Online Appendix for Passive Ownership and Price Informativeness

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1 Model of learning and passive ownership

I incorporate passive ownership into an Admati (1985)-style model with endogenous learning. Investors face two learning decisions: (1) whether or not to pay a fixed cost to receive signals about asset payoffs and (2) how to allocate their limited attention, which determines how precise these signals are for different assets' payoffs. The effect of increasing passive ownership on both learning decisions is ambiguous. Although learning is hard to measure empirically, the model has testable predictions for quantities directly observable in the data: trading volume, returns and volatility.

A one-asset version of this model without endogenous learning is equivalent to the Grossman and Stiglitz (1980)-style model in the main body of the paper.

1.1 Setup

The model has three periods. At time 0, investors decide whether or not to pay a fixed cost c to become informed. If informed, they decide how to allocate their total attention K among the underlying risks. At time 1, informed investors receive signals about asset payoffs, and all investors submit their demands. At time 2, investors consume.

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1.1.1 No passive ownership

Without passive ownership, the model is similar to Admati (1985). The two key differences are (1) endogenous learning and (2) the modeling of systematic risk.

Investors

There are a unit mass of rational investors which fall into two groups: informed and uninformed. At time 1, they both have CARA preferences over time 2 wealth. Informed investors receive signals at time 1 about the assets' time two payoffs. The precision of these signals depends on how informed investors allocate their limited attention. Uninformed investors can only learn about terminal payoffs through prices. The third set of investors are noise traders, who have random demand at time 1, which prevents prices from being fully informative. I restrict to equilibria where there are a positive measure of informed investors.

Assets

There are n assets, which I call stocks. Stock i has time 2 payoff:

$$z_i = a_i + f + \eta_i \tag{1}$$

where $\eta_i \overset{\text{iid}}{\sim} N(0, \sigma_i^2)$, $f \sim N(0, \sigma_f^2)$ and a_i is a constant. In this economy there are $n+1$ risk-factors: one idiosyncratic risk-factor for each stock i, η_i, and one systematic risk-factor, f that affects all stocks.[1] Each stock has $\overline{x}_i$, shares outstanding and noise trader demand shocks $x_i \overset{\text{iid}}{\sim} N(0, \sigma_{i,x}^2)$. The η_i, f and x_i shocks are jointly independent.

In the baseline version of the model, stocks are symmetric: $\sigma_i^2 = \sigma^2$, $\overline{x}_i = \overline{x}$ and, $\sigma_{i,x}^2 = \sigma_x^2$. This is not needed, but it simplifies the intuition for the key learning trade-offs. For an extension where individual stocks load differently on systematic risk, and have heterogeneous volatility of their idiosyncratic risk-factors, see Section 3. An important assumption is that $\sigma^2 > \sigma_f^2$. I find that if this does not hold, the intensive learning margin becomes unimportant, as investors almost always learn only about the systematic risk-factor f. This assumption has empirical support: idiosyncratic risk is more volatile than systematic risk, accounting

[1]There exists an equivalent economy where stock returns have the same correlation structure, but there is no systematic risk-factor. For example, suppose $cov(\eta_i, \eta_j) = \sigma_f^2$ for all i and j. In this case, the number of risks would be equal to the number of assets. Without a systematic risk-factor, however, there is no guarantee the learning technology will be comparable between economies when the ETF i.e., the $n+1^{th}$ asset is and is not present. Subsection 3.18, titled "Equivalence of Learning Technologies Between Rotated and Unrotated Versions of the Model" discusses this representation issue in detail.

for 60-80% of total volatility using the decomposition in Campbell et al. (2001).

I also assume that the number of stocks n is finite, so that idiosyncratic risk cannot be totally diversified away. In the baseline parameterization I set $n = 8$.[2] This restriction to a small number of stocks is a reduced-form way of modeling transaction costs: Trading the first n stocks is free, but then trading costs go to infinity if an investor wanted to trade an additional stock. This could also be viewed as a reduced-form way of modeling time/attention constraints: investors can follow a limited number of stocks and only trade stocks they follow (see e.g., Merton (1987)). Without this assumption, introducing the ETF would have no effect on investors' behavior: The lack transaction costs means that as n goes to infinity, the individual investors could perfectly replicate the systematic risk factor on their own without the ETF.

Signals

If investor j decides to become informed, they receive noisy signals $s_{1,j}, \ldots, s_{n,j}$ at time 1 about the payoffs of the underlying *stocks*:

$$s_{i,j} = a_i + (f + \epsilon_{f,j}) + (\eta_i + \epsilon_{i,j}) \tag{2}$$

where $\epsilon_{i,j} \overset{\text{iid}}{\sim} N(0, \sigma^2_{\epsilon_{i,j}})$, $\epsilon_{f,j} \sim N(0, \sigma^2_{\epsilon_{f,j}})$ and $\epsilon_{i,j}$ are independent for all permutations of i and j, as well as independent from $\epsilon_{f,j}$. The signal noise, ϵ, depends on how much attention investor j devotes to each *risk-factor* that affects the payoff of stock i: η_i and f. The learning technology governs how quickly signal noise decreases as more attention is devoted to a particular risk-factor.

Learning

Investor j can allocate attention $K_{i,j}$ to risk-factors η_i or f to reduce signal noise:

$$\sigma^2_{\epsilon_{i,j}} = \frac{1}{\alpha + K_{i,j}}, \quad \sigma^2_{\epsilon_{f,j}} = \frac{1}{\alpha + K_{n+1,j}} \tag{3}$$

[2] With $n = 8$, consider the case where $\sigma_f = 0.25$ and $\sigma = 0.55$: Then, an equal-weighted portfolio of the 8 stocks would have a standard deviation of about 0.31, 25% larger than the standard deviation of the systematic risk-factor.

where $\alpha > 0$.[3] *Baseline learning*, α, can be viewed as informed investors having a "finger on the pulse" of the market. They know a little bit about each risk-factor, even without explicitly devoting attention to it. I set $\alpha = 0.001$, and discuss the sensitivity of the model's predictions to α in the Section 3.

Informed investors have a total attention constraint of $\sum_{i,j} K_{i,j} \leq K$. They also have a no forgetting constraint, so $K_i \geq 0$ for all i. In the baseline parameterization, learning capacity K is fixed to 1. Section 3 discusses an alternative version of the model where investors can pay to increase learning capacity, rather than pay for a fixed K.

Portfolio Choice

Define terminal wealth:

$$w_{2,j} = (w_{0,j} - \mathbb{1}_{informed,j} c) + \mathbf{q}_j'(\mathbf{z} - \mathbf{p}) \tag{4}$$

where $w_{0,j}$ is initial wealth, c is the cost of becoming informed, $\mathbf{z}$ is the vector of terminal stocks payoffs, $\mathbf{p}$ is the vector of time 1 prices and $\mathbb{1}_{informed,j}$ is an indicator equal to 1 if investor j decides to become informed. Here, and everywhere else in the paper, boldface is used to denote vectors. The gross risk-free rate between time zero and time two is set to 1.

Investor j submits demand $\mathbf{q}_j$ to maximize their time 1 objective function:

$$U_{1,j} = E_{1,j}[-exp(-\rho w_{2,j})] \tag{5}$$

where ρ is risk aversion. $E_{t,j}$ denotes the expectation with respect to investor j's time t information set. For informed investors, the time 1 information set is the vector of signals $\mathbf{s}_j$ and the vector of prices, $\mathbf{p}$. For uninformed investors, the time 1 information set is just prices.

Prices

Suppose we fix the share of informed investors, and the information choice of informed investors at some set of $K_{i,j}$'s. Then, the model is equivalent to Admati (1985). This is

[3] This differs from Kacperczyk et al. (2016), where the learning technology is $\sigma^2_{\epsilon_{i,j}} = \frac{1}{K_{i,j}}$. In my setting, $\sigma^2_{\epsilon_{i,j}}$ needs to be well defined even if an investor devotes no attention to risk-factor η_i or f. This is because with more risks than assets, the risk-factors are not fully separable. For example, if $\epsilon_{1,j}$ has infinite variance, but $\epsilon_{f,j}$ has finite variance, the variance of $s_{1,j}$ is still not well defined. In Kacperczyk et al. (2016), each of the rotated assets is only exposed to one risk, so devoting no attention to any particular risk leads to a precision of zero, but this does not have spill-over effects on other assets.

because investors do not independently receive information about the $n+1^{th}$ risk-factor. Because there are more risks than independent signals/stocks, investors cannot rotate the economy to think in terms of synthetic assets exposed only to risk-factor payoffs, rather than stock payoffs (see e.g., Veldkamp (2011)). The assumption of no independent signal about the $n+1^{th}$ risk-factor is needed to solve the model using the closed form solutions in Admati (1985).[4]

To solve for prices, start by defining μ as the vector of a_i's. Further define $\overline{\mathbf{x}}$ as the vector of $\overline{x}_i$'s. Define the $n \times (n+1)$ matrix Γ as $[I_n \quad 1_{n,1}]$ i.e., concatenating an $n \times n$ identity matrix with a $n \times 1$ vector of 1's. Defining η as a vector of η_i's and f (where f is the last entry), terminal asset payoffs are $\mathbf{z} = \mu + \Gamma\eta$. Define the variance of stock payoffs as the matrix V, and the matrix of stock signal variances for investor j as S_j. I assume all informed investors have the same attention allocation, so $S_j = S$ and $K_{i,j} = K_i$ for all j. Given $\alpha > 0$, S^{-1} will always be positive definite for informed investors.

Define the variance-covariance matrix of noise-trader shocks as $U = \sigma_x^2\mathbf{I}_n$ where $\mathbf{I}_n$ is an $n \times n$ identity matrix. Define the vector of realized noise-trader shocks as $\mathbf{x}$, which is normally distributed with mean zero and variance U. The available supply of each stock to informed and uninformed investors is $\overline{\mathbf{x}}+\mathbf{x}$ i.e., the number of shares outstanding plus/minus demand from noise traders.

The equations for equilibrium prices, beliefs and demands come directly from Admati (1985) (see Section 3 for details):

$$\mathbf{p} = A_0 + A_1\mathbf{z} - A_2(\overline{\mathbf{x}} + \mathbf{x}) \tag{6}$$

Beliefs

All informed and uninformed investors extract an unbiased signal about stock payoffs from prices:

$$s_p = A_1^{-1}\left(p - A_0 + A_2(\overline{\mathbf{x}} + \mathbf{x})\right) \tag{7}$$

[4]Without this assumption, there is no closed-form solution for the price function, as discussed in Section 6 of Admati (1985). To solve the model without this assumption, one would need to numerically solve for prices such that the market clears. The price function would be of the form $p = \tilde{A}_0 + \tilde{A}_1\eta + \tilde{A}_2 f + \tilde{A}_3\mathbf{x}$, where η is the vector of stock-specific risk-factors and $\mathbf{x}$ is a vector of supply shocks. It is difficult to solve for these A_i numerically, because one of the conditions for a solution includes the product of one of the price coefficient matrices, A_1, with the inverse of another one of the price coefficient matrices, A_2^{-1}. This can lead to arbitrarily large offsetting entries in these matrices, and numerical instability.

Informed investors combine their signals $s_{i,j}$, with the information contained in prices s_p and update their prior beliefs using Bayes's law. Uninformed investors update their prior beliefs using only the information contained in prices.

Demands

Demands are a function of private signals and prices. There are separate demand functions for the informed and uninformed:

$$\begin{aligned} \text{Uninformed: Demand} &= G_0 + G_{2,un}\mathbf{p} \\ \text{Informed, investor } j\text{: Demand} &= G_0 + G_1\mathbf{s_j} + G_{2,inf}\mathbf{p} \end{aligned} \tag{8}$$

where $\mathbf{s}_j$ is the vector of signals received by investor j.

Deciding to Become Informed

I follow Kacperczyk et al. (2016) and give investors a preference for the early resolution of uncertainty.[5] At time zero, investor j decides whether or not to pay c and become informed. They make this decision to maximize the time 0 objective function: $U_{0,j} = -E_0[ln(-U_{1,j})]/\rho$ where the time 0 information set is the share of investors who decide to become informed. This simplifies to:

$$U_{0,j} = E_0\left[E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}]\right] \tag{9}$$

because time two wealth is normally distributed.

1.1.2 Introducing passive ownership

Passive ownership is modeled through an $n+1^{th}$ asset, which I call the ETF. With the ETF present, the model is similar to Kacperczyk et al. (2016), with the key difference being that this ETF is endogenously supplied.

Asset payoffs

The ETF is only exposed to the systematic risk-factor f and has terminal payoff:

$$z_{n+1} = a_{n+1} + f \tag{10}$$

[5]Informed investors face two sources of uncertainty: (1) the difference between expected and realized demands (which depends on the $s_{i,j}$ they receive at $t=1$) and (2) the difference between expected and realized payoffs. Investors with a preference for the early resolution of uncertainty are not averse to (1), but are averse to (2) (see e.g., Veldkamp (2011)). Expected utility preferences i.e., $U_{0,j} = E_0[U_{1,j}]$ will *not* induce a preference for the early resolution of uncertainty. See Section 3 for details.

where a_{n+1} is a constant. When it is present, the ETF initially has average supply $\overline{x} = 0$, but is still subject to normally-distributed supply shocks x_{n+1}. Define $x_{n+1} = \tilde{x}_{n+1} + \sum_{z=1}^{n} x_z$ where $\tilde{x}_{n+1}$ has the same distribution as the x_i for assets 1 to n, but is independent of x_i for all i. These assumptions on the supply of the ETF are important for two reasons (1) Without supply shocks in the ETF, its price would be a fully revealing signal for the systematic risk-factor (2) the ETF must initially be in zero average supply so its introduction does not change the average quantity of systematic risk in the economy.

The size of passive ownership

To model the rise of passive ownership, I introduce a new investor who can buy shares of the underlying stocks, and convert them into shares of the ETF. I assume that, unlike the atomistic informed and uninformed investors, this *ETF intermediary* is strategic: she understands that to create more shares of the ETF, she will have to buy more shares of the stocks, which will push up their *expected* prices. I emphasize expected because she still takes prices at $t = 1$ as given. This is because I assume she can only submit a market order at $t = 0$ i.e., she will have to decide how many shares of the ETF to create without knowing the $t = 1$ prices of any security. Section 3 contains a more thorough discussion of the implications of these two assumptions on the equilibrium size of the ETF.

Her objective function is the same as the objective function for the informed and uninformed investors:

$$U_{0,j} = E_0 \left[E_{1,j}[w_{2,int}] - 0.5\rho^{int} Var_{1,j}[w_{2,int}] \right] \tag{11}$$

where ρ^{int} is the intermediary's risk aversion. I assume that because assets 1 to n (the stocks) are symmetric, she must demand the same amount of each of them. If she buys v shares of every stock, this would take $v \times n$ units of systematic risk out of the economy. To ensure that the amount of systematic risk in the economy is constant, I assume this allows her to create $v \times n$ shares of the ETF. These assumptions imply that her only decision is how many shares of each stock to buy v.

Passive ownership is defined as $v/\overline{x_i}$ i.e., the fraction of each stock's shares outstanding which are owned by the ETF. This maps almost exactly to the definition of passive ownership in the empirical exercises, which is the fraction of each stock's shares outstanding owned by all passive funds.

With this technology, the intermediary's terminal wealth will be:

$$w_{2,int} = v \left(\underbrace{\sum_{i=1}^{n} (z_i - p_i)}_{\text{Idio. Risk}} - \underbrace{n(z_{n+1} - p_{n+1})}_{\text{Sys. Risk}} \right) \tag{12}$$

which is the average difference between the stocks' payoffs and their prices, minus the difference between the ETF's payoff and its price, scaled by how many shares she creates.

To create the ETF, the intermediary is essentially stripping out the idiosyncratic risk from an equal-weighted basket of the stocks, and bearing it herself. She sells the systematic risk from this basket to informed and uninformed investors as an ETF. Having the intermediary bear this idiosyncratic risk is a reduced-form way of modeling basis risk that ETF arbitrageurs bear in the real world. While there can be no true basis risk in a model with no transaction costs and no price impact, this assumption is designed to capture the risk inherent in creating shares of an ETF.

The optimal v mainly depends on ρ^{int}: if the intermediary is less risk averse, she will create more shares of the ETF. The increase in passive ownership over the past 30 years would be consistent with a decrease in ρ^{int}, and given improvements in technology, trading speed, etc., it is reasonable to believe that ETF arbitrageurs are exposed to less risk now than they were in the past. The size of passive ownership also depends on n, ρ, σ, σ_f and the share of informed investors. This is because these other parameters influence demand for the ETF, the ETF's price and thus the intermediary's profits. Section 3 discusses how sensitive passive ownership is to these parameter choices.

There are two ways to increase the size of passive ownership through investors' *preferences*: (1) Decrease the intermediary's risk aversion ρ^{int} or (2) Increase informed and uninformed investors' risk aversion ρ. Having these two channels in the model, instead of just directly varying $v/\overline{x}$, is important for thinking about causality in the empirical results. A decrease in ρ^{int} leading to increased v and changes in learning implies causality coming from passive ownership. An increase in ρ, however, would imply the reverse: the intermediary creates more shares of the ETF *because* of changes in investors' demands, which itself is a function of changes in learning behavior.

Signals and Learning Technology

Informed investor j now receives signals about the payoffs of all the underlying assets, including a separate signal for the ETF:

$$\begin{aligned} s_{i,j} = a_i + (f + \epsilon_{f,j}) + (\eta_i + \epsilon_{i,j}) \text{ for } i = 1, \ldots, n \\ s_{n+1,j} = a_i + (f + \epsilon_{f,j}) \end{aligned} \tag{13}$$

The learning technology and total attention constraint are unchanged from the economy where the ETF is not present.

Price and Demands

Having the intermediary submit a market order at $t = 0$ means that the equilibrium price and demand functions are unchanged from the economy without passive ownership. Because this is a rational expectations equilibrium, all the investors anticipate the optimal v, given the model parameters. This means that informed and uninformed investors will treat the expected supply of each stock as $\overline{x} - v$ and the supply of the ETF as $n \times v$ when constructing their demand functions.

1.1.3 Relating ETFs in the model to ETFs in the real world

In this economy the ETF looks like a futures contract: it is a claim, initially in zero net supply, on the payoff of the systematic risk-factor. Futures contracts, however, have existed for much longer than ETFs. If ETFs were equivalent to futures contracts, then we would not expect to see any of the empirical effects of rising ETF ownership (see e.g., Ben-David et al. (2018), Glosten et al. (2021)). The way the ETF is defined in this paper captures some features of the real-world, and misses others.

One thing it captures is that ETFs make it easier for investors to bet on systematic risk. This is consistent with the fact that ETFs are more divisible than futures, which allows more investors to trade them. For example, E-mini S&P 500 futures trade at around $150,000 per contract, while SPY (the largest S&P 500 ETF) trades around $300 per share (as of June 1, 2020). The investors who benefit from this increased divisibility are not just retirees trading in their 401K's. According to Daniel Gamba, former head of Blackrock's ETF business (iShares) *"The majority of investors using ETFs are doing active management. Only about 30% of ETF investors look at these as passive funds...*[6]*"*

[6] Quoted in Balchunas (2016).

Another feature it captures is that ETFs have made it easier to hedge out/short systematic risk. According to Goldman Sachs Hedge Fund Monitor (2016), *"ETFs account for 27% of hedge funds' short equity positions."* This feature of the model is specific to the introduction of ETFs, relative to index mutual funds. Although index mutual funds existed before ETFs, (open-ended) mutual funds cannot be shorted. Finally, ETFs cover more sectors/indexes than futures contracts and mutual funds.

1.2 Equilibrium and learning trade-offs

At time 1, given K_i's and the share of informed investors, the equilibrium is equivalent to that in Admati (1985): the demand functions ensure that the market clears, and beliefs formed using Bayes's law are rational. At time zero, an equilibrium requires: (1) no informed or uninformed investor would improve their expected utility by switching to the other type and (2) no informed investor would improve their expected utility by re-allocating their attention to different risk-factors. Section 3 explains how I use these two conditions to numerically solve the model.

When an investor is deciding whether to devote attention to systematic or idiosyncratic risk, they face the following trade-off: (1) Learning about systematic risk leads to a more precise posterior belief about every asset (2) But, by assumption, the volatility of the systematic risk-factor (σ_f^2) is low, relative to the idiosyncratic risk-factors (σ^2). This difference in volatilities means that there are more profit opportunities in the stock-specific risk factors than in the systematic risk factor. The ETF also affects this trade-off: If the ETF is not present, investors cannot take a bet purely on systematic risk, or idiosyncratic risks. This is because they cannot perfectly hedge the exposure to systematic risk embedded in any given stock. Section 3 presents two asset examples that illustrate these learning trade-offs.

1.3 Effects of passive ownership on learning

There are two learning margins: (1) How informed investors allocate their attention, which I call the intensive margin and (2) how many investors become informed, which I call the extensive margin. In this subsection, I walk through some examples to understand the effect of passive ownership on the intensive and extensive learning margins. Each example shares the baseline parameters in Table 1, which are mostly borrowed from Kacperczyk et al.

(2016). These examples/parameters are not a calibration and are only designed to illustrate the model's learning mechanisms.

Model Object	Symbol	Value
Mean asset payoff	a_i	15
Volatility of idiosyncratic shocks	σ_i^2	0.55
Volatility of noise shocks	σ_x^2	0.5
Risk-free rate	r	1
Initial wealth	w_0	220
Baseline Learning	α	0.001
# of idiosyncratic assets	n	8
Total supply of idiosyncratic assets	$\overline{x}$	20

Table 1 Baseline parameters. Parameters shared across the intensive/extensive learning margin examples.

1.3.1 Intensive learning margin

There are two key forces that govern the effect of passive ownership on the intensive learning margin. The first is the *hedging* channel: the ETF allows investors to better isolate bets on stock-specific risk-factors. The second is the *market-timing* channel: the ETF also allows investors to trade directly on the systematic risk-factor. The hedging channel tends to *increase* attention to stock-specific risks, while the market-timing channel does the opposite.

To isolate the intensive margin effects of passive ownership and understand the relative importance of these two channels, I fix the share of informed investors and compare attention to systematic risk across three scenarios: (1) *No ETF*, when investors cannot trade the ETF (2) *High* ρ^{int}, when the investors have access to the ETF, but the intermediary is risk averse so it is in near zero supply and (3) *Low* ρ^{int}, when investors can trade the ETF and the intermediary is closer to risk neutral, so the ETF is in larger supply.

Figure 1 shows how attention to systematic risk changes when varying the size of passive ownership, fixing the share of informed investors at 60%. The left panel examines the effect of varying investor risk aversion ρ, fixing the volatility of the systematic risk-factor σ_f at 0.35. As risk aversion increases, informed investors devote more attention to systematic risk. The effects of increasing passive ownership, however, are ambiguous. If risk aversion is sufficiently low, passive ownership can *decrease* attention to systematic risk. If risk aversion is high, the opposite is true.

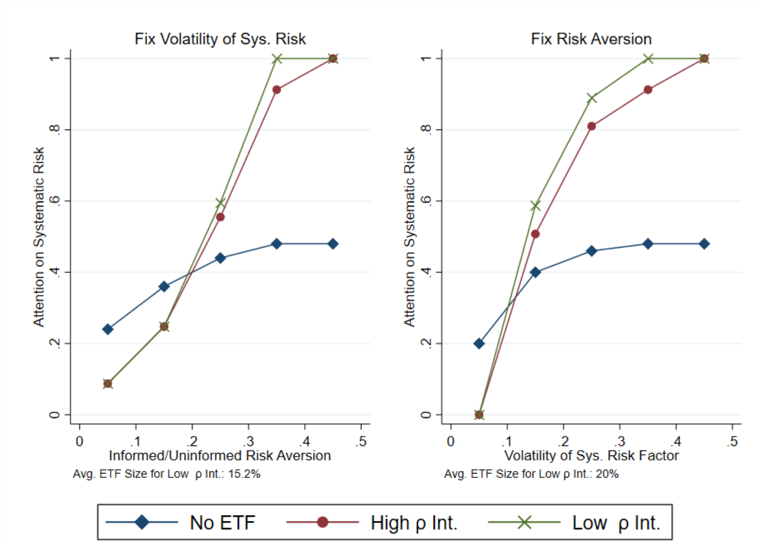

Figure 1. Effect of the ETF on intensive learning margin. In both panels, the share of informed investors is fixed at 60%. In the left panel, $\sigma_f = 0.35$. In the right panel, $\rho = 0.35$. The y-axis reports the share of investors' attention devoted to the systematic risk-factor.

This counterintuitive result, that increases in passive ownership can lead to less learning about systematic risk, is driven by the hedging channel dominating the market-timing channel. When investors are closer to risk neutral they care more about trading profits than risk. When you give them the ETF, it lets them take more targeted bets on volatile individual securities, and they learn more about the stock-specific risk-factors.

On the other hand, the ETF can increase learning about systematic risk when the market timing channel dominates the hedging channel. If investors are risk averse, they 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.

The intensive margin effects also depend on the volatility of the systematic risk-factor σ_f. The right panel of Figure 1 examines the effect of varying σ_f, fixing risk aversion ρ at 0.35. Increasing σ_f leads investors to devote more attention to systematic risk. This makes sense, because as a risk becomes more important to informed investors' terminal wealth, they allocate more attention to that risk. As with the left panel, however, the effect of passive ownership on attention allocation is ambiguous. If σ_f is sufficiently low, increasing passive ownership can lead to less learning about systematic risk, while if σ_f is sufficiently high, the opposite is true.

The strength of the hedging channel doesn't only depend on ρ and σ_f, but also depends on the size of the ETF. Investors are risk averse, so they are willing to pay extra for a security which is not exposed to idiosyncratic risk. As a result, the ETF trades at a premium to an equal-weighted basket of all the underlying stocks. As the ETF becomes larger, this ETF premium shrinks and makes hedging cheaper.

To better understand the hedging channel, it is useful to examine investors' demand functions. For informed investors, G_1 from Equation 8 is a measure of how sensitive demand is to their private signals. Table 2 contains selected the entries of G_1. As with Figure 1, the share of informed investors is fixed at 60%. When the share of informed investors changes, all investors' posterior precision matrices change as well. This affects how aggressive investors are in betting on any signals and would confound the hedging channel effects.

Because all the stocks have the same expected supply and have the same ex-ante risk, G_1 is a symmetric matrix when the ETF is not present. The diagonal entries show how strongly investors react to signals about a particular stock. The off-diagonal entries show how investors hedge these bets. The diagonal entries of G_1 are positive because when an investor gets a good signal about a stock, they buy more of it. The off-diagonal entries of G_1 are negative because they hedge these stock-specific bets by shorting an equal-weighted portfolio of all the other stocks.

For example, row 1 implies that a 1 unit higher signal about asset i leads to demand for 0.968 more shares of that stock, and this position is hedged by shorting -0.117 shares the other 7 stocks. This bet does not fully hedge out systematic risk, as 0.968 is greater than 7 times -0.117 (each stock has a unit loading on the systematic risk factor).

Compare this to the case where the ETF is present in zero average supply: Regardless of risk aversion, informed investors hedge out all the systematic risk embedded in each stock-specific bet with the ETF. Further, after introducing the ETF, informed investors bet *more* aggressively on the stocks with positive signals for low values of risk aversion/systematic risk. Finally, getting a good signal about stock i now has no effect on investors' demand for other stocks, which is why $G_{i,j\neq n+1}$ is always zero.

			No ETF		ETF		
ρ	σ_f^2	$G_{i,i}$	$G_{i,j}$	$7 \times G_{i,j}$	$G_{i,i}$	$G_{i,j\neq n+1}$	$G_{i,n+1}$
0.1	0.2	0.968	-0.117	-0.817	1.260	0	-1.260
0.1	0.5	0.766	-0.069	-0.484	1.010	0	-1.010
0.35	0.2	0.189	-0.014	-0.100	0.046	0	-0.046
0.35	0.5	0.176	-0.012	-0.086	0.003	0	-0.003

Table 2 Effect of the ETF on informed investors' demand functions. The share of informed investors are fixed and 60%. The "No ETF" columns are the entries of G_1 when the ETF is not present, while the "ETF" columns are the entries of G_1 after introducing the ETF in zero average supply. There are $n = 8$ stocks.

1.3.2 Extensive learning margin

There are two key forces that govern the effect of passive ownership on the extensive learning margin. The first is the *hedging* channel: the stock-specific risk factors are more volatile than the systematic risk factor, so there is more money to be made learning about them. The ETF allows investors to better isolate bets on stock-specific risk-factors, increasing the returns to becoming informed. The second is the *diversification* channel: the ETF makes uninformed investors better off by creating a less information-sensitive security (see e.g., Subrahmanyam (1991), Gorton and Pennacchi (1993)). The hedging channel tends to *increase* the share of informed investors, while the diversification channel does the opposite.

To examine the extensive margin effects of passive ownership, I fix the cost of becoming informed c, and compare how many investors become informed across the same three scenarios: (1) no ETF (2) high ρ^{int} and (3) low ρ^{int}.[7] Figure 2 shows the relationship between the cost of becoming informed (in dollars) and the percent of rational investors who decide to become informed in equilibrium.

I use the phrase *risk-bearing capacity* to capture changes in investors' average demand for stocks with respect to model parameters. If the partial derivative of their demand function with respect to a particular parameter is positive, I say increasing that parameter increases risk bearing capacity. Risk-bearing capacity is designed to capture the following intuition:

[7] For each set of parameters/scenarios, I allow investors to optimally re-allocate their attention. Not completely shutting down the intensive margin in this exercise is motivated by the fact that investors' willingness to become informed would be artificially lower if they knew they could not allocate their attention optimally.

In the model, it is possible to change one parameter and offset the effect of this change on the intensive/extensive learning margins by shifting other parameters. For example, consider an increase in ρ: This would tend to decrease the share of informed investors, and increase attention to systematic risk. It is possible, however, to keep learning mostly the same by e.g., simultaneously decreasing σ_f. To examine the effect of passive ownership on learning, it is useful to compare economies with different risk bearing capacities.

The left panel of Figure 2 presents a scenario where risk aversion and the volatility of the systematic risk-factor are high. Demand for stocks is decreasing in both of these parameters, so the risk-bearing capacity of the economy is relatively low. Consistent with common-sense intuition, increasing the cost of becoming informed leads fewer investors to become informed. Increasing the size of passive ownership also leads fewer investors to become informed, evidence of the diversification channel dominating the hedging channel. This is because the more risk averse investors are, the more the uninformed benefit from the introduction of the ETF. The ETF is especially desirable to risk averse uninformed investors because it offers them a way to eliminate their exposure to volitile idiosyncratic risk-factors.

The right panel presents a scenario where risk aversion and the volatility of the systematic risk-factor are low. Again, demand is decreasing in both these parameters, so in this scenario the risk-bearing capacity of the economy is relatively high. With these parameters, as passive ownership increases, more investors become informed, evidence of the hedging channel dominating the diversification channel. This is because investors who are closer to risk-neutral are more willing to bet aggressively on signals about stock-specific risks.

Figures 1 and 2 show that the intensive and extensive margin effects of increasing passive ownership are ambiguous. This is because of the three competing channels outlined above: The hedging channel leads to more investors becoming informed, and increases the share of attention allocated to stock-specific risks. The market timing channel leads investors to devote more attention to systematic risk. Finally, the diversification channel leads fewer investors to become informed.

The natural next step is to calibrate the model to the data, and understand which of these competing effects dominates. It is difficult, however, to empirically observe how many investors are informed and which risks investors are learning about. In the next subsection, I develop measures of price informativeness that are easily observable in the data.

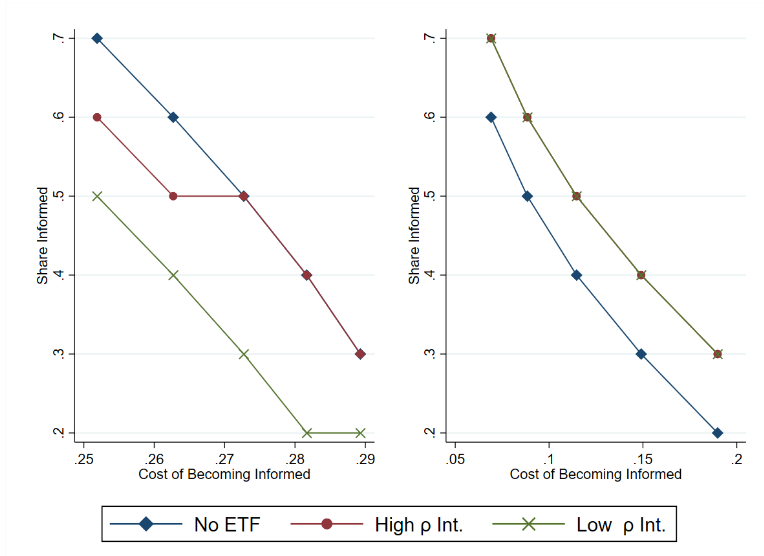

Figure 2. Effect of the ETF on extensive learning margin. Left panel: $\sigma_f = 0.25$, $\rho = 0.15$. Right panel: $\sigma_f = 0.05$, $\rho = 0.05$. The x-axis is the cost in dollars of becoming informed. The y-axis reports the share of investors who become informed in equilibrium at this cost.

1.4 Defining price informativeness

The natural first step in relating passive ownership to price informativeness is to derive a model-based measure of price informativeness at $t = 1$. The issue is that there is no consensus on the right way to theoretically measure price informativeness, and many price informativeness measures are hard to map to the data.

For example, Grossman and Stiglitz (1980) defines price informativeness as a *conditional* covariance, which requires identifying the right set of conditioning variables, which academic economists still disagree on. Based on Grossman-Stiglitz, Bai et al. (2016) measure price informativeness as the variance of fundamentals, conditional on prices. Motivated by an alternative model, Dávila and Parlatore (2018) and Dávila and Parlatore (2021) measure price informativeness as the variance of prices, conditional on fundamentals. These conflicting results suggest that while it may be straightforward to measure price informativeness *within* a given model, it does not mean that measure will be comparable *across* models.

The correct measure of future fundamentals is also not obvious: In a static model like Grossman-Stiglitz, there are a finite number of cash flows, but in reality, firms are long-lived. Maybe fundamentals should be defined as *all* futures cashflows, which are hard to measure. Further, it is also not clear if earnings are the right measure of future fundamentals as management has some control over earnings growth.

Instead, I focus on the observable variables discussed in the introduction: trading volume, returns and volatility. I create model analogues of these objects, and simulate the economy to determine the effect of growing passive ownership on these alternative measures of price informativeness. Although I call these measures of price informativeness, they might be better described as measures of the share of informed investors and investors' attention to stock-specific risk-factors. Intuitively, an increased share of informed investors, or increased precision of informed investor's signals (which in my model is a function of attention) should lead to more informative prices, which is why I use the terms interchangeably.

To map the model to the stylized facts, I label $t = 1$ as the pre-earnings announcement date, and $t = 2$ as the earnings announcement. Because the empirical exercises focus on the firm-specific component of information, in the model I compute these measures for stocks, excluding the ETF.

Pre-Earnings Trading Volume

Although the model features a continuum of investors, when simulating the economy, there are a finite number, which I set to 10,000. At $t = 0$, I assume all of the investors are endowed with $1/10,000^{th}$ of $\overline{x}$. One way to define trading volume is the difference between investors' initial holdings, and their holdings after markets clear. This measure, however, would be contaminated by the noise trader shock. To account for this, I measure trading volume as the difference between initial holdings, adjusting for investor j's share of the noise shock and final holdings.

Let J denote the total number of investors. Then pre-earnings volume is defined as:

$$\sum_{j}^{J} \left| \mathbf{q}_j - \left(\overline{\mathbf{x}} + \mathbf{x}\right) / (J) \right| \tag{14}$$

where the first term $\mathbf{q}_j$ is investor j's demand, and the second term $\left(\overline{\mathbf{x}} + \mathbf{x}\right) / (J)$ is investor j's share of the initial endowment $\overline{\mathbf{x}}$, adjusting for the noise shock $\mathbf{x}$.

There are two main factors that affect trading volume in the model: (1) The share of investors who decide to become informed. As more investors become informed, there are more different signals in the economy, and thus more trading. Uninformed investors all submit the same demand because they all use the same signal s_p from prices to form their posterior beliefs All investors have the same endowment, so if there were only uninformed investors, there would be no trading volume (2) Attention allocation. As more attention is devoted to the individual stocks, informed investors have more precise posterior beliefs, and are more willing to bet more aggressively on their signals. Less trading volume is therefore evidence of fewer informed traders, and less learning about stock-specific risks.

Pre-Earnings Drift

Define the pre-earnings drift as:

$$DM = \begin{cases} \frac{1+r_{(0,1)}}{1+r_{(0,2)}} & \text{if } r_{(1,2)} > 0 \\ \frac{1+r_{(0,2)}}{1+r_{(0,1)}} & \text{if } r_{(1,2)} < 0 \end{cases} \tag{15}$$

where $r_{(0,t)}$ is the cumulative market-adjusted return from 0 to t.[8] The pre-earnings drift will be near one when the return at $t = 2$ is small relative to the return at $t = 1$. $DM_{i,t}$ will be less than one when the $t = 2$ return is large, relative to the returns at $t = 1$. If r_2 is negative, this relationship would be reversed, which is why the measure is inverted when r_2 is less than zero. To compute this measure, I save the prices at $t = 0$, $t = 1$, $t = 2$, and compute returns as $r_{(t-n,t)} = \frac{p_t - p_{t-n}}{p_{t-n}}$ and $r_t = \frac{p_t - p_{t-1}}{p_{t-1}}$.[9] Higher drift is evidence of more informed traders, and more learning about stock-specific risks.

Share of Volatility on Earnings Days

The share of total volatility on earnings days is $\frac{r_2^2}{r_1^2 + r_2^2}$. If prices are not informative before earnings announcements, we would expect earnings-day volatility to be large, relative to

[8]I work with market-adjusted returns to account for the effect of passive ownership on the market risk premium. Market-adjusted returns are defined as the return of the stock minus the average return of all stocks, to make things comparable between the scenario when the ETF is and is not present. Section 3 presents quantitative results on the relationship between passive ownership and the risk premium.

[9]I assume p_2 is the terminal dividend. To compute p_0, let ϕ be the share of informed investors. Because this is a rational-expectations-equilibrium, all investors know ϕ. One way to view the equilibrium is that every (atomistic) investor plays a mixed strategy where they become informed ϕ percent of the time and stay uninformed $1 - \phi$ percent of the time. p_0 is the price such that investors would be happy to hold their endowment i.e., an equal-weighted portfolio of all the stocks, given the strategy they are going to play and the strategies everyone else is going to play *before* they find out whether they will be informed or not. The exact method for computing p_0, however, is unimportant as DM is equivalent to: $\begin{cases} \frac{1}{1+r_{(1,2)}} & \text{if } r_{(1,2)} > 0 \\ 1 + r_{(1,2)} & \text{if } r_{(1,2)} < 0 \end{cases}$.

total volatility. This leads to my third price informativeness measure, QVS, defined as:

$$QVS = 1 - \frac{r_2^2}{r_1^2 + r_2^2} \tag{16}$$

I define QVS this way, rather than $\widehat{QVS} = \frac{r_2^2}{r_1^2+r_2^2}$, so that consistent with the other two measures, higher values of QVS imply more informed investors and more learning about stock-specific risks.

1.5 Effects of learning on price informativeness

It seems natural that these three measures of price informativeness should be related to the intensive and extensive learning margins. While the model does not offer closed-form expressions for these relationships, I examine them using simulated moments. To this end, I simulate the economy 10,000 times for particular choices of ρ, σ_f and the share of informed investors. Then, I calculate the average trading volume, drift and volatility across these simulations for assets 1 to n i.e., the stocks. I show that changes in the intensive and extensive learning margins have unambiguous effects on all three price informativeness measures.

1.5.1 Effect of Learning on Price Informativeness: Directly varying attention and the share of informed investors

To understand the relationship between the intensive learning margin and the price informativeness measures, Panel A of Figure 3 fixes the share of informed investors at 50%, and directly varies attention to systematic risk. As expected, increasing total attention to stock-specific risks increases pre-earnings trading volume, the pre-earnings drift and QVS. All of these plots are consistent with increased attention to stock-specific risks leading to increased price informativeness.

To understand the relationship between the extensive learning margin and price informativeness, Panel B of Figure 3 fixes investors' attention to systematic risk at 50% and directly varies the share of informed investors. Increasing the share of informed investors also increases pre-earnings trading volume, the pre-earnings drift and QVS. These results are consistent with an increased share of informed investors leading to increased price informativeness.

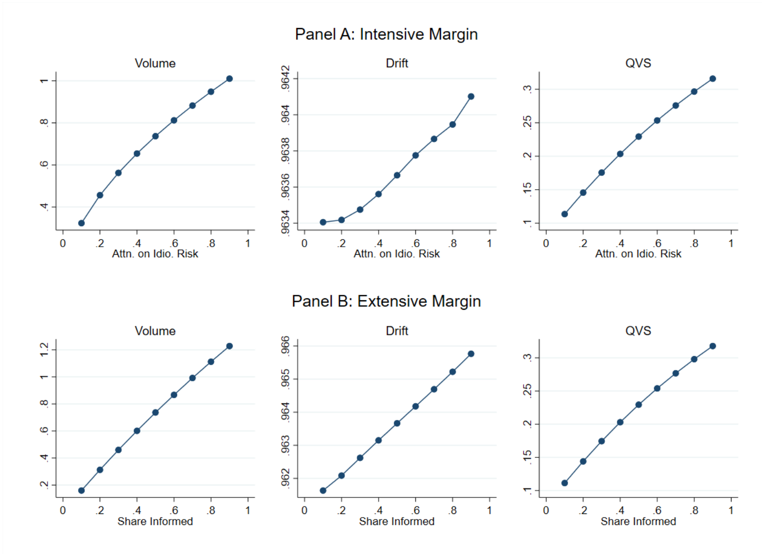

Figure 3. Effect of learning on price informativeness measures (suboptimal attention). Panel A plots the three measures of price informativeness against attention to systematic risk, fixing the share of informed investors at 50%. Panel B plots the three measures of price informativeness against the share of informed investors, fixing attention to systematic risk at 0.5. In all panels, $\rho = 0.15$, $\sigma_f = 0.3$, and the risk aversion of the ETF intermediary, ρ^{int}, is set to infinity so they create no shares of the ETF.

1.5.2 Effect of Learning on Price Informativeness: Indirectly varying attention

When directly varying the share of informed investors and/or investors' attention to systematic risk, there is no guarantee that these learning choices are optimal. To ensure that the relationship between investors' leaning behavior and price informativeness also holds at optimal learning choices, I vary ρ as an indirect way of increasing attention to the systematic risk factor. Risk averse investors prefer to learn about systematic risk, relative to idiosyncratic risk, because volatile stock-specific risk factors can be diversified away. Shifting ρ is one way of varying attention to the systematic risk factor, while ensuring that attention is still optimally allocated.

Panel A of Figure 4 plots the attention to systematic risk and the three price informativeness measures against risk aversion, ρ. To isolate the intensive learning margin's effect on price informativeness, I fix the share of informed investors at 60%. As expected, increasing risk aversion leads to increased attention to the systematic risk factor. At the same time, increased risk aversion leads to decreased pre-earnings trading volume, pre-earnings drift and QVS. This is evidence that increases in attention to systematic risk lead to lower stock price informativeness.

Panel B plots the three measures of price informativeness against ρ for high and low shares of informed investors, highlighting the effect of the extensive learning margin. The blue line represents simulated model moments when the share of informed investors is low, at 20%, while the red line increases the share of informed investors to 70%. Across these two scenarios, I allow investors to optimally re-allocate attention. As expected, increasing the share of informed investors leads to increased pre-earnings trading volume, pre-earnings drift and QVS. This is evidence that increases in the share of informed investors lead to increased stock price informativeness.

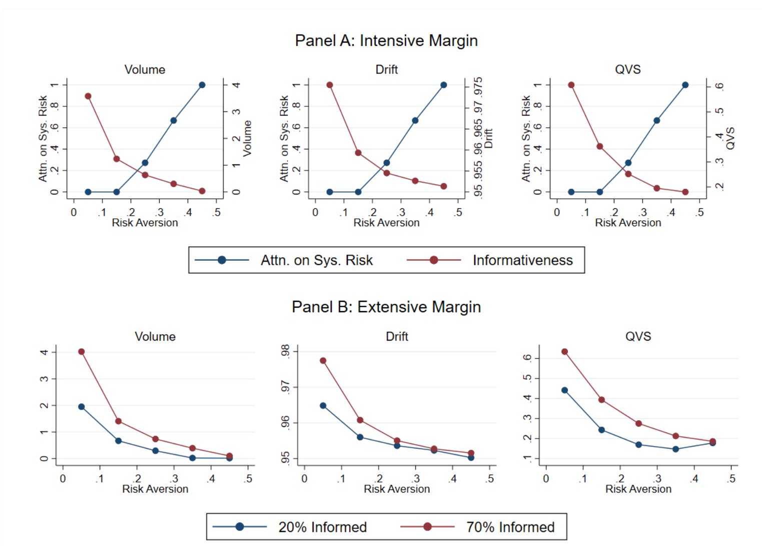

Figure 4. Effect of learning on price informativeness measures (optimal attention). Panel A plots the attention to systematic risk and three measures of price informativeness against informed and uninformed investors' risk aversion, ρ. Panel B plots the three measures of price informativeness against ρ for high and low shares of informed investors. In Panels A and B, the volatility of the systematic risk factor, $\sigma_f = 0.15$, and the risk aversion of the ETF intermediary, ρ^{int}=1. In Panel A the share of informed investors is set to 60%.

Figure 4 confirms that the intensive and extensive learning margins drive changes in price informativeness. The growth of passive ownership affects both of these learning margins, so it should also have an effect of price informativeness. In the next section, I calibrate a version of the model to match the empirical rise of passive ownership.

1.6 Effect of passive ownership on price informativeness

Between 1990 and 2018, passive ownership grew from nothing to owning 15% of the US stock market. In Figure 5, I plot simulated model moments for two scenarios: (1) No ETF (2) ETF owing 15% of each stock. To allow for both intensive and extensive margin learning effects, I fix the cost of becoming informed to match a particular share of informed investors when the ETF is not present. Then, I calculate how many investors optimally become informed in equilibrium at this cost when the ETF owns 15% of the market. All the price informativeness measures are only calculated for the stocks i.e., assets 1 to n.

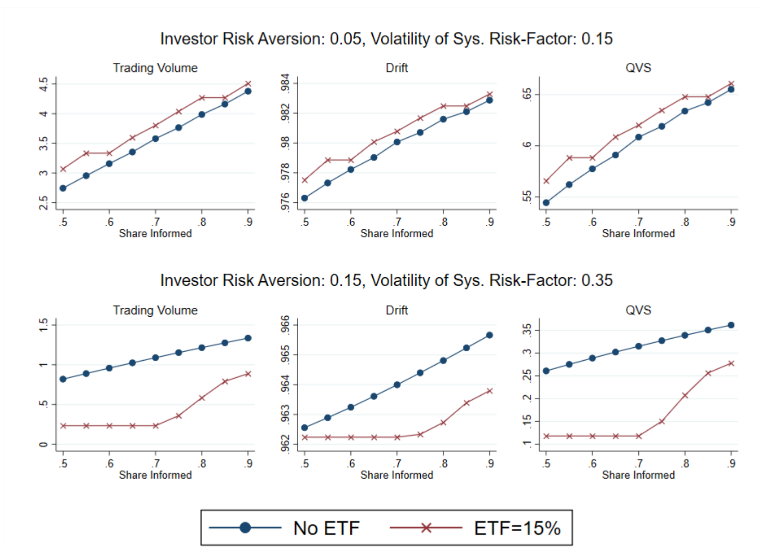

Figure 5. Effect of passive ownership on price informativeness measures. Top panels: $\rho = 0.05$, $\sigma_f = 0.15$. Bottom panels: $\rho = 0.15$, $\sigma_f = 0.35$. The cost of being informed is set so to match the share of investors who become informed when the ETF is not present.

The top 3 panels are averages of the price informativeness measures in an economy with low risk aversion, $\rho = 0.05$, and low volatility of the systematic risk factor $\sigma_f = 0.15$. Consistent with common-sense intuition, increasing the share of informed investors (moving to the right along the x-axis) unambiguously increases price informativeness: it increases the pre-earnings drift, QVS and pre-earnings trading volume. In this economy, growing passive ownership also increases price informativeness: it increases pre-earnings trading volume, the pre-earnings drift and QVS. This is evidence of an economy where the hedging dominates the diversification and market timing channels.

The bottom 3 panels present averages of the price informativeness measures in an economy with higher risk aversion $\rho = 0.15$ and higher volatility of the systematic risk factor $\sigma_f = 0.35$. Volume, drift and volatility all suggest that growing passive ownership leads to less informative prices. This is evidence of an economy where the hedging channel is dominated by the diversification and market timing channels. Figure 5 shows that as with the extensive and intensive learning margins, the net effect of passive ownership on the price informativeness measures is ambiguous.

2 Calibrating the model to match the cross-sectional results

In the model, passive ownership has an ambiguous effect on price informativeness. Equating increasing the size of the ETF in the model to the increases in passive ownership in the data, I can calibrate the model to match the empirical results. I want the calibration to satisfy two conditions. First, passive ownership *quantitatively* matches the data at around 15%. Recall that passive ownership is an equilibrium object, so I cannot set it directly. I target the level of passive ownership indirectly by setting the intermediary's risk aversion ρ^{int}. Second, price informativeness monotonically decreases after introducing the ETF in zero average supply and increasing the ETF's size to to around 15% of the market. To this end, I search on a grid of (1) the cost of becoming informed c (2) risk aversion ρ (3) the volatility of the systematic risk factor σ_f and (4) risk aversion of the ETF intermediary ρ^{int}.

The results are in Table 3. Pre-earnings turnover, the pre-earnings drift and QVS monotonically decrease as passive ownership increases. The cost of becoming informed is set so 60% learn in equilibrium when the ETF is not present. At this cost, 30% learn when the ETF is 16% of the market, evidence of the extensive margin effect at work. Attention to systematic risk increases monotonically from 0.34 to 0.41, evidence that passive ownership also affects the intensive learning margin. In the next section, I perform a counterfactual analysis, examining the effect of increasing passive ownership to 50% of the market with these same parameters.

This calibration reveals the relative importance of the three main channels for explaining the decline in price informativeness. First, it is clear that the diversification and market timing channels dominate the hedging channel: fewer investors become informed and the remaining investors focus their attention to systematic risk. The effect of the diversification channel, however, is quantitatively more important than the market timing channel. To test this, I fix attention to systematic risk (possibly suboptimally) at 0.34 and directly vary the share of informed investors from 0.6 to 0.3. In this world, introducing and increasing the size of passive ownership leads all three price informativeness measures to decline about 90% as much as the *Change* row of Table 3. This suggests that the extensive margin effect i.e., the diversification channel explains most of the decrease in price informativeness.

The row labeled data is the effect of a 16% increase in passive ownership based on estimates from the baseline cross-sectional regressions. Although I am able to qualitatively mirror the empirical patterns with this calibration, the match is not always quantitatively strong. The match on volatility is relatively close, but the matches on volume and drift are off by factors of 4× and 8×. One explanation for this is that in reality, there are many days between earnings announcements, while in the model, there is only one day, $t = 1$, to trade on earnings news before it is made public.

	ρ^{int}	ETF Size	Volume	Drift	Volatility	Share Informed	Attn. on Sys. Risk
Model	N/A	No ETF	0.969	0.9636	0.294	0.6	0.34
	9	0%	0.614	0.9628	0.217	0.35	0.35
	0.6	16%	0.505	0.9626	0.190	0.3	0.41
	Change		-0.464	-0.0010	-0.104		
Data	16% Δ Passive		-1.80	-0.0084	-0.0653		

Table 3 Model calibration to match cross-sectional regression results. The cost of becoming informed is set so 60% learn in equilibrium when the ETF is not present, $\rho = 0.15$, and σ_f=0.3. To roughly match the average passive ownership of 15% in 2018, ρ^{int} is set to 0.6, which leads to an equilibrium level of passive ownership in the model of 16%. Data row is effect of a 16% increase in passive ownership based on equal-weighted cross-sectional estimates with all controls and fixed effects.

Although the model can qualitatively match the empirical results for the three measures of price informativeness, it does not imply that passive ownership *causes* a decrease in price informativeness. Inside the model, it's possible that a change in investors' preferences, and as a result, changes in learning, could lead the ETF intermediary to endogenously supply more shares of the ETF. Outside the model, it's possible that passive ownership endogenously increased the most in stocks that had the biggest decrease in price informativeness for unrelated reasons. To rule out reverse causality, in the main body of the paper, I show my results are robust to quasi-exogenous increases in passive ownership.

3 Model details and discussion

3.1 Numerical method for solving the model

Fixing the share of informed investors, I use the following algorithm to numerically solve for the optimal K_i's:

1. Start all investors at K^0. A simple choice of K^0 is devoting half of total attention to the systematic risk-factors, and distributing half equally among all the stock-specific risk-factors. A more sophisticated choice of K^0 is assuming the assets are independent, and solving the model using the algorithm in Kacperczyk et al. (2016).[10]
2. Consider an atomistic investor j who takes K^0 as given, and calculate their expected utility by deviating to K_j^1 near K^0. Calculate the deviation utility for both a small increase and small decrease in the share of attention spent on the systematic risk-factor.
3. If j can be made better off, move all informed investors to K^1
4. Iterate on steps 2 and 3 until j can no longer improve their expected utility by deviating.

3.2 Prices, Demands and Posteriors

In this subsection, I map the notation and equilibrium functions from Admati (1985) to the notation in Section 2. Define Q as: $\frac{1}{\rho} \times \phi \times (S)^{-1}$, where ϕ is the share of rational traders

[10]While I cannot prove uniqueness of any of these equilibria, I have not found a situation where the starting point affects the optimal attention allocation found using this method.

who decide to become informed at cost c. The price function is:

$$\begin{aligned}
\mathbf{p} &= A_0 + A_1\mathbf{z} - A_2(\overline{\mathbf{x}} + \mathbf{x}) \\
A_3 &= \frac{1}{\rho}\left((V)^{-1} + Q * (U)^{-1} * Q + Q\right) \\
A_0 &= \frac{1}{\rho}A_3^{-1}\left((V)^{-1}\mu + Q(U)^{-1}\overline{\mathbf{x}}\right) \\
A_1 &= A_3^{-1}\left(Q + \frac{1}{\rho}Q(U)^{-1}Q\right) \\
A_2 &= A_3^{-1}\left(\mathbf{I}_n + \frac{1}{\rho}Q(U)^{-1}\right)
\end{aligned} \tag{17}$$

The demand functions for informed/uninformed investors are:

$$\begin{aligned}
\text{Uninformed: Demand} &= G_0 + G_{2,un}\mathbf{p} \\
\text{Informed, investor } j\text{: Demand} &= G_0 + G_1\mathbf{s_j} + G_{2,inf}\mathbf{p}
\end{aligned} \tag{18}$$

where $\mathbf{s}_j$ is the vector of signals received by investor j and:

$$\begin{aligned}
\gamma &= \rho\left(A_2^{-1} - Q\right) \\
G_0 &= A_2^{-1}A_0 \\
G_{2,un} &= \frac{1}{\rho}\gamma \\
G_{2,in} &= \frac{1}{\rho}\left(\gamma + S^{-1}\right) \\
G_1 &= \frac{1}{\rho}S^{-1}
\end{aligned} \tag{19}$$

The coefficients in the demand function can be used to compute investors' posterior beliefs about mean asset payoffs. For informed investors, the posterior mean conditional on signals and prices is:

$$\begin{aligned}
E_{1,j}[\mathbf{z}|\mathbf{s_j},\mathbf{p}] &= B_{0,in} + B_{1,in}\mathbf{s_j} + B_{2,in}\mathbf{p} \\
V_{in}^a &= \left(V^{-1} + QU^{-1}Q + S^{-1}\right)^{-1} \\
B_{0,in} &= \rho V_{in}^a G_0 \\
B_{1,in} &= \rho V_{in}^a G_0 \\
B_{2,in} &= \mathbf{I}_n - \rho V_{in}^a G_{2,in}'
\end{aligned} \tag{20}$$

For uninformed investors, the posterior mean conditional on prices is:

$$\begin{aligned}
E_{1,j}[\mathbf{z}|\mathbf{p}] &= B_{0,in} + B_{2,un}\mathbf{p} \\
V_{un}^a &= \left(V^{-1} + QU^{-1}Q\right)^{-1} \\
B_{0,un} &= \rho V_{un}^a G_0 \\
B_{2,un} &= \mathbf{I}_n - \rho V_{un}^a G_{2,un}'
\end{aligned} \tag{21}$$

3.3 Model Objects in Matrix Form

This subsection presents key model objects (Γ, V, and S_j) in matrix form. Define the $n \times (n+1)$ matrix Γ as:

$$\Gamma = \begin{bmatrix} 1 & 0 & \dots & 0 & 1 \\ 0 & 1 & \dots & 0 & 1 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 & 1 \end{bmatrix} \tag{22}$$

Defining η as a vector of η_i's and f (where f is the last entry), terminal asset payoffs are $\mathbf{z} = \mu + \Gamma\eta$. If the stocks had different loadings on systematic risk, the 1's in the last column would be replaced by β_i's, i.e., the loadings of each stock on systematic risk, as discussed in the Section 3.15.2.

Define the variance of stock payoffs, V as:

$$V = \Gamma \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 & 0 \\ 0 & \sigma_2^2 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_n^2 & 0 \\ 0 & 0 & \dots & 0 & \sigma_f^2 \end{bmatrix} \Gamma' \tag{23}$$

Define the matrix of stock signal variances for investor j as:

$$S_j = \Gamma \begin{bmatrix} \frac{1}{\alpha+K_{1,j}} & 0 & \dots & 0 & 0 \\ 0 & \frac{1}{\alpha+K_{2,j}} & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{1}{\alpha+K_{n,j}} & 0 \\ 0 & 0 & \dots & 0 & \frac{1}{\alpha+K_{n+1,j}} \end{bmatrix} \Gamma' \tag{24}$$

3.4 Model Timeline

Table 4 is a timeline of events in the model.

$t = 0$	◦ Binary decision: pay fixed-cost c and become informed or stay uninformed ◦ Informed allocate K units of attention to the underlying risks
$t = 1$	◦ Informed investors receive signals about asset payoffs ◦ Informed/ uninformed submit demands
$t = 2$	Payoffs realized, investors consume

Table 4 Model Timeline.

3.5 Supply shocks to the ETF

The supply shocks to the ETF, x_{n+1}, have a different strcture than the supply shocks to the individual stocks. Define $x_{n+1} = \tilde{x}_{n+1} + \sum_{z=1}^{n} x_z$ where $\tilde{x}_{n+1}$ has the same distribution as the x_i for assets 1 to n, but is independent of x_i for all i. This implies that the supply shock for the $n+1^{th}$ asset, the ETF, is the sum of the supply shocks to the n stocks, as well as another independent supply shock $\tilde{x}_{n+1}$. I define the ETF noise shocks this way based Ben-David et al. (2018) and Chinco and Fos (2021), which document transmission in noise shocks between the ETFs and the underlying assets. Assuming $\tilde{x}_{n+1} \sim N(0, \sigma_x^2)$, the noise shock for the $n+1^{th}$ asset has total volatility $\sigma_{n,x}^2 = (n+1) \times \sigma_x^2$. The variance-covariance matrix of the noise shocks with the ETF is: $\tilde{U} = (\Gamma')^{-1} \sigma_x^2 \mathbf{I}_{n+1} (\Gamma')^{-1}$.

3.6 Signals on Assets vs. Signals on Risk Factors

To clarify the effect of defining private signals in terms of asset payoffs, consider the following example. Investor j's stock 1 signal is: $s_{1,j} = a_1 + (f + \epsilon_{f,j}) + (\eta_1 + \epsilon_{1,j})$. This is centered on $a_1 + f + \eta_1$ so it is an unbiased signal about the payoff of stock 1. The variance of this signal is $var(\epsilon_{f,j}) + var(\epsilon_{1,j})$ because all signal noise is independent. All investors know the correlation structure of stock returns, so when investor j is calculating a posterior mean for stock 2, they still consider the information in their signal for stock 1, as the stocks are correlated via their common exposure to systematic risk. Further, when deciding what to learn about, investors understand that devoting attention to systematic risk will reduce the variance of all of their stock signals.

3.7 Assumptions about the ETF intermediary

In this sub-section, I discuss (1) why I assumed the intermediary considers the effect of her trade on expected prices and (2) why I assumed the intermediary submits a market order i.e., why her demand does not depend on prices.

The main reason for the first assumption is that I want the intermediary to be different from the informed/uninformed investors. Any of those investors could implement a trading strategy where they buy shares of the underlying stocks, and sell shares of the ETF. When risk aversion is low, informed investors will (collectively) implement a strategy like this.

Given that the group of investors (informed or uninformed) 'creating' shares of the ETF (i.e., shorting the ETF when it is in zero average supply) is not always the same, it is not obvious how to define passive ownership. With my assumptions about the ETF creation process, passive ownership can be measured as the percent of shares of each stock purchased by the intermediary. This has the added benefit of being almost identical to the definition of passive ownership I use for the empirical exercises.

A way to model non-strategic ETF creation would be to have a continuum of competitive investors who can create shares of the ETF for a fixed cost (this cost maps to the creation/redemption fee charged by ETF custodians). Because these investors are competitive, in equilibrium the ETF creators will make zero economic profit, and so will be indifferent to the number of shares they create. By making the ETF creator a monopolist I get a unique solution for the size of the ETF.

The second assumption is needed because of the first assumption. At $t = 1$, if the intermediary could have her demand depend on prices, say through a simple linear rule, there would be an interaction between a strategic investor (the intermediary) and atomistic investors (informed and uninformed investors). On top of that, informed and uninformed investors are learning from prices, while the intermediary, at least as she is defined now, does not. Without additional assumptions, it's not obvious what an equilibrium would look like in this setting.

3.8 Determinants of the size of the ETF

Initially, the ETF is in zero average supply, similar to a futures contract. This means that if an investor wants to go long the ETF, there needs to be another investor taking an exactly offsetting short position in the ETF. Unlike futures contracts, however, almost all ETFs are in positive net supply; few ETFs have short interest equal to 100% or more of their AUM[11]. The mechanism for this is that investors can take a pre-specified basket of underlying securities and give them to an ETF custodian in exchange for shares of the ETF. These shares of the ETF then trade on the secondary market.

The size of the ETF depends on the intermediary's risk aversion, ρ^i. Figure 6 shows that as the intermediary's risk aversion increases, the number of shares of the ETF decreases.

[11] See e.g., data here on the most shorted ETFs. As of 8/1/2020 only 3 ETFs have short interest greater than or equal to 100%.

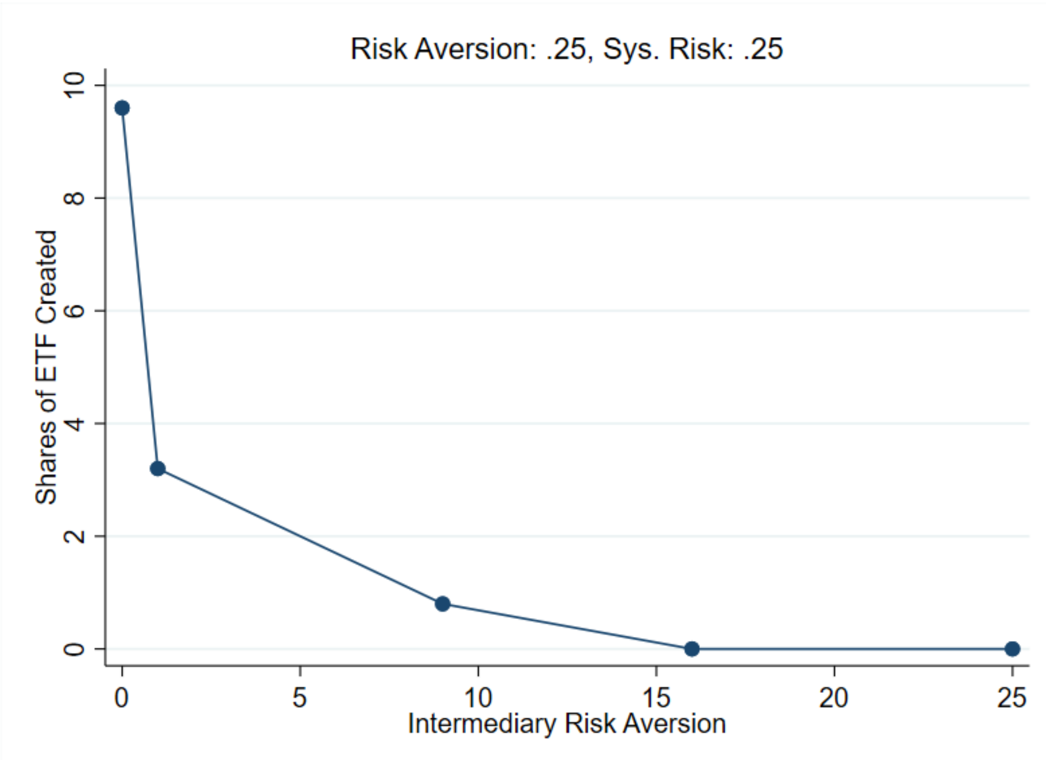

Figure 6. Relationship between size of the ETF and the intermediary's risk aversion. Risk aversion of informed/uninformed investors $\rho = 0.25$. Volatility of the systematic risk factor $\sigma_f = 0.25$ The share of informed investors is set to 50%. If the ETF owned all the shares of the underlying stocks, it would have 20 shares outstanding.

The size of the ETF also depends on ρ, σ_n and the share of informed investors: if the risk-bearing capacity of the economy is low, investors will generally be willing to pay a higher price for the ETF, so the intermediary will create more shares. Figure 7 shows that as risk aversion of informed and uninformed investors increases, the equilibrium size of the ETF increases as well: The amount of the ETF created, as a function of ρ^i, shifts out to the right as we increase ρ.

3.9 Discussion: ETF in the Model vs. ETFs in the Real World

In Section 1, I discuss how ETFs differ from futures contracts and index mutual funds. In this subsection, I discuss alternative mappings between the ETF in the model and ETFs in the real world.

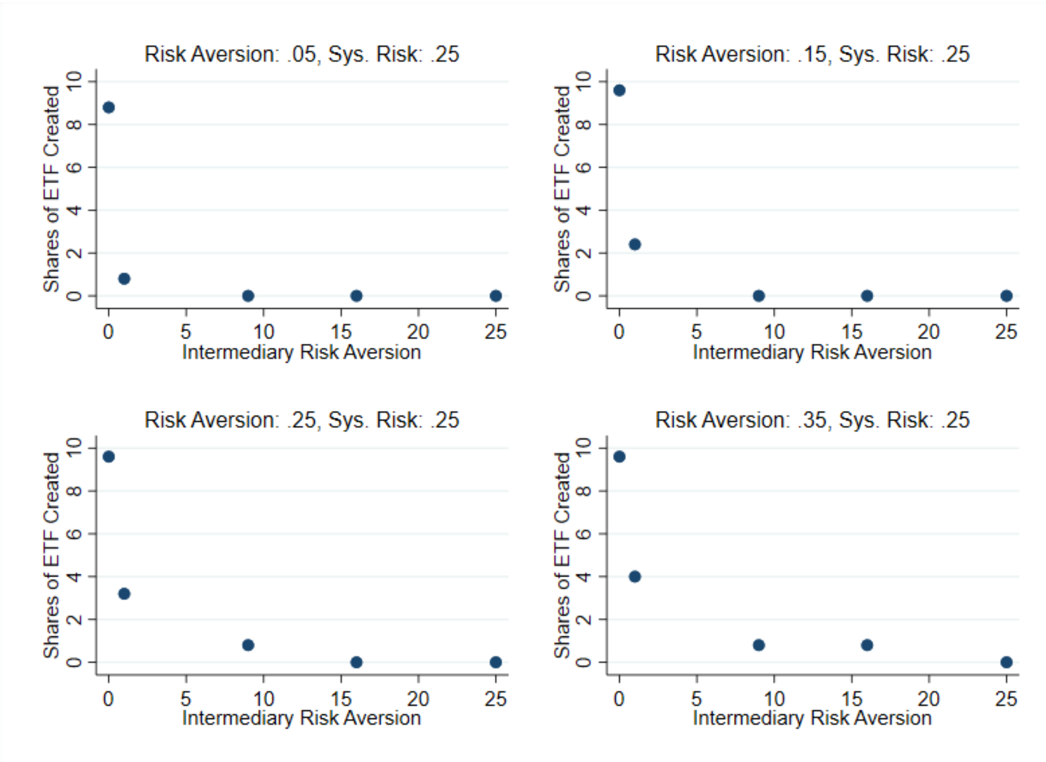

Figure 7. Relationship between the size of the ETF and informed/uninformed investors' risk avesrion. The share of informed investors is set to 50%. The volatility of the systematic risk-factor $\sigma_f = 0.25$. If the ETF owned all the shares of the underlying stocks, it would have 20 shares outstanding.

f as Sector-Specific Risk

Another way to link the ETF in the model to the real world comes from viewing f as a sector-specific risk, rather than an economy-wide risk. ETFs cover more indexes and industries than futures contracts. These sector ETFs are popular: as of June 1, 2020, there was over \$170 Billion investment in State Street's 30 Sector ETFs. Another interpretation of the model is introducing an ETF that offers cheap diversification for particular industry.

ETF Creation/Redemption

The model does not capture the creation/redemption mechanism of ETFs, an important feature that distinguishes them from index mutual funds and futures contracts. Other models like Cong et al. (2020) have this feature. While this is an important channel, especially when talking about market-making in a Kyle (1985)-style model, I abstract away from this to focus on learning.

Another way my simplified ETF creation technology does not exactly match the real world is in the behavior of the ETF intermediary. ETF arbitrageurs do not hold on to the shares of the stocks they buy to create shares of the ETFs – they transfer them to an ETF custodian (e.g., State Street, BlackRock, Vanguard). This could be modeled by having the intermediary transfer the stocks she buys at $t = 1$ to another (new) agent, an ETF custodian, who gives her shares of the ETF, which she sells immediately at $t = 1$. With this setup, the intermediary would have no asset holdings at $t = 2$.

With these alternative assumptions, all the qualitative results are unchanged. The quantitative difference is that creating shares of the ETF is less risky, so in equilibrium, the intermediary makes the ETF larger. In this scenario, the intermediary is only exposed to risk on her market order i.e., that the average prices of the stocks is higher than the price of the ETF due to positive realizations of stock-specific risk-factors or negative realizations of the stock-specific noise trader shocks.

3.10 Model timeline with ETF intermediary

The model timeline for the economy with the intermediary is in Table 5. The differences from the original timeline 4 are in bold.

3.11 Discussion of baseline parameters

Table 1 contains the baseline parameters. I take most of them from Kacperczyk et al. (2016) with a few exceptions: (1) I have effectively set the gross risk-free rate r to 1 because I want to de-emphasize the effect of time-discounting (2) I have 8 idiosyncratic assets, instead of 2, so investors can better attempt to replicate the systematic risk-factor with a diversified portfolio of stocks before the ETF is introduced (3) I increase the supply of the stocks. In Kacperczyk et al. (2016), the supply of the $n + 1^{th}$ risk-factor i.e., the supply of the ETF in the rotated economy is 15 units, and the supply of the two stock-specific risks is 1 unit each. This implies that there is systematic risk in the economy outside the systematic risk in the stocks: $\beta_1 \times$ (supply of asset 1) + $\beta_2 \times$ (supply of asset 2) is less than 15.

I make the total supply of all idiosyncratic assets equal to 20, and split this equally among 8 stocks. I keep the number of stocks relatively small, because if there are too many stocks,

$t = 0$	∘ Binary decision: pay fixed-cost c and become informed or stay uninformed ∘ Informed allocate one unit of attention to the underlying risks ∘ **Intermediary submits market order to buy v shares of the each stock.**
$t = 1$	∘ **Intermediary's market order clears, leaving $\overline{x} - v$ shares of each stock, and $v \times n$ shares of the ETF available for purchase** ∘ Informed investors receive private signals ∘ Informed/ uninformed submit demands
$t = 2$	Payoffs realized, investors consume

Table 5 New Model Timeline. Differences from original timeline in bold.

introducing the ETF has no effect. In the limit, if there were an infinite number of stocks, investors could perfectly replicate the payoff of the ETF with the underlying securities. In reality, this is stopped by trading costs, but these are absent in the model. We can view the small number of stocks as a reduced-form way of modeling transaction costs.

In this economy, increasing the share of investors who become informed (via decreasing the cost of becoming informed), decreasing the volatility of the systematic risk-factor and decreasing risk aversion have similar effects. This is because all of these changes are effectively increasing the *risk-bearing capacity* of the economy.

3.12 Sensitivity to Parameter Choice

In this sub-section, I examine how sensitive the model is to varying risk aversion and systematic risk. In Figure 8 I fix the share of investors who decide to become informed at 20% (the baseline choice in Kacperczyk et al. (2016)), and look at the effect on learning about systematic risk. As risk aversion increases, learning about systematic risk increases. This is because as risk aversion increases, the investors' diversification motive starts to dominate their profit motive. The relationship is steeper in the economy with the ETF and when the volatility of the systematic risk factor is high.

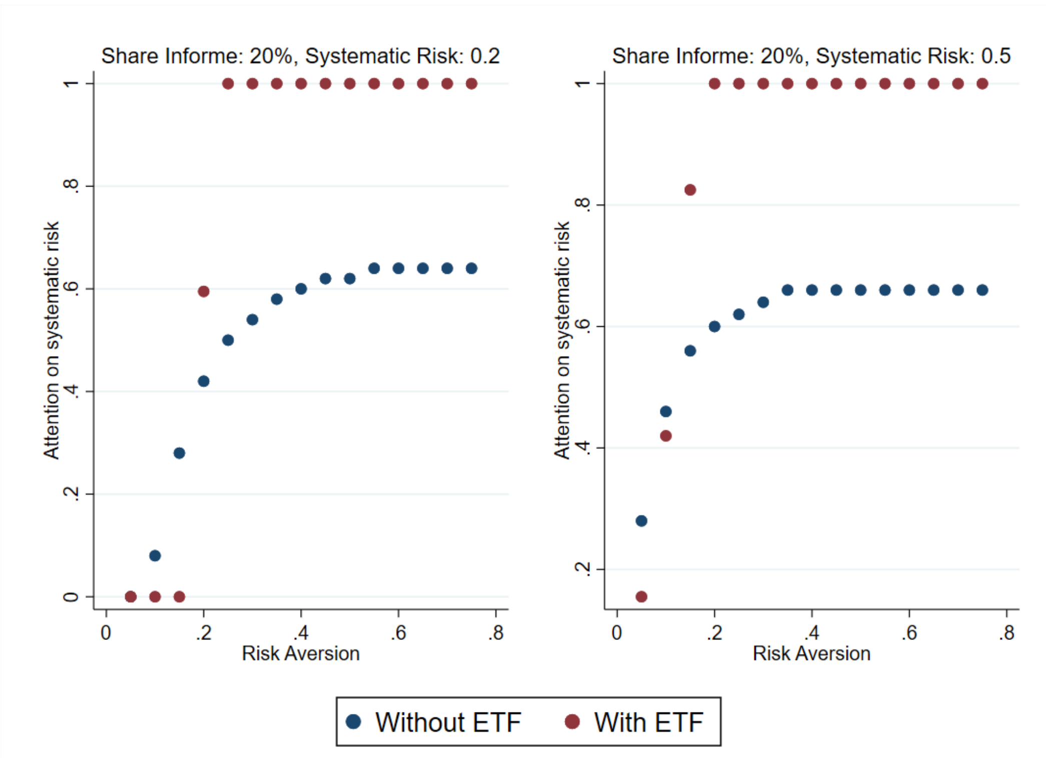

Figure 8. Relationship between risk aversion and attention to systematic risk-factor. In the left panel, σ_n^2 is set to 0.2, while in the right panel, σ_n^2 is set to 0.5. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

In Figure 9, I again fix the share of informed investors at 20% and vary σ_n^2. As expected, increasing systematic risk leads to increased learning about systematic risk. The effect is steeper when risk aversion is high and when the ETF is present.

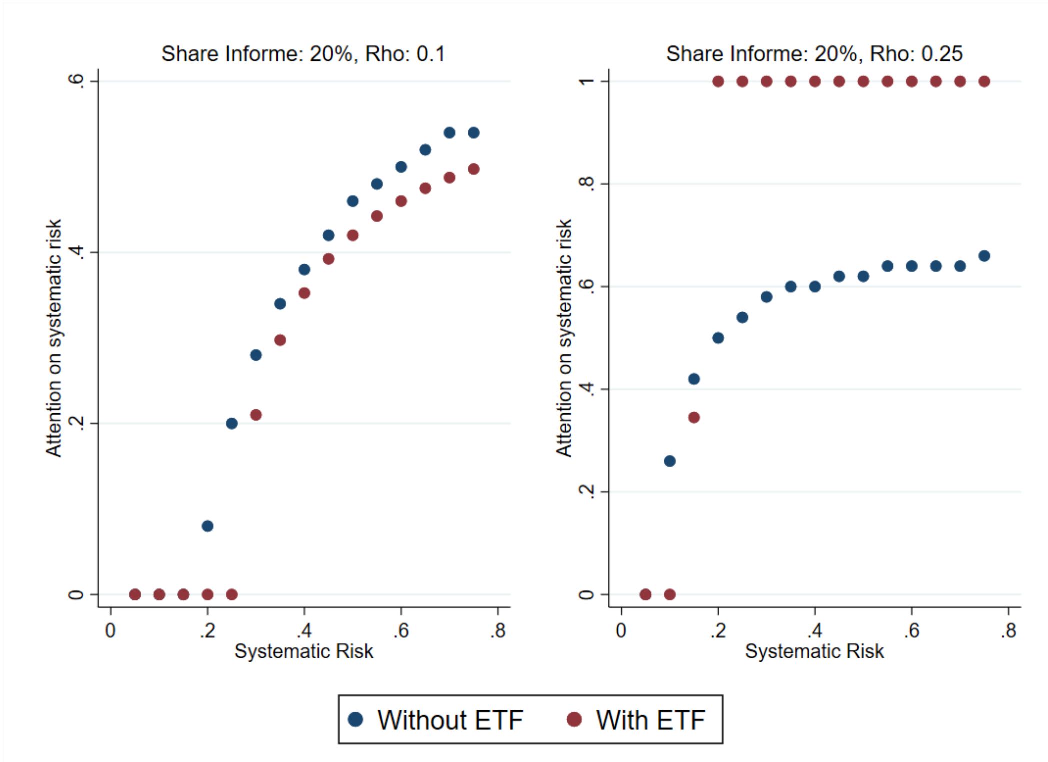

Figure 9. Relationship between systematic risk and attention to systematic risk-factor. In the left panel, risk aversion, ρ is set to 0.1, while in the right panel, risk aversion is set to 0.25. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

3.13 Discussion of alternative ways to solve the model

Two possible non-numerical ways to solve the model are (1) Adding the $n+1^{th}$ risk to Admati (1985). This will not work, as discussed in the original paper, as there is no closed form solution for prices and demands with more risks than assets. (2) Deleting the $n+1^{th}$ asset from Kacperczyk et al. (2016). This is not viable because the rotation used to isolate risk-factors and solve the model will not work if the number of risks is greater than the number of assets.

Finally, we cannot use a benevolent central planner to solve the problem: I find that in the competitive equilibrium, attention is more concentrated on a small number of risks, relative to what would maximize total expected utility for informed *and* uninformed investors.

It also seems as though it should be possible to map the no-ETF economy to an economy with independent assets/risks via an eigendecomposition (see e.g., Veldkamp (2011)). Having done this, it would be straightforward to solve the model using closed-form solution in Kacperczyk et al. (2016). While this is possible, it would still rely on numerical methods. This is because there is no guarantee that after reversing the rotation, the solution is feasible under the proposed learning technology. See Section 3.17 for more details.

Solving for the share of informed investors

Because there are more risks than assets, there are no closed form solutions for $U_{0,informed}$ and $U_{0,uninformed}$, but I can obtain them through simulation. Solving for c directly would be computationally intensive, as the model would have to be re-solved at each proposed combination of c and share of informed investors to check that $U_{0,informed} = U_{0,uninformed}$. It is easier to solve for c by creating a grid for the share of informed investors between 0 and 1. Then, at each point on the grid, compute the difference in expected utility between informed and uninformed to back out c.

Solving for the size of the ETF

I solve for the optimal v numerically using the following procedure. First, I restrict v to be greater than or equal to zero. Then, I loop over all possible values of v between 0 and $\overline{x}$, and select the v which maximizes the intermediary's expected utility. The expectations in the arbitrager's expected utility are computed by simulating 10,000 draws of the z and x shocks for each possible choice of v.

3.14 Preferences: Recursive utility vs. expected utility

In line with Kacperczyk et al. (2016), I define investors' time 0 objective function as: $-E_0[ln(-U_{1,j})]/\rho$ which simplifies to: $U_0 = E_0\left[E_{1,j}[w_{2,j}] - 0.5\rho Var_{1,j}[w_{2,j}]\right]$. This simplification comes from the fact that (1) $w_{2,j}$ is normally distributed, and (2) $E[exp(ax)] = exp(a\mu_x + \frac{1}{2}a^2\sigma_x^2)$ where x is a normally distributed random variable with mean μ_x and standard deviation σ_x, and a is a constant. This objective function leads to a preference for an early resolution of uncertainty, relative to expected utility.

Too see how the log transformation, $-E_0[ln(-U_{1,j})]/\rho$, induces a preference for an early resolution of uncertainty relative to expected utility $E_0[U_{1,j}]$, I follow Veldkamp (2011) and cast preferences as recursive utility (Epstein and Zin (1989)).

3.14.1 Formulation as Epstein-Zin Preferences I

Start by writing down a general formulation of Epstein-Zin preferences:

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

where the elasticity of intertemporal substitution (EIS) is $1/(1-\alpha)$ and μ_t is the certainty equivalent (CE) operator. I've re-labeled what is usually ρ to α it to avoid confusion with the CARA risk aversion at time 1.

In my setting, all consumption happens at time 2, which simplifies things because there is no intermediate consumption. To further simplify things, set $\beta_1 = 1$. Choose the von Neumann-Morgenstern utility index $u(w) = -exp(-\rho w)$ i.e., the CARA utility at time 1. Define the certainty equivalent operator $\mu_t(U_{t+1}) = E_t\left[-ln(-U_{t+1})/\rho\right]$. This μ_t is just the inverse function of the von Neumann-Morgenstern utility index. It makes sense to call this a certainty equivalent operator because it returns the amount of dollars for sure that would yield the same utility as the risky investment. Given $U_{1,j} = E_{1,j}[-exp(-\rho w_{2,j})]$ and normally distributed terminal wealth, $U_{1,j} = -exp(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}])$

Now, setting $\beta_0 = 1$ and $c_1 = 0$: $U_0 = \left[\mu_0\left(U_1\right)^{\alpha}\right]^{1/\alpha}$

Substituting in the expression for the CE operator: $U_0 = \left[E_0\left[-ln(-U_1)/\rho\right]^{\alpha}\right]^{1/\alpha}$

Substituting in the expression for U_1: $U_0 = \left[E_0\left[-ln(exp(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}]))/\rho\right]^{\alpha}\right]^{1/\alpha}$

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

Setting $\alpha = 1$ i.e., an 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). This shows that their utility function can be derived from Epstein-Zin preferences, but does make it totally clear what this transformation has to do with an early vs. late resolution of uncertainty.

To make things clearer, I can start with a more well-known version of Epstein-Zin preferences: $V_t = \left((1-\beta)c_t^{1-\rho} + \beta[E_t(V_{t+1}^{1-\alpha})]^{(1-\rho)/(1-\alpha)}\right)^{1/(1-\rho)}$

Setting $t = 0$, $c_0 = 0$, $c_1 = 0$, $\beta = 1$: $V_0 = \left([E_0(V_1^{1-\alpha})]^{(1-\rho)/(1-\alpha)}\right)^{1/(1-\rho)}$

$c^{1-\alpha}$ is a version of Constant Relative Risk Aversion (CRRA) utility. CRRA utility simplifies to log utility if relative risk aversion is equal to 1. So, with this in mind, set $\alpha = 1$: $V_0 = \left(exp[E_0(ln[V_1])]^{(1-\rho)}\right)^{1/(1-\rho)}$

Set $\rho = 0$ (i.e., infinite EIS as above): $V_0 = exp[E_0(ln[V_1])]$

This is equivalent to maximizing: $V_0 = E_0(ln[V_1])$ because $exp(x)$ is a monotone function.

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

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

There is a preference for an early resolution of uncertainty if $\alpha > (1/EIS)$. As set up here, $\alpha = 1$ and $1/EIS = 0$, so investors have a preference for early resolution of uncertainty. To recover expected utility, set $\alpha = 0$, and then there would be no preference for early resolution of uncertainty.

Why early resolution of uncertainty matters

There are two types of uncertainty in the model: (1) uncertainty about payoffs at $t = 2$, conditional on signals at $t = 1$ (2) uncertainty about portfolio you will hold at $t = 1$ from the perspective of $t = 0$. With these preferences, investors are not averse to uncertainty resolved before time two i.e., are not averse to the uncertainty about which portfolio they will hold.

An intuitive way to see this is that increases in expected variance of terminal wealth, $E_0\left[Var_{1,j}[w_{2,j}]\right)$, linearly decrease utility. With expected utility, $-E_0[E_1[exp(-\rho w)]]$, simplifies to $-E_0[exp\left(-\rho E_{1,j}[w_{2,j}] + 0.5\rho^2 Var_{1,j}[w_{2,j}]\right)]$. Because variance is always positive, utility is decreasing faster than linearly in expected variance.

A more nuanced argument requires a discussion of why learning about particular risks is useful. Expected excess portfolio return achieved through learning depends on the covariance between your portfolio q and asset payoffs $f - p$, $cov(q, f - p)$. Specializing in learning about one asset leads to a high covariance between payoffs and holdings of that asset. The actual portfolio investors end up holding, however, can 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 $cov(q, f - p)$.

With expected utility, investors 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 $E_0[q]$. The utility cost of higher uncertainty from specialization 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. They lower their time 2 portfolio risk by loading their portfolios heavily on assets whose payoff risk will be reduced by learning.

This also shows why it is desirable to introduce a preference for an early resolution of uncertainty in endogenous learning models. Consider an investor who wants to learn about AAPL. They do this so they can hold a lot of Apple (AAPL) when it does well, and hold little AAPL when it does poorly. An expected utility investor would be hesitant to learn too much about AAPL, because the fact that their portfolio will vary substantially depending on the signal they get seems risky to them.

3.15 Extensions

3.15.1 Extension 1: Endogenous capacity choice

In Section 1, the extensive learning margin is a binary choice: Pay the fixed cost c and become informed, or stay uninformed. This can be made into a continuous choice as follows: Fix the share of informed investors, but allow them to optimally choose their total attention K. I consider two functional forms for the cost of adding capacity: (1) Linear: $c(K) = aK+b$ and (2) Convex $c(K) = aK^2 + b$.

The effect of varying K depends on the share of informed agents. Figure 10 shows two features of this extended version of the model when $\rho = 0.25$ and $\sigma_n = 0.25$: (1) For any share of informed investors, as you increase total attention, investors devote less attention to systematic risk (2) For any amount of total attention, as you increase the share of informed investors, they devote less attention to systematic risk.

These patterns arise because in economies with medium to low *risk-bearing capacity*, investors follow a threshold rule for learning. When the total amount of information in the economy is small, either because capacity is low, or because the share of informed investors is low, investors devote all their attention to systematic risk. This is the market-timing channel at work: when investors are risk averse, they care more about systematic risk than idiosyncratic risk, because idiosyncratic risk can be diversified away.

Eventually, the price of the ETF becomes informative enough that investors want to start spreading out their attention. Given that $\sigma = 0.55 > \sigma_f = 0.25$, there is more money to be made betting on individual stocks than on the ETF. So once the total information in the economy is large enough, informed investors want to learn more about stock specific risks.

To numerically solve this version of the model, I loop over values of K, and find the point where the ex-ante utility of the informed and uninformed investors is equal, given $c(K)$.

I find the predictions of this extensions for the extensive learning margin and all three

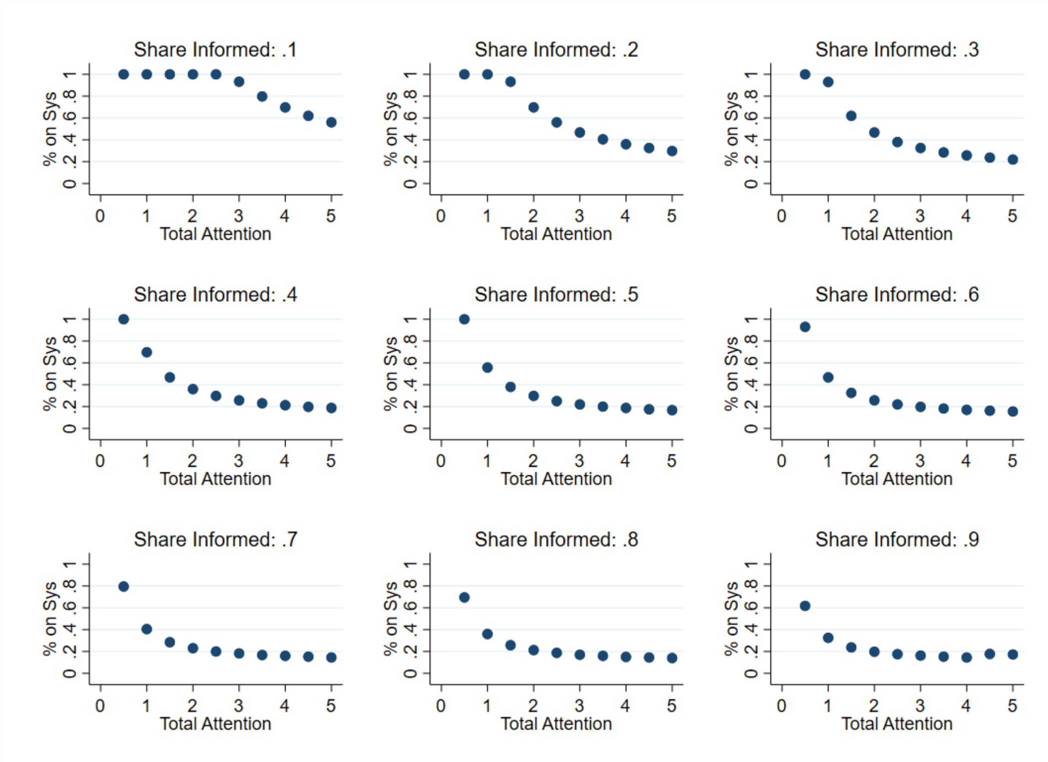

Figure 10. Effect of Varying K and Share Informed. x-axis is total attention K, y-axis is the share of total attention allocated to systematic risk. Parameters: $\rho = 0.25$, $\sigma_n = 0.25$. ETF is present in zero average supply.

measures of price informativeness unchanged from the baseline model. If the risk-bearing capacity of the economy is low, increasing passive ownership leads investors to choose less capacity, and allocate that capacity mostly to systematic risk. This is true for both the linear and convex $c(K)$.

3.15.2 Extension 2: Heterogeneous assets

In the baseline version of the model, I assume all informed investors have the same $K_{i,j} = K_i$. In addition, I assume that assets 1 to n have the same: (1) Mean (2) Systematic risk (3) Idiosyncratic risk (4) Supply shock variance. These assumptions reduce an otherwise n dimensional problem – the $n + 1^{th}$ dimension is accounted for by the total information constraint – to a two dimensional problem: Informed investors must only decide to allocate K_{n+1} attention to systematic risk, and $(1 - K_{n+1})/n$ to each idiosyncratic risk-factor.

Suppose now that each asset i now has the payoff:

$$z_i = a_i + \beta_i f + \eta_i \tag{25}$$

where β_i and $var(\eta_i)$ is different for each asset. In this setting, informed investors' choice is not just a trade-off between learning about systematic and idiosyncratic risk. To solve for information choice in this version of the model, I need to modify the numerical method:

1. Start all investors at K^0
2. Consider an atomistic investor j who takes K^0 as given, and considers their expected utility by deviating to K_j^1 on a $n \times n$ dimensional grid around K^0. Even though there are $(n+1)$ risks to learn about, we don't need the $n+1^{th}$ dimension because of the total information constraint.
3. Calculate the gradient numerically at K^0 using this grid of expected deviation utilities. Then, move j on the grid in the direction of the gradient.
4. If j's expected utility increased, move all informed investors to K_j^1
5. Iterate on steps 2-4 until j can no longer improve their expected utility by deviating.

When the ETF is present, this method is able to match closed form solutions from Kacperczyk et al. (2016) with heterogeneous β_i's. For $n > 3$, however, this method can take a long time to find the solution. Allowing for heterogeneous assets does not drastically change the model's predictions for the effect of passive ownership on pre-earnings volume, pre-earnings drift or earnings-day volatility, so I focus on the symmetric asset case in Section 1.

3.16 Additional theoretical results

3.16.1 Two-Asset Examples of Learning Trade-Offs

To illustrate the learning trade-offs, I present a few examples with only two stocks. Figure 11 shows the effect of learning on trading profits when there is no ETF and the assets are not exposed systematic risk i.e., $z_i = a_i + \eta_i$. Define excess trading profits as the difference between the profits of informed and uninformed investors in a particular security. These excess profits are *not* net of the cost of becoming informed c. The black line plots the excess profits of the informed investors in stock one, while the red line plots the excess profits of the informed investors in stock two. As we move to the right along the x-axis, informed investors are increasing their attention on stock 1. Initially, allocating more attention to stock one increases the informed investors' profit advantage in that stock, but eventually it hits a point of diminishing returns. The black line starts to slope down when the price becomes too informative about η_1. Because the stocks are symmetric, it is optimal for informed investors to allocate half their attention to each stock (vertical red line).

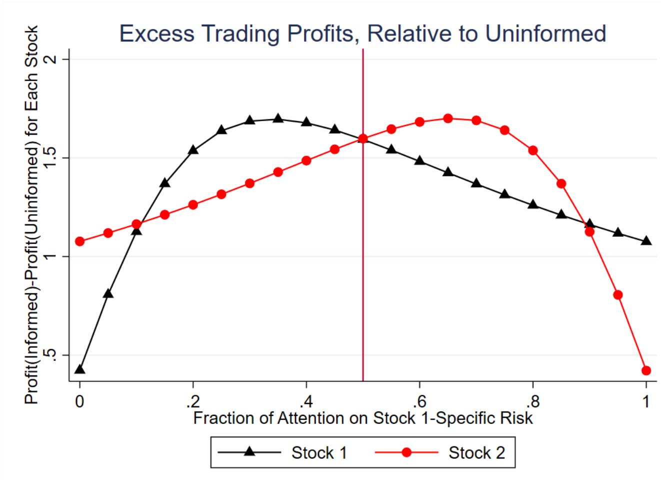

Figure 11. Two Stock Example, No Systematic Risk. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on Stock 2-specific risk. $\rho = 0.1$, $\sigma^2 = 0.55$

Compare this to Figure 12, where there are two stocks, but they are both exposed to a systematic risk-factor. Learning more about stock-specific risks (moving to the right along the x-axis) increases the informed investors' profit advantage, but eventually there are diminishing returns for two reasons. One reason is that prices become too informative, which is what also happened in the first example. The other reason is that both stocks are exposed to systematic risk, and informed investors are not learning much about a risk that affects both stocks. Another factor is that without the ETF, informed investors cannot take targeted bets on the stocks without bearing some systematic risk. However, increasing attention on stock-one specific risk eventually has diminishing returns in Figure 11, where there is no systematic risk, which ensures this is not entirely driving the results in Figure 12.

I run a regression of excess profits on attention to idiosyncratic risk separately for data to the left and right of the optimal attention allocation (red vertical line). The slopes are different to the right/left of the optimum because the volatility of the systematic risk is lower than that of the stock-specific risks.

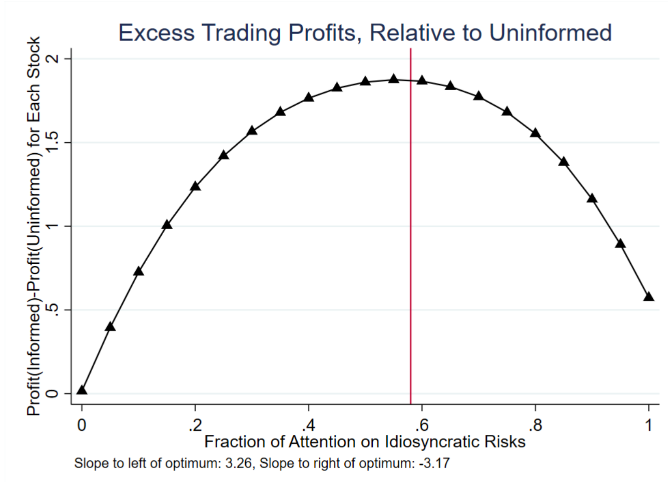

Figure 12. Two stock example, systematic risk, no ETF Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Attention on stock-specific risks is equal. Residual attention is on systematic risk-factor. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$

Finally, Figure 13 illustrates this learning trade off when there are two stocks, both exposed to systematic risk and idiosyncratic risks, and we introduce the ETF in zero average supply. Informed investors can now almost uniformly increase their profits in each stock by learning more about them. This is because they are able to take targeted bets on the stock-specific risk-factors by buying the stocks, and shorting the ETF. In equilibrium, informed investors learn more about stock-specific risks because there is more money to be made betting on η_i's – the stock specific risk-factors are more volatile than the systematic risk-factor f. And because the investors are not very risk averse, with a CARA risk-aversion ρ of 0.1, they don't mind loading up on these volatile stock-specific risks.

3.16.2 Effect of introducing the ETF on investors' posterior mean and variance

Introducing the ETF changes the way investors form beliefs about asset payoffs. Define $\mathbf{s_p} = \mathbf{z} + \epsilon_\mathbf{p}$ as the signal about asset payoffs contained in prices. From the price function, this can be written as: $\mathbf{s_p} = A_1^{-1}(\mathbf{p} - A_0)$, which implies that $\epsilon_\mathbf{p} = A_1^{-1}A_2(\overline{\mathbf{x}} + \mathbf{x})$ and $\Sigma_p = A_1^{-1}A_2U$ where U is the variance-covariance matrix of supply shocks. This implies that

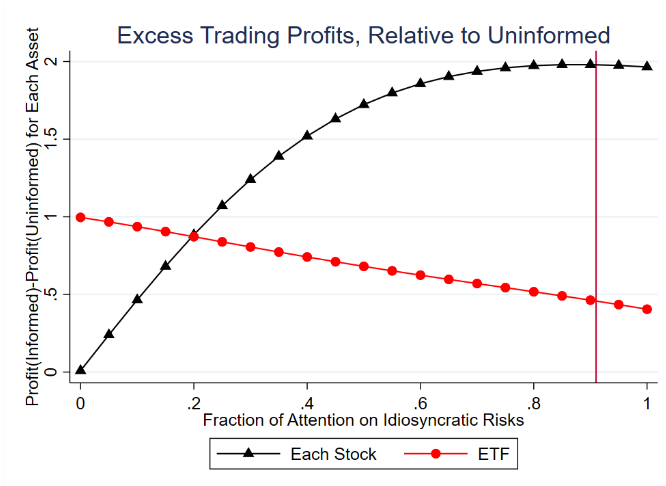

Figure 13. Two stock example, systematic risk, ETF present. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on systematic risk-factor. ETF is in zero average supply. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$

$\mathbf{s_p} \sim N(0, \Sigma_p)$. Without the ETF:

$$\underbrace{\widehat{\Sigma_j^{-1}}}_{\text{Posterior Precision}} = \underbrace{V^{-1}}_{\text{Prior Precision}} + \underbrace{\Sigma_p^{-1}}_{\text{Price Precision}} + \underbrace{S_j^{-1}}_{\text{Signal Precision}} \tag{26}$$

With the ETF, investors observe $s_{\mathbf{p},n+1}$ i.e., the signal about payoff of the $n+1^{th}$ asset contained in asset prices. This will change Σ_p^{-1} i.e., the price precision, but nothing else. This is because fixing attention allocation, introducing the ETF has no effect on S_j^{-1} for assets 1 to n. For any asset i, $s_{i,j} = (f + \epsilon_{f,j}) + (\eta_i + \epsilon_{i,j})$, so $var(s_{i,j}) = var(\epsilon_{f,j} + \epsilon_{i,j}) = var(\epsilon_{f,j}) + var(\epsilon_{i,j})$ by independence of the signal noises.

When the ETF is not present, the posterior mean of f will be:

$$\underbrace{E_{1,j}[\mathbf{z}]}_{\text{Posterior Mean}} = \underbrace{\hat{\Sigma}_j}_{\text{Posterior Variance}} \times \left(\underbrace{S_j^{-1}}_{\text{Precision on Asset Signals}} \mathbf{s_j} + \underbrace{\Sigma_p^{-1}}_{\text{Price Precision}} \mathbf{s_p} \right) \tag{27}$$

With the ETF, investors can separately weigh their signal for f by its own precision:

$$\underbrace{E_{1,j}[\mathbf{z}]}_{\text{Posterior Mean}} = \underbrace{\hat{\Sigma}_j}_{\text{Posterior Variance}} \times \left(\underbrace{S_j^{-1}}_{\text{Precision on Risk-Factor Signals}} \mathbf{s_j} + \underbrace{\Sigma_p^{-1}}_{\text{Price Precision}} \mathbf{s_p} \right) \tag{28}$$

where the terms that have changed are in color. To see how this works, I apply the eigendecomposition in Veldkamp (2011) to isolate the risk-factors. Pre-multiplying $\mathbf{z}$ by Γ, creates synthetic assets exposed to only one risk-factor each:

$$\begin{aligned} \mathbf{z} = \mu + \Gamma\eta \leftrightarrow \tilde{\mathbf{z}} = \Gamma^{-1}\mu + \eta \\ \tilde{s}_i = \eta_i + \tilde{\epsilon}_i \text{ for } i = 1, \ldots, n \end{aligned} \tag{29}$$

With this rotation, the supply of the synthetic assets is $(\Gamma')^{-1}(\overline{\mathbf{x}} + \mathbf{x})$, but at this point, the signals may still be correlated. After another transformation to make the signals independent, I can solve for the equilibrium in this economy using the numerical technique in Kacperczyk et al. (2016)[12], and then rotate back to the economy with payoffs $\mathbf{z}$ and signals $\mathbf{s}$. In this rotated economy, it is clear that investors are going to independently use the $n + 1^{th}$ signal, and the price of the $n + 1^{th}$ asset to learn about $\mathbf{z}$, something they cannot do in the no-ETF world.

To quantify the effect of introducing the ETF on investors' posterior precisions, Table 6 contains selected entries of $\hat{\Sigma}$. Introducing the ETF always increases the precision of both the informed and uninformed for assets 1 to n.

3.16.3 Effect of passive ownership on risk premia

Fixing the share of investors who become informed in equilibrium, introducing the ETF almost always decreases expected returns in the economy. This is not surprising, as the ETF increases the information in the economy: it adds an $n + 1^{th}$ public signal, the price of the ETF. Table 7 shows that introducing the ETF decreases average asset returns, as long as risk aversion and the volatility of systematic risk are not too high. Once we allow the share of informed investors to vary, however, risk premia can actually increase. This is because as the number of informed investors in the economy decreases, the effective risk-bearing capacity

[12] I would like to thank the authors for sharing their solution code with me.

Panel A: Matching Cost of Becoming Informed

		Share Informed		Precision Informed		Precision Uninformed	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF	no ETF	ETF
0.1	0.2	0.05	0.2	1.82	2.24	1.66	2.06
0.1	0.5	0.35	0.2	2.04	2.06	1.93	1.94
0.25	0.2	0.5	0.2	1.85	1.87	1.74	1.82
0.25	0.5	0.5	0.2	1.78	1.87	1.69	1.82

Panel B: Share Informed at 10%

		Share Informed		Precision Informed		Precision Uninformed	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF	no ETF	ETF
0.1	0.2	0.1	0.1	1.85	2.05	1.70	1.88
0.1	0.5	0.1	0.1	1.75	1.90	1.64	1.83
0.25	0.2	0.1	0.1	1.76	1.87	1.65	1.82
0.25	0.5	0.1	0.1	1.71	1.87	1.62	1.82

Panel C: Share Informed at 30%

		Share Informed		Precision Informed		Precision Uninformed	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF	no ETF	ETF
0.1	0.2	0.3	0.3	2.20	2.54	2.05	2.37
0.1	0.5	0.3	0.3	1.96	2.30	1.85	2.16
0.25	0.2	0.3	0.3	1.79	1.92	1.68	1.84
0.25	0.5	0.3	0.3	1.73	1.88	1.64	1.83

Table 6 Posterior Precision. Diagonal entries of $\hat{\Sigma}$ for one of the stocks i.e., assets 1 to n. In panel A, the cost of being informed is chosen such that 20% of investors become informed when the ETF is present. In Panels B and C, the share of informed investors are fixed and 10% and 30% respectively. The "no ETF" column has the (1,1) entry of $\hat{\Sigma}$ when the ETF is not present, while the "ETF" column has the (1,1) entry of $\hat{\Sigma}$ after introducing the ETF. In the "ETF" column, the ETF is in zero average supply.

of the economy decreases, so risk premia must increase.

I view the effect of the ETF on risk premia as more of a modeling artifact than a testable prediction, and want to take out this effect when studying price informativeness. To do this, I work with market-adjusted returns: I calculate the returns of each asset as the actual return, minus the market returns, as discussed in Campbell et al. (2001). Market-adjusted returns are also used for all the empirical exercises in this paper. Whether or not the ETF is present, the market is defined as the average return of all the stocks, to ensure an apples-to-apples comparison. The results are unaffected if the market is defined as the return of the ETF when it is present.

Panel A: Fix 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%

Panel B: Fix Cost of Becoming Informed

		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%

Table 7 Effect of introducing the ETF on Expected Returns. In Panel A, the share informed is the same whether the ETF is present or not. In Panel B, the share informed when the ETF is not present is set to 50%. After introducing the ETF, the share informed are 0.55, 0.2, 0.3 and 0.3 in rows 1-4. The risk premium is defined as the average stock return between period 0 and period 2. When the ETF is present, it is in zero average supply.

3.16.4 Expected utility of informed and uninformed investors

Table 8 contains information on the percentage difference in expected utility between informed and uninformed investors when the ETF is and is not present.

Panel A: Matching Cost of Becoming Informed					
		Share Informed		Diff. in EU	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF
0.1	0.2	0.05	0.2	0.154%	0.163%
0.1	0.5	0.35	0.2	0.181%	0.177%
0.25	0.2	0.5	0.2	0.229%	0.229%
0.25	0.5	0.5	0.2	0.572%	0.571%
Panel B: Share Informed at 10%					
		Share Informed		Diff. in EU	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF
0.1	0.2	0.1	0.1	0.154%	0.177%
0.1	0.5	0.1	0.1	0.226%	0.186%
0.25	0.2	0.1	0.1	0.251%	0.296%
0.25	0.5	0.1	0.1	0.727%	1.103%
Panel C: Share Informed at 30%					
		Share Informed		Diff. in EU	
ρ	σ_n^2	no ETF	ETF	no ETF	ETF
0.1	0.2	0.3	0.3	0.132%	0.141%
0.1	0.5	0.3	0.3	0.190%	0.154%
0.25	0.2	0.3	0.3	0.237%	0.211%
0.25	0.5	0.3	0.3	0.650%	0.300%

Table 8 Effect of Introducing the ETF on Expected Utility of Informed and Uninformed. This table quantifies the effect of introducing the ETF on the expected utility of informed and uninformed investors. The columns of interest are under the header "Diff. in EU". The "no ETF" column is the % difference in expected utility between informed and uninformed investors when the ETF is not present. The ETF column repeats this exercise after introducing the ETF in zero average supply.

3.16.5 Sensitivity of demand to prices

As shown in Section 1, when investors get good signals about a particular asset, they invest more in it. At the same time, they hedge this bet by either (1) shorting an equal-weighted portfolio of all the other stocks when the ETF is not present (2) shorting the same number of shares of the ETF when it is present.

Similar to the hedging demand from informed investors' private signals, all investors use prices as a signal, and thus may do a similar hedging. Table 9 shows this is true in examples where the cost of becoming informed is fixed. Table 10 shows this is also true in examples where the share of investors becoming informed is fixed.

				Uninformed				
		Share Informed		No ETF Present		ETF Present		
ρ	σ_n^2	no ETF	ETF	Own	Stock Hedge	Own	Stock Hedge	ETF Hedge
0.1	0.2	0.05	0.2	6.333	-0.278	2.273	0.000	-2.273
0.1	0.5	0.35	0.2	1.764	-0.170	3.082	0.000	-3.082
0.25	0.2	0.5	0.2	2.380	-0.181	5.510	0.000	-5.510
0.25	0.5	0.5	0.2	2.550	-0.291	5.510	0.000	-5.510
				Informed				
		Share Informed		No ETF Present		ETF Present		
ρ	σ_n^2	no ETF	ETF	Own	Stock Hedge	Own	Stock Hedge	ETF Hedge
0.1	0.2	0.1	0.2	7.872	-0.489	4.023	0.000	-4.023
0.1	0.5	0.35	0.2	2.865	-0.270	4.307	0.000	-4.307
0.25	0.2	0.5	0.2	2.803	-0.218	5.710	0.000	-5.710
0.25	0.5	0.5	0.2	2.913	-0.317	5.710	0.000	-5.710

Table 9 Sensitivity of Demand to Prices (fixed c). Entries of $G_{2,inf}$ and $G_{2,un}$ for one of the stocks i.e., assets 1 to $n-1$. The cost of being informed is chosen such that 20% of investors become informed when the ETF is present. The "Own" columns are diagonal entries e.g., (1,1). The "Stock Hedge" column is one of the edge entries excluding the n^{th} e.g., (1,2) or (2,1). The "ETF Hedge" column is the n^{th} edge entry. ETF is present in zero average supply.

3.16.6 Effect of varying baseline learning α

One of the effects of setting α to larger values than the baseline of 0.001 is that a kink forms in the relationship between the cost of becoming informed and the share of investors who decide to learn when the ETF is present. To the right of the kink, the cost of becoming informed is high, so relatively few investors are becoming informed. Given that systematic risk affects all assets, informed investors initially devote all their attention to learning about this risk-factor.

To the left of the kink, learning about the systematic risk-factor has become crowded, and informed investors start devoting some attention to the individual-asset risks. All informed investors get some information for *free* about each risk-factor from α. This means that there is a meaningful difference between devoting zero attention to a risk-factor, and devoting a small positive amount of attention to that same risk-factor.

Figure 14 focuses on the case where $\rho = 0.25$ and $\sigma_n^2 = 0.2$. The top panel shows two things: (1) The relationship between the cost of becoming informed, and the share of attention devoted to systematic risk [blue dots]. To the right of the kink, all attention is being devoted to the systematic risk-factor. (2) $U_{1,j}$ i.e., the time one objective function for informed [red squares] and uninformed investors [green triangles]. One of the counter-intuitive features of the kink is that the line is *steeper* once investors are devoting some attention to the idiosyncratic assets. For both informed and uninformed investors, the lines become steeper to the left of the kink.

The second panel shows why the slope changes: To the right of the kink informed and uninformed investors are making roughly the same profits on stocks, but informed investors are making significantly larger profits on the ETF. To the left of the kink, informed investors gain an advantage over uninformed investors on the individual stocks. This increases the relative benefit of becoming informed, which can explain the changes in slopes around the kink.

3.17 Representation as economy with independent assets

Consider an alternative economy with no ETF, where all asset payoffs are:

$$z_i = a_i + \eta_i \tag{30}$$

i.e., with no systematic component, but instead of having the η_i be $i.i.d.$, have them correlated in a way that replicates the structure of the payoffs with a systematic component. This model can be solved the same way as the baseline version of the model in Section 1.

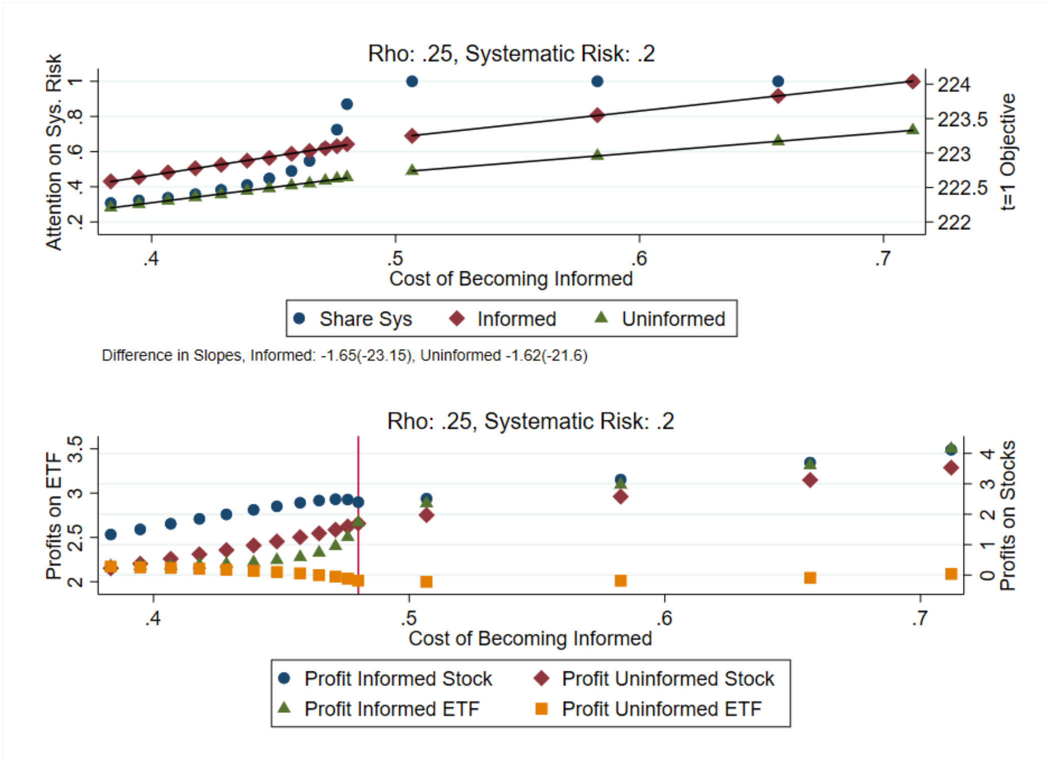

Figure 14. Effect of larger α. Top panel: Effect of the cost of becoming informed on the share of attention on systematic risk. Bottom panel: Effect of the cost of becoming informed on trading profits. $\alpha = 0.05$. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

There is no guarantee, however, that there will be an apples-to-apples learning comparison with the economy when the ETF is present. This happens when the solution to the rotated model proposes values for K_i which do not satisfy the total information constraint. For example, suppose we have two assets and three risks. Using the notation in the appendix of

Kacperczyk et al. (2016):

$$
\begin{aligned}
\text{Define: } \Sigma^{1/2} &= \text{Square root of } V\text{, the variance-covariance matrix of payoffs} \\
\text{Define: } \Sigma_s &= S\text{, the variance-covariance matrix of signals} \\
\text{Define: } \Sigma_s^1 &= \Sigma^{-1/2} \times \Sigma_s \times \Sigma^{-1/2} \\
\text{We can re-write: } \Sigma_s &= \Sigma^{1/2} \times G \times L \times G \times \Sigma^{1/2} \\
\text{where } G \text{ and } L &\text{ come from the eigen-decomposition of } \Sigma_s^1 \\
\text{Define orthogonal signal matrix: } \tilde{\Sigma}_s &= G' \times \Sigma^{-1/2} \times \Sigma_s \times \left(\Sigma^{-1/2}\right)' \times G
\end{aligned}
\tag{31}
$$

This implies that:

$$
\tilde{\Sigma}_s = \begin{bmatrix} 1/(\alpha + \tilde{K}_1) & 0 \\ 0 & 1/(\alpha + \tilde{K}_2) \end{bmatrix} \tag{32}
$$

After solving the model, the optimal $\tilde{K}_i$ rotated back to the original economy may require K_i that do not satisfy $\sum_i \tilde{K}_i \leq K$, where K is the original total information constraint.

In the next subsection, I outline how to ensure the learning technologies are comparable between the economy with and without the ETF.

3.18 Equivalence of Learning Technologies Between Rotated and Unrotated Versions of the Model

In the baseline version of the model, assets have correlated payoffs because of their common exposure to the systematic risk-factor. In addition, investors receive correlated signals about the payoffs of the *assets*, rather than the payoffs of the underlying orthogonal *risk-factors*. When the ETF is present, however, the number of risk-factors is equal to the number of assets. This condition implies that there exists an equivalent economy where asset payoffs and signals are orthogonal (see e.g., Appendix B of Kacperczyk et al. (2016)).

The existence of this equivalent economy means the assumption of correlated signals has no effect on investors' optimal attention allocation. The intuition for this claim is that any investor could rotate the set of correlated signals/payoffs to a set of orthogonal signals/payoffs, and back out an independent signal about each risk-factor.

When the ETF is not present, the learning technology and asset payoffs are written as though there are *more* risk-factors than assets. There is, however, an equivalent economy where the number of risk-factors is *equal* to the number of assets. This can be accomplished by e.g., (1) removing the systematic risk-factor f from each stock's payoff, and (2) rather than having the stock-specific risk-factors η_i be independent, make them correlated such that $cov(\eta_i, \eta_j) = \sigma_f^2$ where σ_f^2 is the volatility of the systematic risk-factor.

When the ETF is not present, the assumption of correlated signals may affect the optimal attention allocation. Although investors could rotate the economy to a set of orthogonal signals/payoffs, there is no way to isolate an independent signal about what I label as the systematic risk-factor f i.e., the common component in the η_i's in the equivalent economy with an equal number of risk-factors and assets.

Despite this, I solve the model numerically with correlated assets and signals, instead of rotating the economy and using the closed-form solutions in Kacperczyk et al. (2016). This is to ensure that the total attention allocated by investors is equal between economies with and without the ETF[13]. This note explains why my solution method preserves total attention, and shows examples where the rotation method may not.

3.18.1 General Mapping

Even when the ETF is present, investors get signals about the payoffs of the underlying *assets* rather than the payoffs of the underlying *risk-factors*. The attention allocation problem is solved numerically assuming investors receive these correlated signals. The model can also be solved by: (1) rotating the model to have orthogonal asset payoffs and signals (2) using the formulas in Kacperczyk et al. (2016) to find the optimal attention allocation and (3) rotating the economy back to the original covariance strcture.

Numerical methods, however, would still be required to find the rotation matrix and find the corresponding total attention constraint between the rotated and unrotated versions of the economy. Here are the steps in that procedure:

1. Choose some range for the total attention constraint in the rotated version of the model. Loop over every $\hat{K}$ between some lower-bound $\underline{K}$ and some upper-bound $\overline{K}$.
2. For each of these $\hat{K}$'s, determine what the optimal attention allocation would be if each stock had a β_i of zero on the systematic risk-factor f.

[13] Another reason this assumption is tractability: According to Admati (1985), there is no closed-form solution for prices in the scenario where investors receive an independent signal about the systematic risk-factor, but cannot trade on it directly i.e., there are more risk-factors with *independent* signals than assets.

3. Using an eigendecomposition, find the rotation matrix Q that maps the economy with orthogonal asset payoffs and signals to the economy with correlated asset payoffs and signals.
4. Choose the $\hat{K}$ where the total attention constraint is satisfied in the unrotated version of the economy. In the case of $K = 1$, choose $\hat{K}$ such that after applying the rotation factor Q, the attention allocations, i.e., the K_i's, add up to one.

3.18.2 Specific Procedure

Here is a more detailed version of the procedure outlined above:

1. Choose some range for the total attention constraint in the rotated version of the model, $\hat{K}$, say between 0.025 and 2, in increments of 0.025 for $K = 1$.
2. For each of these $\hat{K}$'s, determine what the optimal attention allocation would be if all the assets were independent i.e., if all the stocks had a β_i of zero on the systematic risk-factor f. This is given by the formulas in Kacperczyk et. al. [2016]. Call these optimal attention allocations K_i^*.
3. For any (not necessarily optimal) attention allocation, define L as a diagonal matrix with $1/K_i$ in every (i, i) entry. Define L^* as a particular case of L when using the K_i^*'s. With independent risk-factors and signals, $L^* = \Sigma_e$, where Σ_e denotes the variance-covariance matrix of signal noises.
4. Risk-factors and signals are not independent, so L^* is not necessarily equal to Σ_e. Instead, Σ_e is equal to $\Gamma L \Gamma$, where Γ is a matrix defining each asset's exposure to the systematic risk-factor i.e., an identity matrix with an extra column containing the β_i's. All the β_i's in the baseline version of the model are assumed to be one. L here can be any (possibly non-optimal) attention allocation in the unrotated version of the economy.
5. For every L feasible with the total attention constraint K (in the baseline specification $K = 1$), do an eigendecomposition of $\hat{\Sigma}_e = \Gamma L \Gamma'$ into $G \Lambda G'$ (note that Γ is not usually equal to G because L's diagonal elements are not usually the eigenvalues of $\hat{\Sigma}_e$) to solve for the rotation factor G. Define a function which returns the normalized difference between $G L^* G'$ and $\hat{\Sigma}_e$. This value, which I call diff(L), will be equal to zero if L in the unrotated version of the economy maps to the optimal attention allocation L^* in

the rotated version of the economy.

- Note: L^* is not necessarily equal to L because L^* is from the orthogonal version of the economy, while Σ_e is from the non-orthogonal version of the economy.

6. For each total attention allocation looped over, $\hat{K}$, find the K_i's that minimize diff(L).

   - This is a non-linear problem, so try many starting points when doing this optimization to avoid getting stuck at a local minimum.

7. Find the $\hat{K}$ to minimize the distance between the sum of the K_i's in L and the total information constraint K (which is set to 1 in the baseline). If this distance is zero, there is an equivalence between the learning capacity K in the unrotated economy and $\hat{K}$ in the rotated economy.

   - Whether $\hat{K}$ is bigger or smaller than K depends on the risk-bearing capacity of the economy. If there is a lot of risk bearing capacity, $\hat{K}$ will tend to be bigger than K. Otherwise, $\hat{K}$ will tend to be smaller than K.

3.18.3 Numerical Examples

There is no guarantee that the sum of the $K_i's$ in L^* (the optimal attention allocation in the rotated economy) are the same as the sum of the $K_i's$ in L (the optimal attention allocation in the unrotated economy). This makes it difficult to compare total learning capacities (K's) between rotated and unrotated economies. Here are two numerical examples of this phenomenon:

1. Suppose the share of informed investors is 50%, investor risk aversion $\rho = 0.05$, the volatility of the systematic risk factor $\sigma_f = 0.05$ and total attention $K = 1$. The corresponding $\hat{K}$ in the rotated economy is 1.125, so in the rotated economy, we need to give investors more total attention to allocate if we want things to be equivalent to the unrotated economy.
2. Suppose the share of informed investors is 50%, investor risk aversion $\rho = 0.15$, the volatility of the systematic risk factor $\sigma_f = 0.25$ and total learning capacity $K = 1$. The $\hat{K}$ in the rotated economy is 0.175, so in the rotated economy, we need to give investors less total attention to allocate if we want things to be equivalent to the unrotated economy.

In both these cases, the total attention capacity is different in the unrotated economy and the rotated economy. This illustrates why it is not meaningful to compare total attention capacities across different rotated economies. Solving the unrotated model is one way to ensure that the total attention capacity is equal across the rotated and unrotated economies. As a result, solving the unrotated model sidesteps the fact that rotation factors (and therefore equivalent total learning capacities) will be different for economies with and without the ETF, even though all the other parameters are equal.

3.19 Counterfactual: What if passive funds own half the market?

Currently, passive funds *only* own about 15% of the market. A natural question is: What would happen if passive ownership continues to grow exponentially over the next 30 years? The model can be used to evaluate this scenario. In Section 2, I calibrated the model to quantitatively match the empirical rise of passive ownership and qualitatively match the results from the value-weighted cross-sectional regressions. In this subsection, I keep the parameters from that calibration fixed, except I set the risk aversion of the ETF intermediary ρ^{int} to zero. With these parameters, passive ownership grows to nearly 50% of the market.

Table 11 contains the effects of growing passive ownership on the three measures of price informativeness, as well as the intensive and extensive learning margins. Although the sign does not change, the rate of change diminishes: the effect of going from no ETF to the ETF at 12% is roughly the same as the effect of going from the ETF at 12% to the ETF at 50%. This suggests that if passive ownership continues to grow, prices could become even less informative about firm-specific information, albeit at a lower rate.

4 Solving the 2-Period Kyle (1985) Model

This section borrows heavily from Alex Chinco's "Two Period Kyle (1985) Model" notes.

4.1 Model setup and beliefs

There are two trading periods $t = 1$ and $t = 2$. There is a single risky assets whose value is:

$$v \sim N(0, \sigma_v^2) \tag{33}$$

There are a set of competitive market makers who observe total order flow x_t each period:

$$x_t = y_t + z_t \tag{34}$$

where y_t is demand from an informed trader, and $z_t \sim N(0, \sigma_z^2)$ is random demand from noise traders.

There is perfect competition among market makers, so they must set prices equal to the expected fundamental value of the asset given total demand:

$$p_1 = E[v|x_1] \quad \text{and} \quad p_2 = E[v|x_1, x_2] \tag{35}$$

Before the first trading period, the informed investor receives an unbiased signal s about v

$$s = v + \epsilon \quad \text{where} \quad \epsilon \sim N(0, \sigma_\epsilon^2) \tag{36}$$

which implies that $s \sim N(v, \sigma_\epsilon^2)$.

In period 1, the informed investor chooses demand y_t to solve:

$$H_0 = max_{y_1} E\left[(v - p_1)\, y_1 + H_1 | s\right] \tag{37}$$

where H_{t-1} is the informed investor's value function entering period t.

In period 2, they choose y_2 to maximize:

$$H_1 = max_{y_2} E\left[(v - p_1)\, y_2 | s, p_1\right] \tag{38}$$

An equilibrium is made up of two components: (1) a linear demand rule for the informed investor in each period

$$y_t = \alpha_{t-1} + \beta_{t-1} s \tag{39}$$

And (2) a liner pricing rule for the market makers in each period:

$$p_t = \kappa_{t-1} + \lambda_{t-1} x_t \tag{40}$$

The informed investor updates their beliefs about v after observing s. Their posterior beliefs about the mean and variance are:

$$\mu_{v|s} = \left(\frac{\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2}\right) \times \quad \text{and} \quad \sigma_{v|s}^2 = \left(\frac{\sigma_\epsilon^2}{\sigma_v^2 + \sigma_\epsilon^2}\right) \times \sigma_v^2 \tag{41}$$

where going forward, I will use θ in place of $\left(\frac{\sigma_v^2}{\sigma_v^2+\sigma_\epsilon^2}\right)$.

The market makers extract an unbiased signal about v from total demand. Substituting in the informed trader's demand rule, the $t = 1$ signal is:

$$v = \frac{x_1}{\beta_0} - \epsilon - \frac{z_1}{\beta_0} \tag{42}$$

This implies that the market makers' posterior beliefs after observing x_1 are:

$$\mu_{v|x_1} = \left(\frac{\beta_0^2\sigma_v^2}{\beta_0^2\sigma_s^2 + \sigma_z^2}\right) \times x_1 \quad \text{and} \quad \sigma_{v|x_1}^2 = \left(\frac{\beta_0^2\sigma_\epsilon^2 + \sigma_z^2}{\beta_0^2\sigma_s^2 + \sigma_z^2}\right) \times \sigma_v^2 \tag{43}$$

Another way to think about this scenario is that the total order flow x_1 is a signal about the informed trader's signal s rather than the fundamental value of the asset v. This would imply the $t = 1$ signal is:

$$s = \frac{x_1}{\beta_0} - \frac{z_1}{\beta_0} \tag{44}$$

which gives posterior beliefs:

$$\mu_{s|x_1} = \left(\frac{\beta_0^2\sigma_s^2}{\beta_0^2\sigma_s^2 + \sigma_z^2}\right) \times x_1 \quad \text{and} \quad \sigma_{s|x_1}^2 = \left(\frac{\sigma_z^2}{\beta_0^2\sigma_s^2 + \sigma_z^2}\right) \times \sigma_s^2 \tag{45}$$

4.2 Solving the model

Given the market makers' zero profit condition $\kappa_0 = 0$ and

$$\kappa_1 = E[v|x_1] - \lambda_1 E[x_2|x_1] = p_1 - \left(\theta\mu_{s|x_1} - p_1\right) = p_1 \tag{46}$$

where the last equality comes from $\theta\mu_{s|x_1} = p_1$.

Substituting in the market makers' linear pricing rule into H_1

$$H_1 = max_{y_2} E\left[(v - \kappa_1 - \lambda_1 x_2)\, y_2 | s, p_1\right] \tag{47}$$

Taking the first order condition with respect to y_2 yields optimal demand:

$$y_2 = -\frac{p_1}{2\lambda_1} + \frac{\theta}{2\lambda_1} s \tag{48}$$

so $\alpha_1 = -\frac{p_1}{2\lambda_1}$ and $\beta_1 = \frac{\theta}{2\lambda_1}$.

With this, we can partially solve for the market makers' price impact coefficient, λ_t, in period 2:

$$\lambda_1 = \frac{Cov[x_2, v|x_1]}{Var[x_2|x_1]} = \frac{\beta_1 \sigma^2_{v|x_1}}{\beta_1^2 \sigma^2_{s|x_1} + \sigma^2_z} \tag{49}$$

Now, turning to the period one solution, we start by taking a guess at at the informed investors' value function which we will verify later:

$$E[H_1|s] = \phi_1 + \omega_1 \left(\mu_{v|s} - p_1\right)^2 \tag{50}$$

Substituting in the price impact and demand coefficients into H_0 yields:

$$H_0 = max_{y_1} E\left[(v - p_1)\, y_1 + \phi_1 + \omega_1 \left(\theta s - p_1\right)^2 |s\right] \tag{51}$$

Taking the first order condition with respect to y_1 implies:

$$y_1 = \frac{\theta}{2\lambda_0} \left(\frac{1 - 2\omega_1 \lambda_0}{1 - \omega_1 \lambda_0}\right) s \tag{52}$$

With all this, we can now solve for the time 1 price impact coefficient:

$$\lambda_0 = \frac{Cov[x_1, v]}{Var[x_1]} = \frac{\beta_0 \sigma^2_v}{\beta_0^2 \sigma^2_s + \sigma^2_z} \tag{53}$$

To verify the guess about H_1, substitute the equilibrium coefficients for demands and prices into Equation 50:

$$H_1 = \left[\frac{1}{2\lambda_1}\left([v - \theta s] + \frac{1}{2}[\theta s - p_1] - \lambda_1 z_2\right)(\theta s - p - 1)\, |s\right] \tag{54}$$

which simplifies to:

$$H_1 = \text{Constant} + \frac{1}{4\lambda_1}\left(\mu_{v|s} - p_1\right)^2 \tag{55}$$

This reveals that $\omega_1 = \frac{1}{4\lambda_1}$ and that H_1 is consistent with the original guess.

To solve the model, start with some initial guess for $\hat{\beta}_0$, and use this to compute other equilibrium coefficients. This can be done in stages, first computing $\hat{\sigma^2_{v|x_1}}$ and $\hat{\sigma^2_{s|x_1}}$, then using these to compute $\hat{\lambda_1}$:

$$
\begin{aligned}
\hat{\lambda_0} &= \frac{\hat{\beta}_0 \sigma_v^2}{\hat{\beta}_0^2 \sigma_s^2 + \sigma_z^2} \\
\hat{\sigma^2_{v|x_1}} &= \frac{\hat{\beta}_0^2 \sigma_\epsilon^2 + \sigma_z^2}{\hat{\beta}_0^2 \sigma_s^2 + \sigma_z^2} \sigma_v^2 \\
\hat{\sigma^2_{s|x_1}} &= \frac{\sigma_z^2}{\hat{\beta}_0^2 \sigma_s^2 + \sigma_z^2} \sigma_s^2 \\
\hat{\lambda_1} = \frac{1}{\sigma_z} &\sqrt{\frac{\theta}{2}\left(\hat{\sigma^2_{v|x_1}} - \frac{\theta}{2}\hat{\sigma^2_{s|x_1}}\right)}
\end{aligned} \tag{56}
$$

A solution has been found that when you have minimized the distance between the guess $\hat{\beta}_0$ and $\frac{\theta}{2\hat{\lambda_0}}\left(\frac{1-2\hat{\omega_1}\hat{\lambda_0}}{1-\hat{\omega_1}\hat{\lambda_0}}\right)$, which is a condition $\hat{\beta}_0$ has to satisfy in equilibrium.

5 Data details

5.1 IBES

I merge CRSP to I/B/E/S (IBES) using the WRDS linking suite. Before 1998, nearly 90% of observations in IBES have an announcement time of "00:00:00", which implies the release time is missing. In 1998 this share drops to 23%, further drops to 2% in 1999, and continues to trend down to nearly 0% by 2015. This implies that before 1998, if the earnings release date was a trading day, I will always classify that as the effective earnings date, even if earnings were released after markets closed, and it was not possible to trade on that information until the next trading day.

This time-variation in missing observations is not driving my results for two reasons: (1) I re-run every regression using only post-2000 data when ruling out the influence of Regulation Fair Disclosure and the results are similar and (2) These missing earnings times could only move the day I identify as the effective earnings date *earlier* in calendar time, which would bias both the pre-earnings drift and earnings-day volatility measures toward finding nothing.

Specifically, it would lead to selecting days where no news was released, which likely have smaller, rather than larger moves on average, pushing DM toward 1, and QVS toward 4.3%.

5.2 Computing passive and institutional ownership

To calculate passive ownership, I need to identify the holdings of passive funds, which I obtain from the Thompson S12 data.[14] I use the WRDS MF LINKS database to connect the funds identified as passive in CRSP with the S12 data. If a security never appears in the S12 data, I assume its passive ownership is zero. S12 data is only reported at the end of each calendar quarter, so to get a monthly estimate of passive ownership, I linearly interpolate passive ownership between quarter-ends. All results are quantitatively unchanged if I instead fix passive ownership at its last reported level between the ends of calendar quarters.

Institutional ownership computed by adding up the holdings of all 13-F filings institutions to the CUSIP/Quarter level. It is then merged to CRSP on historical CUSIP or CUSIP. If a CUSIP never appears in the 13-F data, institutional ownership is assumed to be zero. 13-F forms are filed quarterly, so I linearly interpolate institutional ownership between quarter-ends

5.3 CRSP volume vs. total volume

A possible explanation for decreased pre-earnings turnover is that informed trading before earnings announcements has moved to dark pools. This could occur e.g., because on lit exchanges, informed traders are getting front-run by algorithm traders. To test this, I obtained data on dark pool volume from FINRA. There does not appear to be an increase in dark pool volume in the weeks before earnings announcements, either in aggregate, or for stocks with high passive ownership.

[14] The S12 database is constructed from a combination of mutual funds' voluntary reporting and SEC filings on which securities they hold.

6 Robustness of Stylized Facts

6.1 Decomposition of earnings days' share of volatility

Figure 15 decomposes the rise of $r_{i,t}^2 / \sum_{\tau=-22}^{0} r_{i,t+\tau}^2$ i.e., the decline of QVS into rise in the numerator (volatility on earnings days) and the denominator (volatility on leading up to the earnings announcement plus volatility on the earnings day itself). The trend in QVS was driven by a simultaneous increase in the numerator, and decrease in the denominator.

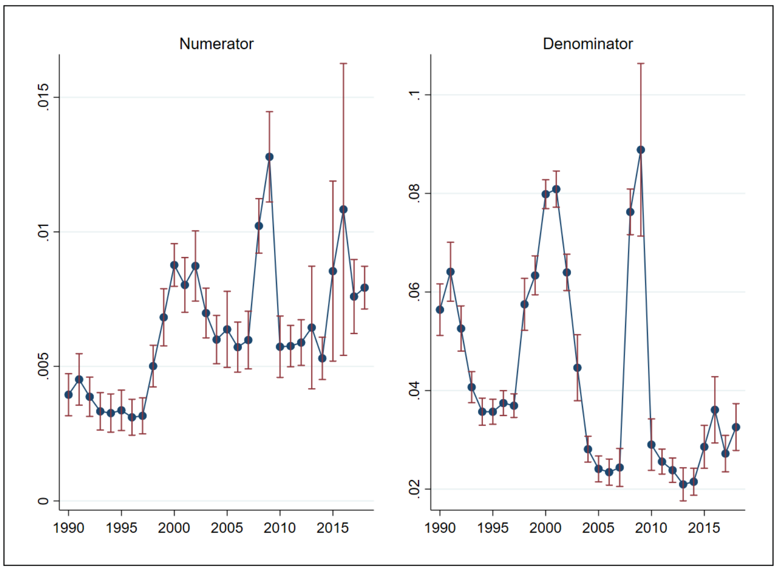

Figure 15. Decomposition of QVS. This figure plots coefficients from a regression of the numerator and denominator of the term in parenthesis in QVS on a set of year dummy variables. The constant term for the omitted year (1989) is added to each coefficient. For firm i around earnings announcement t the quadratic variation share (QVS) is defined as: $QVS_{i,t} = 1 - \left(r_{i,t}^2 / \sum_{\tau=-22}^{0} r_{i,t+\tau}^2 \right)$, where r denotes a market-adjusted daily return. The numerator of the term in parenthesis is the squared earnings-day return, while the denominator is the sum of squared returns from $t - 22$ to t. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level.

6.2 Placebo tests for stylized facts

In this subsection, I conduct three placebo tests for the stylized facts: (1) Using the start of the pre-earnings announcement window as a placebo announcement date (2) Using randomly selected days and (3) Using FOMC meetings as placebo announcement dates.

6.2.1 22 Days before each earnings announcement

For all the placebo tests, I run the following regression:

$$Outcome_{i,t} = \alpha + \sum_{k=1990}^{2018} 1_{year(t)=k} + \phi_q + \epsilon_{i,t} \tag{57}$$

Here, *Outcome* is pre-earnings abnormal turnover, pre-earnings drift and earnings-day volatility computed with respect to the placebo earnings announcement dates, which in this case are 22 trading days before the actual announcements. $\sum_{k=1990}^{2018} 1_{year(t)=k}$ are a set of dummy variables for each year between 1990 and 2018. ϕ_q is a quarter-of-year fixed effect to account for seasonal patterns. Standard errors are clustered at the security level.

I select these days because they are the start of the pre-earnings window for all three price informativeness measures. Figure 16 shows that there is no trend toward decreased price informativeness before these placebo earnings dates.

6.3 Random days

In this sub-section, I randomly select 4 days each year to be placebo earnings announcements, and re-run regression 57. Although this seems like a more natural test than using the dates 22 trading days before each earnings announcement, it has the disadvantage that there can be overlapping placebo announcements in the 23-day windows of interest. Figure 17 shows that for all three measures, there is no trend toward decreased informativeness before these placebo earnings dates either. In unreported results, I try several different seeds for identifying the random placebo earnings dates, and find no qualitative or quantitative difference from Figure 17.

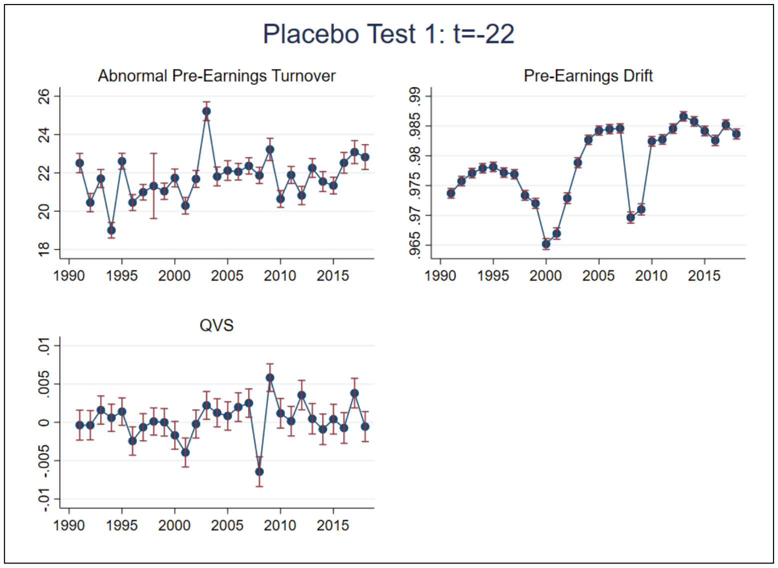

Figure 16. Placebo Test 1: 22 trading days before each earnings announcement. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

6.3.1 Scheduled FOMC Announcement Dates

The final set of placebo earnings days are FOMC announcements. To create an apples-to-apples comparison with the anticipated nature of earnings announcements, I restrict to scheduled FOMC meetings.

Figure 18 plots coefficients on the year fixed effects from regression 57. There is no drop in average pre-FOMC abnormal turnover, nor is there a drop in average pre-FOMC drift. There is a slight trend toward increased volatility on FOMC announcement dates i.e., decreases in QVS, but the magnitude is significantly smaller than the downward trend for actual earnings announcement dates documented in the main body of the paper (-0.25% vs. nearly -20%).

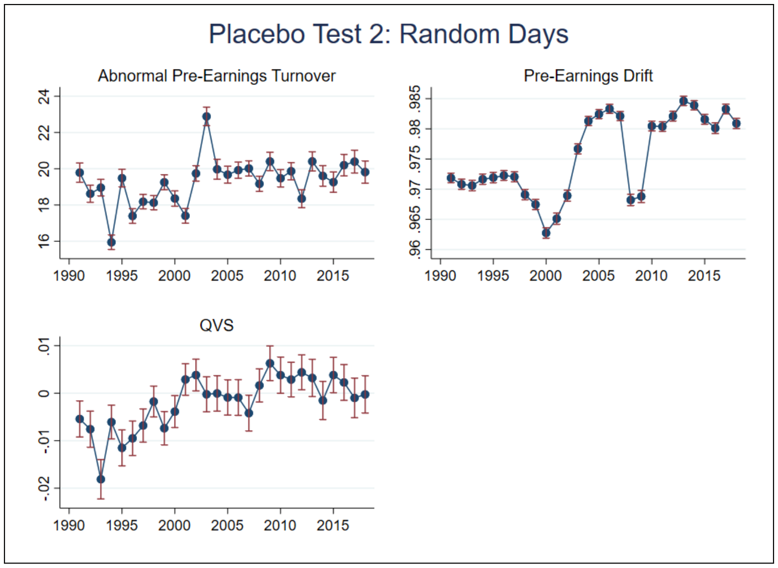

Figure 17. Placebo Test 2: Randomly selected dates. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

7 Robustness of Cross-Sectional Regression Results

7.1 Placebo tests for cross-sectional regressions

Table 12 contains placebo tests for the cross-sectional regressions of QVS on passive ownership. For placebo earnings announcements, Panel A uses the date 22 trading-days before each earnings announcement, Panel B uses random days and Panel C uses scheduled FOMC announcements. Results are robust to using multiple different seeds when constructing Panel B. During my sample (1990-2018), there are at least 22 trading days between each scheduled FOMC announcement, so there are no overlapping announcements in any of the 23-day windows (22 pre-earnings days + the earnings day itself). The row labeled “Cross-Sectional Estimates” is copied from the corresponding table in the main body of the paper.

In Panels A and B, the coefficients are all economically small and statistically insignificant. For Panel C, all the equal weighted coefficients are negative and statistically significant. This is evidence that prices may have become less informative before the release of systematic information. In the model, this is consistent with passive ownership decreasing the overall

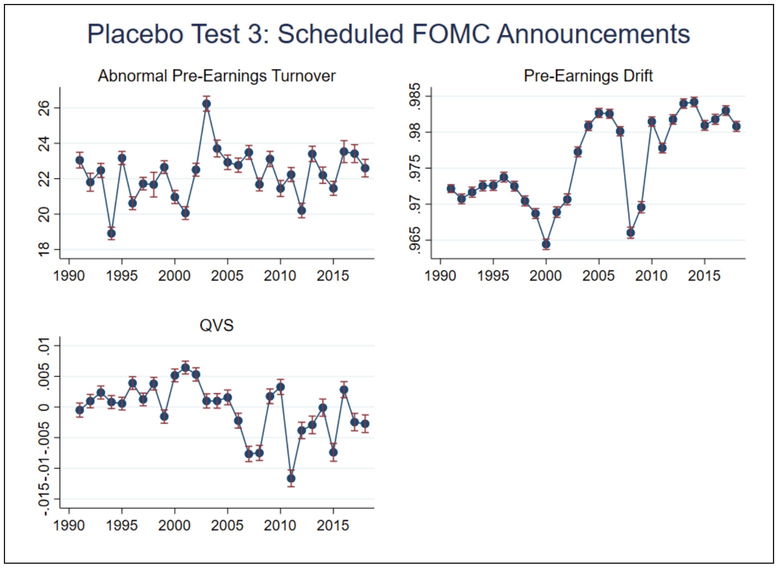

Figure 18. Placebo Test 3: Scheduled FOMC announcement dates. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

share of informed investors. The magnitude of these coefficients, however, is small, at about 1/20th the size of the baseline cross-sectional estimates.

7.2 Effect of passive ownership on the post-earnings announcement drift

Martineau (2018) shows that the post-earnings announcement drift has disappeared over the past 30 years. Given that passive ownership accounts for about 40% of the average decline in the pre-earnings announcement drift, a natural question is whether passive ownership is also related to the post-earnings announcement drift.

Motivated by the definition of the pre-earnings announcement drift magnitude in the main body of the paper, define the post-earnings announcement drift magnitude as:

$$PDM_{i,t,n} = \begin{cases} \frac{1}{1+r_{(t+1,t+n)}} & \text{if } r_{(t+1,t+n)} > 0 \\ 1 + r_{(t+1,t+n)} & \text{if } r_{(t+1,t+n)} < 0 \end{cases} \tag{58}$$

where t is an earnings-announcement day and r is a market-adjusted return. With this definition, if the stock experiences a significant drift upward or downward after the announcement, $PDM_{i,t,n}$ will be relatively smaller.

To test for this relationship, I regress the post-earnings announcement drift magnitude on passive ownership, controls and fixed effects:

$$PDM_{i,t,n} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t} \tag{59}$$

which is the same regression as Equation 9 in Section 4.2, but swapping the left-hand-side variable to $PDM_{i,t,n}$.

Table 13 contains the results. At horizons of $n = 5, 10$ and 22 days, there is no statistically significant relationship between passive ownership and the post earnings announcement drift. Given that the point estimates in Columns 5 and 6 are positive, at minimum this suggests that once information is released, passive ownership *does not* facilitate its rapid incorporation into prices.[15]

As an additional check, I perform an exercise more in the spirit of Martineau (2018), who examines changes in β over time from the following regression:

$$CR_{i,(t+1,t+n)} = a + \beta \cdot Surpriserank_{i,t} + \epsilon_{i,t} \tag{60}$$

where $CR_{i,(t+1,t+n)}$ is the cumulative market-adjusted returns from day $t+1$ to n days after the announcement and $Surpriserank_{i,t}$ is the within-quarter decile of firm i's earnings surprise at time t. Surprises are defined both relative to analyst expectations $\left(\left(EPS_{i,t} - E[EPS_{i,t}]\right)/Price_{i,t}\right)$ and relative to past earnings $\left(\left(EPS_{i,t} - EPS_{i,t-4}\right)/Price_{i,t}\right)$. Here, $E[EPS_{i,t}]$ – the mean analyst estimate of $EPS_{i,t}$ – is calculated in the last IBES statistical period before the earnings announcement and $Price_{i,t}$ is the last closing price before the effective earnings announcement date. Martineau (2018) shows that β has been declining over time i.e., firms with good (bad) news no longer have significant price increases (decreases) *after* that news is released.

To measure the relationship between the post-earnings announcement drift and passive

[15] Recall that higher values of PDM suggest a larger post-earnings announcement drift.

ownership, I run the following regression:

$$CR_{i,(t+1,t+n)} = a+b\cdot Surpriserank_{i,t}+c\cdot Passive_{i,t}+d\cdot Surpriserank_{i,t}\times Passive_{i,t}+\epsilon_{i,t} \quad (61)$$

This is an extended version of Equation 60, including passive ownership and its interaction with *Surpriserank*. As in the main body of the paper, I control for firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio and total institutional ownership. I also include CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility, all computed over the previous 252 trading days. Finally, I include firm fixed effects and year-quarter fixed effects.

Table 14 contains the results for $n = 5, 10$ and 22. If anything, d is consistently positive, suggesting stocks with more passive ownership have relatively larger post-earnings announcement drifts. This corroborates the results in Table 13, which showed that stocks with more passive ownership didn't have smaller post-earnings announcement drifts.

7.3 Alternative explanations for the decline of price informativeness

In this subsection, I discuss two threats to identification in my baseline regressions (1) Regulation Fair Disclosure and (2) The rise of algorithmic trading.

7.3.1 Regulation Fair Disclosure (Reg FD)

Before Reg FD was passed in August, 2000, firms would disclose earnings information to selected analysts before it became public. This information leakage could increase the share of earnings information incorporated into prices before it was formally announced. After Reg FD passed, firms were no longer allowed to selectively disclose material information, and instead must release it to all investors at the same time.

Reg FD could be driving the trends in decreased price informativeness, as there was a large negative shock to information released by firms after it was passed. All of the information measures, however, continue to trend in the same direction after Reg FD was implemented. Reg FD could still explain these results if the value of the information received by analysts before Reg FD decayed slowly. While this is possible, my prior is that information obtained in 2000 would not be relevant for more than a few years.

Another possibility is that Reg FD changed the way insiders (directors or senior officers) behaved, or led to changes in the enforcement of insider trading laws (see e.g., Coffee (2007)). Time-series changes in enforcement should be accounted for by year fixed-effects. To rule out the insider behavior channel, I used the Thompson Insiders data to compute insider buys/sells as a percent of total shares outstanding for each firm in my dataset. Insider buys and sells have been decreasing since the mid-1990's. Both average annual buys and sells went down slightly more for stocks with increases in passive ownership, but this effect is only weakly statistically significant. I then examined insider buys/sells in 22-day windows before/after earnings announcements. Both buys and sells have decreased before and after earnings announcements, broadly following the trend toward decreased insider activity. There is no statistically significant relationship, however, between passive ownership and insider buys/sells before or after earnings announcements.

For Reg FD to be driving the cross-sectional relationship between passive ownership and pre-earnings price informativeness, it would have to disproportionately affect firms with high passive ownership. This is because all the regressions have year-quarter fixed effects, which should account for any level shifts in price informativeness before/after Reg FD was passed.

To further rule out this channel, I re-run the cross-sectional regressions using only post-2000 data in Tables 15, 16 and 17. The results are qualitatively similar, which alleviates concerns that my results being driven by Reg FD.

7.3.2 The Rise of algorithmic trading (AT) activity

Weller (2018) shows that Algorithmic Trading (AT) activity is negatively correlated with pre-earnings price informativeness. The proposed mechanism is algorithmic traders back-run informed traders, reducing the returns to gathering firm-specific fundamental information. AT activity increased significantly over my sample period, and could be responsible for some of the observed decrease in average pre-earnings price informativeness.

It is difficult to measure the role of algorithmic traders in the trends toward decreased pre-earnings price informativeness as I cannot directly observe AT activity, and only have AT activity proxies between 2012-2018. I can, however, measure the effect of AT activity on the cross-sectional regression results. For AT activity to influence the regression estimates, it would have to be correlated with passive ownership, which I find plausible because: (1)

Passive ownership is higher in large, liquid stocks, where most AT activity occurs. This, however, should not affect my results, as I condition on firm size in all the cross-sectional regressions and (2) High ETF ownership will attract algorithmic traders implementing ETF arbitrage. The effect of time trends in AT activity should be absorbed by the year fixed effects.

To rule out this channel, I construct the 4 measures of AT activity used in Weller (2018) from the SEC MIDAS data. MIDAS has daily data for all stocks traded on 13 national exchanges from 2012 to 2018. The AT measures are (1) odd lot ratio, (2) trade-to-order ratio, (3) cancel-to-trade ratio and (4) average trade size. Measures 1 and 3 are positively correlated with AT activity, while the opposite is true for measures 2 and 4. Consistent with Weller (2018), I (1) Truncate each of the AT activity variables at the 1% and 99% level by year to minimize the effect of reporting errors (2) calculate a moving average for each of these measures in the 21 days leading up to each earnings announcement and (3) take logs to reduce heavy right-skewness. Only 1% of MIDAS data cannot be matched to CRSP, so the drop in sample size relative to the baseline cross-sectional regressions is almost entirely the result of the year restrictions.

I re-run all the cross-sectional regressions, but restrict to the years with matched MIDAS data: 2012-2018. I then add the 4 AT activity measures to $X_{i,t}$ to determine whether they reduce the ability of passive ownership to explain decreases in price informativeness. Tables 18, 19 and 20 contain the results. The pre-earnings drift estimates are qualitatively and quantitatively similar when (1) restricting to the 2012-2018 sample and (2) including the AT controls. This is also true for the QVS regressions.

The pre-earnings turnover result is weaker in the 2012-2018 sample, with the coefficient dropping by about 30% (column 1). The equal weighted regression with the AT controls (column 3) is the same sign as the baseline, but smaller by a factor of about 1/2 and is statistically insignificant. The value weighted regression, however, is actually stronger than the baseline and remains statistically significant. One explanation for the loss of significance and smaller effect in column 3 is the correlation between passive ownership and the AT activity measures. To test this, I calculate an AT activity score as the first principal component of the 4 AT measures. The relationship between passive ownership and AT activity is positive and statistically significant. I also find AT activity increases in stocks after they are added to the S&P 500.

7.4 Effect of Passive Ownership on Real Outcomes

The main body of the paper shows the negative relationship between passive ownership and price informativeness. In this subsection, I show the real effects of passive ownership on investment, and argue why this is related to price informativeness.

7.4.1 Effects on Investment

Bai et al. (2016) argue that managers learn about their own firm's fundamentals from stock prices. They also argue that this learning has implications for aggregate efficiency. Given that firms with high passive ownership have less informative prices, it might be that managers at those firms learn less from prices, and thus make different real decisions. In this subsection, I test whether or not passive ownership affects how sensitive a firm's investment is to Tobin's Q.

To test this, I run the following regression based on the cross-sectional regressions in the main body of the paper:

$$\frac{CAPX_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_1 Q_{i,t} + \beta_2 Passive_{i,t} + \beta_3 Q_{i,t} \times Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t} \tag{62}$$

where $CAPX$ is capital expenditures and $Assets$ is total assets, both obtained from the CRSP/Compustat merged annual firm fundamentals database. Results are also similar when $CAPX$ is replaced with $R\&D$ or $SG\&A$. Q is the market-to-book ratio, the inverse of the book-to-market ratio from the WRDS financial ratios suite, and I exclude observations with $Q \leq 0$. To reduce the influence of outliers, I Winsorize Q and $\frac{CAPX_{i,t}}{Assets_{i,t-1}}$ at the 1% and 99% level by year. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility.

Table 21 contains the regression results. Across all columns, there is a positive relationship between investment and Q, consistent with previous literature (see e.g., Eberly et al. (2009)). If passive ownership makes investment less sensitive to market-based information, β_3 should be negative. This is indeed the case, as the interaction term between Q and Passive Ownership is always negative and statistically significant. As in the main body of the paper, I consider the specification with equal weights and all controls/fixed effects as the baseline (column 3).

A 15% increase in passive ownership, the average in my sample between 1990 and 2018, would lead investment to be less responsive to Q by a factor of 0.0017. Given that the coefficient on Q itself is 0.0018, this means that an average amount of passive ownership would lead to an almost zero relationship between investment and Q. One interpretation is that when passive ownership is high, managers essentially ignore the market value of the firm when making investment decisions.

8 Robustness of quasi-experimental results

8.1 S&P Index Addition Details

The treatment effect of being added to the S&P 500 index has been increasing over time. Figure 19 shows the average increase in passive ownership by year. In the early 1990s, firms experienced less than a 1% increase in passive ownership after being added to the index, while now the increase is over 3%.

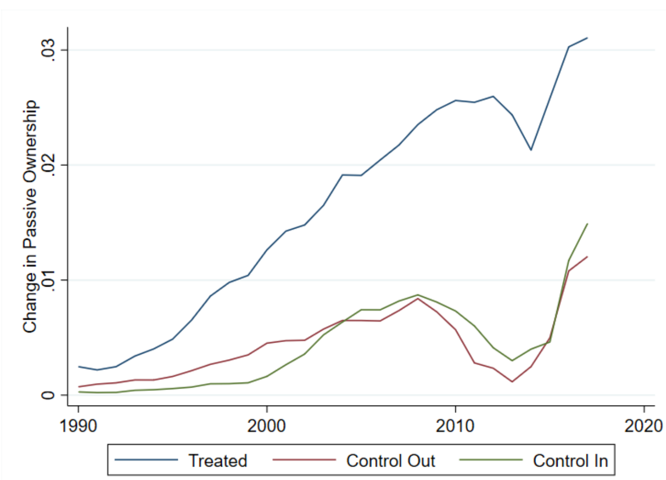

Figure 19. Increase in Passive Ownership from S&P 500 Index Addition. 5-year moving average of increase in passive ownership associated with index addition. Increase in passive ownership is computed from 6 months before index addition to 6 months after index addition.

8.2 Russell Details

8.2.1 May Market Capitalizations and Treated/Control Firms

I use the following procedure, based on Chang et al. (2015) and Coles et al. (2020), to compute the proxy for Russell's May market capitalization ranks. I also incorporate the improvement from Ben-David et al. (2019), which accounts for the exact day Russell rebalances the indices:

- Compute the number of shares outstanding/market capitalization on the index rebalancing date according to CRSP. To do this, start with the CRSP daily security file. Merge this with the list of dates from Ben-David et al. (2019) to identify the trading date closest to the Russell index rebalancing date.
  - An adjustment has to be made if a PERMCO (permanent company identifier in CRSP) has multiple associated PERMNOs (permanent security identifier in CRSP). There are two broad cases to consider: (1) If only one of the PERMNOs is in the Russell 3000 universe, for each PERMNO, compute total market capitalization at the PERMCO level (2) If more than one of the PERMNOs is in the Russell 3000 universe, compute the market capitalization for each PERMNO individually.[16]
- Use the raw Compustat data to identify the release date of quarterly earnings (RDQ). If this is missing, follow the procedure in Chang et al. (2015). Specifically, if the missing RDQ is associated with a fiscal year end (10K):
  - If the fiscal year end is before 2003, set RDQ to 90 days after the period end date.
  - If the fiscal year end is between 2003 and 2006, and the firm has a market capitalization greater than 75 million, set RDQ to 75 days after the period end date. If the firm has a market cap less than 75 million, set RDQ to 90 days after the period end date.
  - If the fiscal year end is 2007 or later, and the firm has a market capitalization great than 700 million, set RDQ to 60 days after the period end date. If the firm has a market capitalization between 75 and 700 million set RDQ to 75 days after

[16] I would like to thank Simon Gloßner for bringing this to my attention, for more details, see Gloßner (2018).

the period end date. Finally, if the firm has a market capitalization less than 75 million, set RDQ to 90 days after the period end date.

If the missing RDQ is associated with a fiscal quarter end (10Q):

  - If the fiscal year-quarter is before 2003, set RDQ to 40 days after the end of the fiscal period.
  - If the fiscal year-quarter is in or after 2003, and the firm has a market capitalization of more than 75 million, set RDQ to 40 days after the fiscal quarter end. If the firm has a market capitalization smaller than 75 million, set RDQ to 45 days after the fiscal quarter end.

- Compute the number of shares outstanding on the index rebalancing date according to the Compustat data. Start with the number of shares outstanding in Compustat (CSHOQ). Then, adjust for changes in the number of shares outstanding between the release date of earnings information (RDQ), and the Russell index rebalancing date. To do this, start at RDQ, and apply all of the CRSP factor to adjust shares between RDQ and the rebalancing date.
- Map the Russell index member data to CRSP using the following procedure:
  - First, create a new CUSIP variable that is equal to historical CUSIP if that is not missing, and is equal to current CUSIP otherwise. Merge on this new CUSIP variable and date.
  - For the remaining unmatched firms, merge on ticker, exchange and date.
  - For the remaining unmatched firms that had non-missing historical CUSIP, but weren't matched on historical CUSIP to the Russell data, merge on current CUSIP and date.
  - For the remaining unmatched firms, merge on ticker and date. Note that in some of these observations, the wrong field is populated (e.g., the actual ticker was put into the CUSIP field in the Russell data), so that needs to be fixed before doing this last merge.
- Merge CRSP and Compustat using the CRSP/Compustat merged data.
- Use the following procedure to compute May market capitalization: If the shares outstanding from the Compustat data is larger than the shares outstanding from CRSP, use that number of shares outstanding to compute market capitalization. Otherwise,

use the shares outstanding in the CRSP data to compute market capitalization. In either case, compute market capitalization using the closing price on the day closest to the index rebalancing date.

With this May market capitalization proxy, I use the following procedure, also based on Coles et al. (2020) to predict index membership and identify the cohorts of treated/control firms:

- Each May, rank stocks by market capitalization.
- Identify the 1000th ranked stock, and compute the bands as $\pm$ 2.5% of the total market capitalization of the Russell 3000.[17]
- Identify the cutoff stocks at the top and bottom bands. For stocks switching to the 2000, this will be the first stock that is ranked below the lower band. For stocks switching to the 1000, this will be the first stock that is ranked above the upper band.
- The cohorts of treated/control firms are those within $\pm$ 100 ranks around these cutoff stocks. For the possible switchers to the 2000, they must have been in the 1000 the previous year, while for possible switchers to the 1000, they must have been in the 2000 the previous year.
- If a firm was in the 1000 last year, as long it has a rank higher than the cutoff, it will stay in the 1000. If a firm was in the 2000 last year, as long as it has a rank lower than the cutoff, it will stay in the 2000. Otherwise, the firm switches.
  - When using this data, to identify actual switchers, it is easy to miss that in 2013, Russell records the rebalancing in July, rather than June

8.3 Increase in passive ownership when switching from the 1000 to the 2000

The treatment effect of switching from the Russell 1000 to 2000 has been increasing over time. Figure 20 shows the average increase in passive ownership by year. In 2007, firms

[17] In reality, the bands are $\pm$ 2.5% of the Russell 3000E, not the Russell 3000. The data I have from FTSE Russell only has Russell 3000 firms, which is why I use that instead. I discussed this with the authors of Coles et al. (2020) and they find using the total market capitalization of the 3000 vs. 3000E makes almost no difference to the accuracy of predicted index membership.

switching to the 2000 experienced a less than 2% increase in passive ownership, while now the increase is over 4%.

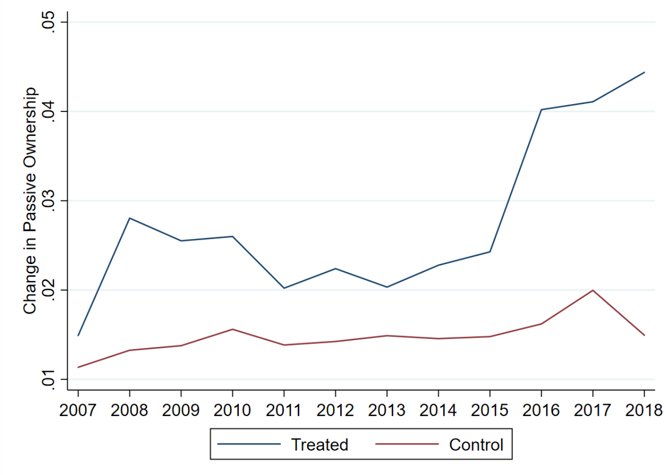

Figure 20. Increase in Passive Ownership from Russell 1000/2000 Reconstitution. 5-year moving average of increase in passive ownership associated with switching from the Russell 1000 to the Russell 2000. Increase in passive ownership is computed from 6 months before index rebalancing to 6 months after index rebalancing.

8.4 Alternative quasi-exogenous changes in passive ownership

8.4.1 Moving from the Russell 2000 to the Russell 1000

Firms experience a decrease in passive ownership after they are moved from the Russell 2000 to the Russell 1000. This is because they go from being the largest firm in a value-weighted index of small firms, to the smallest firm in a value-weighted index of large firms.

Again, following Coles et al. (2020), I choose the control firms to be those within ± 100 ranks of the upper band that were in the Russell 2000 the previous year. Figure 21 shows the problem with this setup: the treatment is small and temporary. Within 12 months of switching, passive ownership is almost back at the pre index-rebalancing level.

8.4.2 Blackrock's acquisition of Barclays Global Investors

Another well-known source of quasi-exogenous variation in passive ownership is Blackrock's acquisition of Barclays' iShares ETF business in December 2009. This is not an ideal

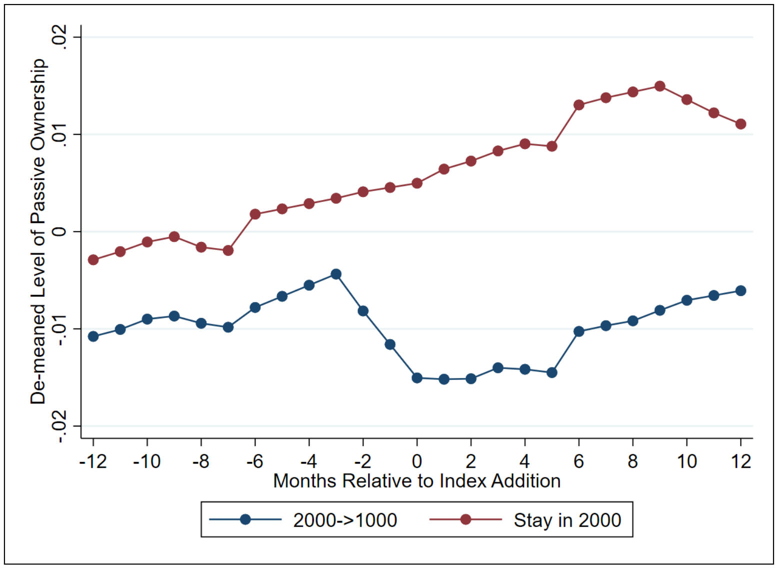

Figure 21. Russell 1000/2000 Reconstitution and Changes in Passive Ownership. Average level of passive ownership for firms that stay in the Russell 2000 (control firms) and firms that moved from the Russell 2000 to the Russell 1000 (treated firms). Passive ownership is demeaned within each cohort.

setting for testing my hypothesis because: (1) My theory has no predictions for the effects of increased concentration of ownership among passive investors (Azar et al. (2018), Massa et al. (2021)) (2) While there may have been a *relative* increases in flows to iShares ETFs, relative to all other ETFs (see e.g., Zou (2018)), I do not find a significant increase in overall ETF ownership for the stocks owned by iShares funds. Given that my right-hand-side variable of interest is the percent of shares owned by passive investors, the model has no predictions for the effect of moving dollars from iShares ETFs to non-iShares ETFs.

9 Mechanisms Details

9.1 Earnings Responses

I aim to quantify market responses to earnings information of a given size. To measure trends in earnings responses, I run two types of regressions. The baseline comes from Kothari and Sloan (1992):

$$r_{i,t} = \alpha + \sum_{y=1990}^{2019} \beta_y 1_{year=y} \times SUE_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + \epsilon_{i,t} \tag{63}$$

where $SUE_{i,t} = \frac{E_{i,t} - E_{i,t-4}}{\sigma_{(t-1,t-8)}(E_{i,t} - E_{i,t-4})}$. $E_{i,t}$ is earnings-per-share from IBES i.e., "street" earnings, so the numerator is the year-over-year (YOY) earnings growth, while the denominator is the standard deviation of YOY earnings growth over the past 8 quarters. I compute SUE this way, following Novy-Marx (2015), because it avoids (1) using prices as an input, whose average informativeness has changed over time and (2) using analyst estimates of earnings as an input, whose average accuracy has also changed over time. As a result, the average absolute value of $SUE_{i,t}$ is roughly constant over my sample, except for large spikes during the tech boom/bust as well as during the global financial crisis.

$r_{i,t}$ denotes the market-adjusted return on the effective quarterly earnings date i.e., the first day investors could trade on earnings information. I also design an earnings-response regression which allows for asymmetry between positive and negative surprises:

$$\begin{aligned} r_{i,t} = \alpha + \sum_{y=1990}^{2019} \beta_y^p 1_{year=y} \times 1_{SUE_{i,t} \geq 0} \times SUE_{i,t} + \\ \sum_{y=1990}^{2019} \beta_y^n 1_{year=y} \times 1_{SUE_{i,t} < 0} \times |SUE_{i,t}| + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + \epsilon_{i,t} \end{aligned} \tag{64}$$

I plot 5-year rolling averages of the β's from these regressions in Figure 22. Over the past 30 years, earnings responses have increased by a factor of almost 3×. Most of this increase was driven by increased responsiveness to SUEs greater than zero. In recent years, however, this trend has reversed, with the response to positive news decreasing and the response to negative news increasing.

9.2 Option Implied Volatility

To map the methodology in Kelly et al. (2016) to my setting, I start by identifying all of the regular monthly option expiration dates, which typically occur on the 3rd Friday of each month. Letting τ denote an earnings announcement date, the goal is to identify expiration

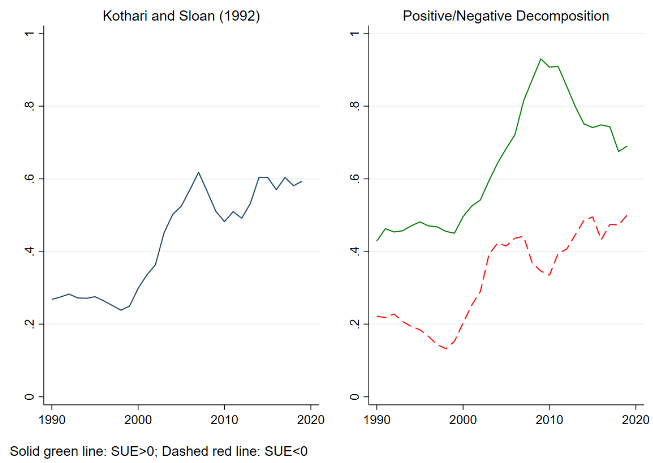

Figure 22. Trends in Earnings Response. Left panel has estimates of β_y from:

$$r_{i,t} = \alpha + \sum_{y=1990}^{2019} \beta_y 1_{year=y} \times SUE_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + \epsilon_{i,t}$$

Right panel has estimates of β_1 and β_2 from Equation 64 i.e., breaking SUE into positive and negative components. Lines represent 5-year rolling averages of the βs. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. All regressions contain year-quarter fixed effects, ϕ_t, quarter-of-year fixed effects, ζ_q and firm fixed effects ψ_i.

dates a, b, and c, such that $a < \tau < b < c$. To avoid issues inherent in the calculating implied volatility for short-maturity options (see e.g., Beber and Brandt (2006)), b is selected so that it is at least 5 days after τ.[18]

Having identified a, b, and c, the next step is to compute the average implied volatility associated with each of these expiration dates. For each firm i, on each trading day t, compute $IV_{i,t,e}$, defined as the equal-weighted average implied volatility across all at-the-money options expiring on date e. Then, take an equal-weighted average of $IV_{i,t,b}$ over the

[18]This means that if the first regular expiration after the earnings announcement has at least 6 days to maturity at τ, that expiration will be b, and a will be one month before b. If the first regular expiration after the earnings announcement has fewer than 5 days to expiration at τ, b will be the next regular expiration date, and a will be two months before b. c is always chosen to be one month after b.

20-day window before τ:

$$\overline{IV}_{i,b} = Mean\left[IV_{i,(b-s,b),b} : b - s \in [\tau - 20, \tau - 1]\right] \tag{65}$$

$\overline{IV}_{i,a}$ and $\overline{IV}_{i,c}$ are defined analogously, as averages of $IV_{i,t,e}$ over the 20-day windows that end $b - \tau + 1$ days before a and c.

The final variable of interest, the implied volatility difference, is defined as:

$$IVD_{i,\tau} = \overline{IV}_{i,b} - \frac{1}{2}\left(\overline{IV}_{i,a} + \overline{IV}_{i,c}\right) \tag{66}$$

higher values of $IVD_{i,\tau}$ imply that options which span earnings announcements are relatively more expensive i.e., there is more ex-ante uncertainty.[19]

Implied volatility is computed by OptionMetrics and runs from 1996 until the end of my sample. I use the WRDS linking suite to match the OptionMetrics data with CRSP. Following Kelly et al. (2016), I keep all options with positive open interest, and define at-the-money options as those with absolute values of delta between 0.4 to 0.5. For a firm/earnings-announcement pair to be included, it must be that a and b are no more than two months apart, and c is no more than one month after b.[20]

Figure 23 plots the cross-sectional average of IVD by quarter. Numbers greater than zero are evidence that options which span earnings announcements are more expensive than those with surrounding maturities. Consistent with the increase in earnings-day volatility, on both an equal-weighted and value-weighted basis, IVD has increased by about 0.05 over the past 25 years. This is evidence that there is more uncertainty about fundamentals before earnings announcements now than there was in the late 1990's.

[19] One concern with this definition of IVD is that subtracting the average of $\overline{IV}_{i,a}$ and $\overline{IV}_{i,c}$ from $\overline{IV}_{i,b}$ accounts for firm-specific time trends in implied volatility, but not *level* differences in implied volatility across firms. All the results that follow are qualitatively unchanged using $I\tilde{V}D_{i,\tau} = \overline{IV}_{i,b}/\frac{1}{2}\left(\overline{IV}_{i,a} + \overline{IV}_{i,c}\right)$.

[20] Suppose firm i has an earnings announcement on 1/5/2021. Then a should be 12/18/2020, b should be 1/15/2021 and c should be 2/19/2021. Suppose, however, that between 1/21/2021 and 2/10/2021 there are no options expiring on 2/19/2021 with positive open interest and absolute values of delta between 0.4 and 0.5. This last filter prevents e.g., the use of options expiring 3/19/2021 in place of options expiring 2/19/2021 to compute $\overline{IV}_{i,c}$.

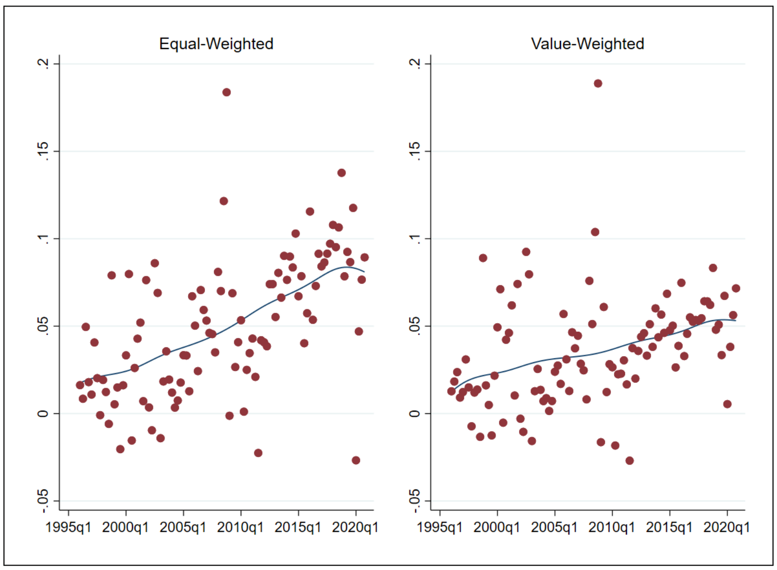

Figure 23. Time-series trends in IVD. Equal-weighted and value-weighted averages of IVD by quarter. Red dots represent cross-sectional averages and blue lines represent LOWESS filters with bandwidths equal to 20% of quarters in the dataset.

Panel A: Share Informed Fixed at 10%

Uninformed

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	No ETF Present Own	No ETF Present Stock Hedge	ETF Present Own	ETF Present Stock Hedge	ETF Present ETF Hedge
0.1	0.2	0.1	0.1	4.096	-0.036	4.040	0.000	-4.040
0.1	0.5	0.1	0.1	4.899	-0.528	7.656	0.000	-7.656
0.25	0.2	0.1	0.1	4.884	-0.464	6.270	0.000	-6.270
0.25	0.5	0.1	0.1	4.976	-0.601	6.270	0.000	-6.270

Informed

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	No ETF Present Own	No ETF Present Stock Hedge	ETF Present Own	ETF Present Stock Hedge	ETF Present ETF Hedge
0.1	0.2	0.1	0.1	5.597	-0.236	5.790	0.000	-5.790
0.1	0.5	0.1	0.1	5.979	-0.623	8.343	0.000	-8.343
0.25	0.2	0.1	0.1	5.299	-0.499	6.470	0.000	-6.470
0.25	0.5	0.1	0.1	5.331	-0.626	6.470	0.000	-6.470

Panel B: Share Informed Fixed at 30%

Uninformed

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	No ETF Present Own	No ETF Present Stock Hedge	ETF Present Own	ETF Present Stock Hedge	ETF Present ETF Hedge
0.1	0.2	0.3	0.3	1.774	0.059	1.581	0.000	-1.581
0.1	0.5	0.3	0.3	2.020	-0.197	1.950	0.000	-1.950
0.25	0.2	0.3	0.3	3.190	-0.266	4.018	0.000	-4.018
0.25	0.5	0.3	0.3	3.364	-0.393	4.914	0.000	-4.914

Informed

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	No ETF Present Own	No ETF Present Stock Hedge	ETF Present Own	ETF Present Stock Hedge	ETF Present ETF Hedge
0.1	0.2	0.3	0.3	3.198	-0.117	3.331	0.000	-3.331
0.1	0.5	0.3	0.3	3.121	-0.296	3.337	0.000	-3.337
0.25	0.2	0.3	0.3	3.614	-0.303	4.356	0.000	-4.356
0.25	0.5	0.3	0.3	3.728	-0.419	5.114	0.000	-5.114

Table 10 Sensitivity of Demand to Prices (fixed share informed). Entries of $G_{2,inf}$ and $G_{2,un}$ for one of the stocks i.e., assets 1 to $n-1$. In Panels A and B, the share of informed investors are fixed and 10% and 30% respectively. The "Own" columns are diagonal entries e.g., (1,1). The "Stock Hedge" column is one of the edge entries excluding the n^{th} e.g., (1,2) or (2,1). The "ETF Hedge" column is the n^{th} edge entry. ETF is present in zero average supply.

ρ^{int}	ETF Size	Volume	Drift	Volatility	Share Informed	Attn. on Sys. Risk
N/A	No ETF	0.969	0.964	0.294	0.6	0.34
9	0%	0.614	0.963	0.217	0.35	0.35
1	12%	0.505	0.963	0.190	0.3	0.41
0	48%	0.256	0.963	0.125	0.2	0.65

Table 11 Counterfactual Analysis. All parameters are chosen to match the equal-weighted cross-sectional regression results. The cost of becoming informed is set so 60% learn in equilibrium when the ETF is not present, $\rho = 0.15$, and σ_f=0.3.

	Panel A: 22 trading-days before each earnings announcement				
	(1)	(2)	(3)	(4)	(5)
Passive Ownership	0.00341	0.00258	0.00308	0.00521	0.000
	(0.007)	(0.007)	(0.007)	(0.025)	(0.028)
Observations	416,166	386,668	386,668	386,668	386,668
R-Squared	0.035	0.036	0.036	0.036	0.036
	Panel B: randomly selected dates				
	(1)	(2)	(3)	(4)	(5)
Passive Ownership	0.00158	-0.00134	-0.00571	0.0327	0.026
	(0.008)	(0.008)	(0.008)	(0.039)	(0.041)
Observations	386,327	352,500	352,500	352,500	353,546
R-Squared	0.036	0.037	0.037	0.031	0.032
	Panel C: scheduled FOMC announcements				
	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-0.0209***	-0.0210***	-0.0162**	-0.0255	-0.026
	(0.007)	(0.007)	(0.007)	(0.036)	(0.026)
Observations	985,513	902,595	902,595	902,595	902,595
R-Squared	0.025	0.026	0.026	0.031	0.032
Baseline Estimates	-0.524***	-0.501***	-0.408***	-0.214*	-0.232**
Firm + Year/Quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value

Table 12 Cross-Sectional Regression Placebo Tests: Earnings-Day Volatility. Table with estimates of β from:

$$QVS_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

$QVS_{i,t} = 1 - \left(r_{i,t}^2 / \sum_{\tau=-22}^{0} r_{i,t+\tau}^2 \right)$, where t is a placebo earnings date. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	5-day		10-day		22-day	
	(1)	(2)	(3)	(4)	(5)	(6)
Passive Ownership	-0.00688	0.001	-0.00495	0.00655	0.0035	0.014
	(0.005)	(0.008)	(0.008)	(0.010)	(0.010)	(0.017)
Observations	419,524	419,524	419,422	419,422	419,063	419,063
R-Squared	0.225	0.235	0.241	0.246	0.265	0.267
Firm + Year/Quarter FE	✓	✓	✓	✓	✓	✓
Matched to Controls	✓	✓	✓	✓	✓	✓
Firm-Level Controls	✓	✓	✓	✓	✓	✓
Weight	Equal	Value	Equal	Value	Equal	Value

Table 13 Passive ownership and post-earnings drift. Estimates of β from:
$PDM_{i,t,n} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$
Where $PDM_{i,t}$ is a measure of the post-earnings drift, with smaller values denoting more drift. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	Panel A: Surprise Relative to Past Earnings Growth					
	5-day		10-day		22-day	
	(1)	(2)	(3)	(4)	(5)	(6)
Passive Ownership	-0.0153*	-0.00946	-0.0197*	-0.000698	-0.013	-0.0129
	(0.008)	(0.011)	(0.011)	(0.013)	(0.015)	(0.023)
Surprise Rank	0.000097	0.000125	0.000169*	0.000246	0.000243*	0.000141
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Passive x Rank	0.00298***	0.00277**	0.00411***	0.00172	0.00393**	0.00532*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Observations	378,005	378,005	377,927	377,927	377,630	377,630
R-Squared	0.23	0.232	0.247	0.243	0.269	0.264
Firm + Year/Quarter FE	✓	✓	✓	✓	✓	✓
Matched to Controls	✓	✓	✓	✓	✓	✓
Firm-Level Controls	✓	✓	✓	✓	✓	✓
Weight	Equal	Value	Equal	Value	Equal	Value

	Panel B: Surprise Relative to Analyst Expectations					
	5-day		10-day		22-day	
	(1)	(2)	(3)	(4)	(5)	(6)
Passive Ownership	-0.00969	-0.00371	-0.0119	-0.0127	-0.0156	-0.0188
	(0.009)	(0.010)	(0.011)	(0.014)	(0.014)	(0.022)
Surprise Rank	0.000356***	0.000345***	0.000339***	0.000281*	0.000357***	0.000129
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Passive x Rank	0.0012	0.00185	0.00213*	0.00401**	0.00369**	0.00705**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.003)
Observations	339,470	339,470	339,418	339,418	339,247	339,247
R-Squared	0.234	0.236	0.252	0.247	0.278	0.268
Firm + Year/Quarter FE	✓	✓	✓	✓	✓	✓
Matched to Controls	✓	✓	✓	✓	✓	✓
Firm-Level Controls	✓	✓	✓	✓	✓	✓
Weight	Equal	Value	Equal	Value	Equal	Value

Table 14 Passive ownership and post-earnings announcement returns. Estimates of b, c and d from:
$CR_{i,(t+1,t+n)} = a + b \cdot Surpriserank_{i,t} + c \cdot Passive_{i,t} + d \cdot Surpriserank_{i,t} \times Passive_{i,t} + \epsilon_{i,t}$
where $CR_{i,(t+1,t+n)}$ is the cumulative market-adjusted returns from day $t+1$ to n days after the announcement and $Surpriserank_{i,t}$ is the within-quarter decile of firm i's earnings surprise at time t. Panel A calculates the surprise rank based on year-over-year earnings growth, while Panel B calculates surprise rank based on analyst expectations. All specifications include controls for firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. They also include firm and year-quarter fixed effects. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-17.24***	-17.54***	-15.06***	-7.417**	-6.806**
	(3.498)	(3.575)	(3.666)	(3.508)	(3.268)
Observations	243,108	232,867	232,867	232,867	232,867
R-Squared	0.065	0.067	0.089	0.206	0.208
Firm + year-quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value

Table 15 Passive Ownership and Pre-Earnings Turnover (2001-2018). Estimates of β from:

$$CAT_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

where $CAT_{i,t}$ is cumulative abnormal pre-earnings turnover. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-0.0365***	-0.0398***	-0.0482***	-0.0397*	-0.0413***
	(0.007)	(0.007)	(0.007)	(0.021)	(0.015)
Observations	268,918	250,874	250,874	250,874	250,874
R-Squared	0.191	0.195	0.21	0.225	0.246
Firm + year-quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value

Table 16 Passive Ownership and Pre-Earnings Drift (2001-2018). Table with estimates of β from:

$$DM_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

Where $DM_{i,t}$ is a measure of the pre-earnings drift. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-0.472***	-0.444***	-0.364***	-0.123	-0.156
	(0.030)	(0.032)	(0.034)	(0.134)	(0.106)
Observations	272,811	254,430	254,430	254,430	254,430
R-Squared	0.203	0.206	0.207	0.183	0.184
Firm + Year/Quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value

Table 17 Passive Ownership and Earnings Day Share of Volatility (2001-2018). Table with estimates of β from:

$$QVS_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

where $QVS_{i,t}$ is a measure of earnings days' share of volatility. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-9.624***	-8.858**	-5.041	-8.528**	-17.94***
	(3.219)	(3.467)	(5.072)	(3.325)	(5.022)
Observations	81,332	76,317	76,317	76,317	76,317
R-Squared	0.088	0.092	0.225	0.172	0.252
Firm + year-quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value
Baseline	-13.52***	-14.03***	-11.23***	-9.826***	-10.27***

Table 18 Passive Ownership and Pre-Earnings Turnover (Algorithmic Trading). Estimates of β from:

$$CAT_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

where $CAT_{i,t}$ is cumulative abnormal pre-earnings turnover. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-0.0505***	-0.0492***	-0.0536***	-0.0615*	-0.0707***
	(0.011)	(0.010)	(0.010)	(0.033)	(0.019)
Observations	92,167	83,683	83,683	83,683	83,683
R-Squared	0.247	0.253	0.258	0.277	0.287
Firm + year-quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value
Baseline	-0.0432***	-0.0478***	-0.0528***	-0.0568***	-0.0474***

Table 19 Passive Ownership and Pre-Earnings Drift (Algorithmic Trading). Table with estimates of β from:

$$DM_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

Where $DM_{i,t}$ is a measure of the pre-earnings drift. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Passive Ownership	-0.389***	-0.334***	-0.322***	-0.306	-0.405***
	(0.047)	(0.047)	(0.050)	(0.199)	(0.128)
Observations	92,159	83,667	83,667	83,667	83,667
R-Squared	0.24	0.242	0.245	0.187	0.195
Firm + Year/Quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value
Baseline	-0.524***	-0.501***	-0.408***	-0.214*	-0.232**

Table 20 Passive Ownership and Earnings Day Share of Volatility (Algorithmic Trading). Table with estimates of β from:

$$QVS_{i,t} = \alpha + \beta Passive_{i,t} + \gamma X_{i,t} + \phi_t + \psi_i + \zeta_q + e_{i,t}$$

where $QVS_{i,t}$ is a measure of earnings days' share of volatility. Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis.

	(1)	(2)	(3)	(4)	(5)
Q	0.00174***	0.00170***	0.00188***	0.00186***	0.00152***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Passive Ownership	0.0569***	0.0581***	-0.0366**	-0.0366**	-0.0912***
	(0.012)	(0.012)	(0.015)	(0.015)	(0.021)
Q x Passive Ownership	-0.0102***	-0.00979***	-0.0114***	-0.0113***	-0.0102***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Observations	104,573	103,563	104,573	103,563	103,563
R-Squared	0.059	0.059	0.598	0.601	0.609
Firm + year-quarter FE	✓	✓	✓	✓	✓
Matched to Controls		✓	✓	✓	✓
Firm-Level Controls			✓		✓
Weight	Equal	Equal	Equal	Value	Value

Table 21 Passive Ownership, Tobin's Q and Investment. Estimates of β_1, β_2 and β_3 from:

$$\frac{CAPX_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_1 Q_{i,t} + \beta_2 Passive_{i,t} + \beta_3 Q_{i,t} \times Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t}$$

Controls in $X_{i,t}$ include firm age, one-month lagged market capitalization, returns from t-12 to t-2, one-month lagged book-to-market ratio, total institutional ownership, CAPM beta, CAPM R-squared, total volatility and idiosyncratic volatility. Passive ownership is expressed as a decimal, so 0.01 = 1% of firm i's shares are owned by passive funds. Standard errors double clustered at the firm and year-quarter level in parenthesis. Standard errors are double clustered at the firm-quarter.

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