Sigma} = (inv(V) + Q \times inv(U) \times Q + inv(S))^{-1}$$

$$E_{1,j}[w_{2,j}] = q'(E[z] - p)$$

$$Var_{1,j}[w_{2,j}] = q' \times \hat{\Sigma} \times q$$

where B_0, B_1, B_2, V, Q, and U are defined as in Admati (1985). Numerically integrate over draws of s, η and x to compute U_0.

back

Solving a Rotated Version of the Model

Based on Kacperczyk et. al. (2016):

1. Guess an initial total attention for informed investors
2. Solve orthogonal model with this total attention constraint
3. Loop over possible attention choices in un-rotated model
4. See if optimal attention from rotated model matches the guess after rotation i.e. $\Sigma_e = GL^*G'$ where $GLG' = \Sigma_e$ is the eigen-decomposition of the signal precision matrix and L^* is the optimal precision matrix in the rotated model
5. Loop over all possible max attention allocations for the orthogonal model until it matches desired total attention in the un-rotated model

Note, if assets are not independent need $\Sigma_e = \Sigma^{1/2} G L^* G \Sigma^{1/2}$, where Σ is the covariance matrix of asset payoffs.

back

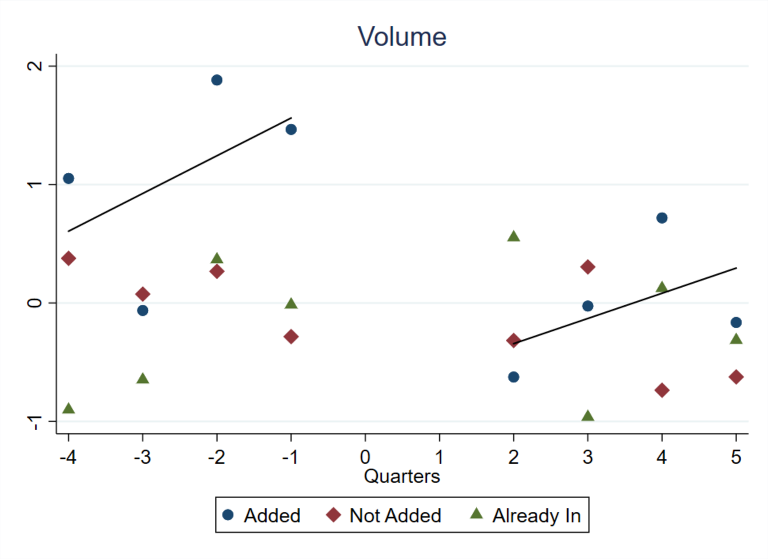
Modeled ETF's Features

In the model, ETF looks like a futures contract

- What features of ETFs does this capture?
  - ETFs are more divisible than futures, which allows more investors to trade. E-mini trades at $150K per contract, SPY trades around $300 per share.
    - *"The majority of investors using ETFs are doing active management. Only about 30% of ETF investors look at these as passive funds..."* Daniel Gamba, Blackrock (2016)
  - ETFs cover more indices than futures, can think of the model as applying to a particular industry
  - Ease of shorting: ETFs account for 27% of hedge funds short equity positions [Source: Goldman Sachs Hedge Fund Monitor (2016)]
- What features of ETFs does this not capture?
  - Creation/redemption mechanism

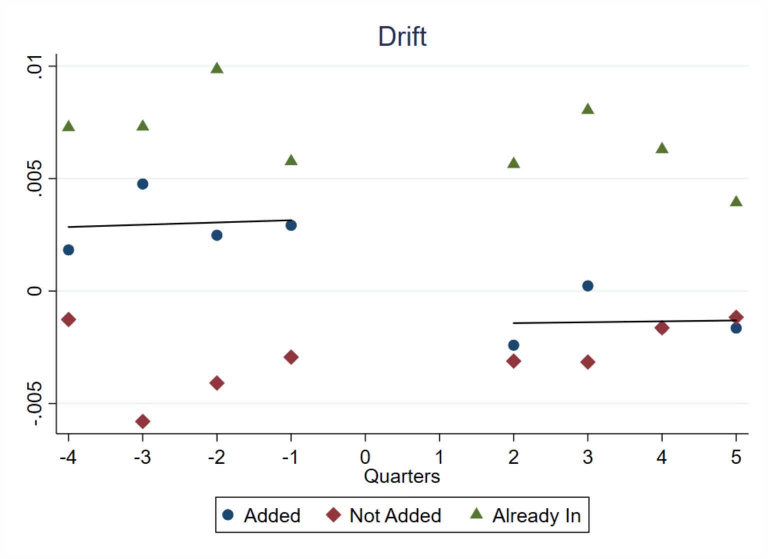
back

Pre/Post S&P 500 Addition Trends: Volume



back

Pre/Post S&P 500 Addition Trends: Drift



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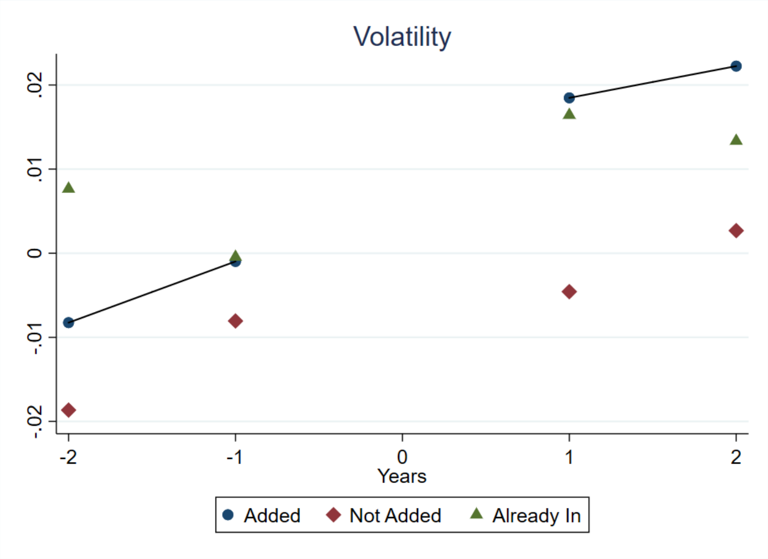
Pre/Post S&P 500 Addition Trends: Volatility



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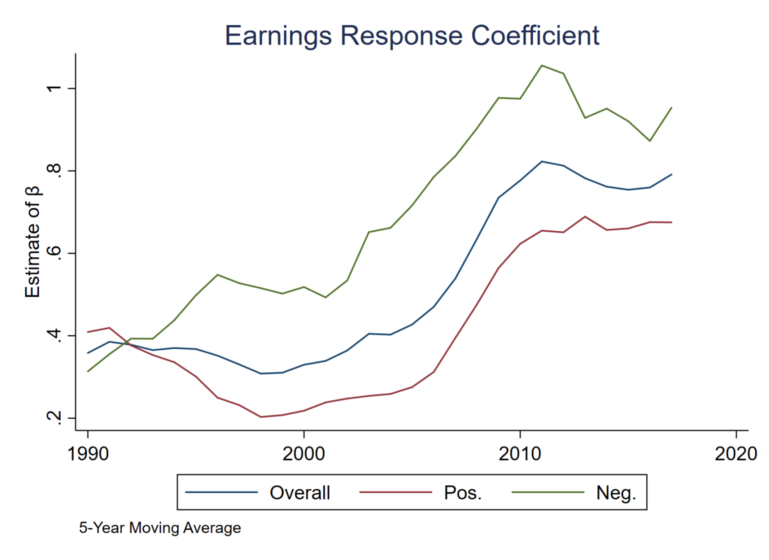
Response to Earnings News has Increased



Notes: *Overall* is coefficient from baseline earnings-response regression. *Pos.* and *Neg.* are coefficients from the earnings-response regression which allows for asymmetric effects of positive and negative earnings surprises. back

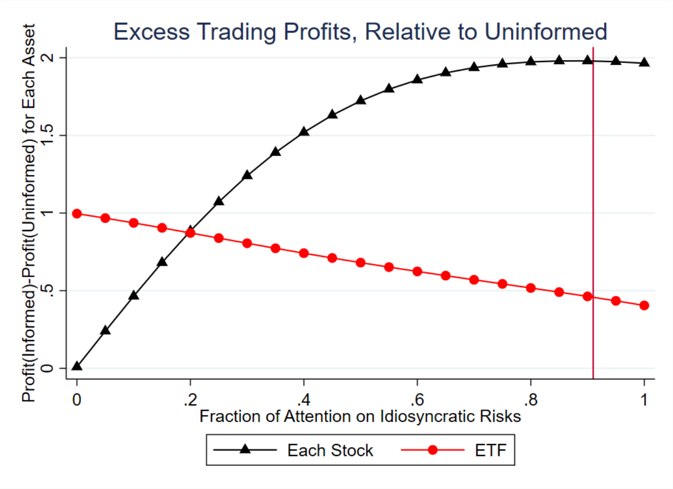
Literature Review (1)

- Admati and Pfleiderer (1988): Give liquidity traders discretion over when to trade. Leads to concentration of trading.
- Wang (1994): Uninformed investors risk trading against informed investors' private information. As information asymmetry increases, trading volume decreases.
- Ball and Brown (1968): Testing efficiency with accounting numbers (EPS)
- Foster et. al. (1984): Relationship between sign and magnitude of earnings surprise and the post-earnings drift
- Weller (2017): Algorithmic trading reduces information acquisition

Literature Review (2)

- Chen, Goldstein and Jiang (2006): Evidence that firm managers learn about own firm from stock prices, and use this to make investment decisions.
- Dow, Goldstein and Guembel (2017): How investors incentives to gather information changes when firms condition investment decisions on stock prices. Leads to a positive feedback effect.
- Edmans et. al. (2012): Evidence that prices matter for takeovers, and thus can discipline managers through threats.
- Goldstein and Guembel (2007): Limit of allocation role of stock prices.
- Dow and Rahi (2003): Welfare effects of more informative prices on investment.
- Dow and Gorton (1997): Stock market can guide investment by conveying information about investment opportunities and past decisions by management.
- Berk, van Binsbergen and Liu (2017): Firms reward managers by giving the more capital.

Learning Tradeoffs, ETF Present



Notes: Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on systematic risk-factor. ETF is in zero average supply. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$ higher σ_f^2 demand functions back

Passive Correlated with Increased Earnings-Day Volatility (by Earnings Announcement)

$$\Delta \frac{r_{i,\tau}^2}{\Sigma_{t=0}^{22} r_{i,t-\tau}^2} = \alpha + \beta \times \Delta Passive_{i,t} + controls + \epsilon_{i,t}$$

	(1)	(2)	(3)	(4)
Inc. Passive	-0.0877***	-0.0670**	-0.0753*	-0.115
	(0.028)	(0.030)	(0.042)	(0.181)
Observations	239,724	239,719	239,719	239,719
R-squared	0.000	0.005	0.017	0.019
Quarter FE	Yes	Yes	Yes	Yes
Controls	No	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
Weight	Eq.	Eq.	Eq.	Val.

Notes: Panel Newey-West standard errors with 4 lags. Firm-level controls: lagged passive ownership, lagged market capitalization, lagged idiosyncratic volatility, lagged institutional ownership, growth of market capitalization. All specifications include year/quarter fixed effects. LHS (level) has a value-weighted mean of 0.879 and a standard deviation of 0.141. back

Drift Examples

$$Drift_{it} = \begin{cases} \frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} & \text{if } r_t > 0 \\ \\ \frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} & \text{if } r_t < 0 \end{cases}$$

$r_{t-22,t-1}$	$r_{t-22,t}$	r_t sign	intuition	$Drift_{i,t}$	$\frac{(1+r_{t-22,t-1})}{(1+r_{t-22,t})}$
4%	5%	positive	most info.	0.99	0.99
1%	5%	positive	less info.	0.96	0.96
-1%	5%	positive	least info.	0.94	0.94
-4%	-5%	negative	most info.	0.99	1.01
-1%	-5%	negative	less info.	0.96	1.04
1%	-5%	negative	least info.	0.94	1.06

back