Online Appendix for Passive Ownership and Price Informativeness

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1 Model Details

1.1 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).[1]
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.

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[1] 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.

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

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

The demand functions for informed/uninformed investors are:

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

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

$$\begin{aligned}
\gamma &= \rho\left(A_2^{-1} - Q\right) \\
G_0 &= A_2^{-1}A_0 \\
G_{2,un} &= \frac{1}{\rho}\gamma \\
G_{2,in} &= \frac{1}{\rho}\left(\gamma + S^{-1}\right) \\
G_1 &= \frac{1}{\rho}S^{-1}
\end{aligned} \tag{3}$$

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:

$$
\begin{aligned}
E_{1,j}[\mathbf{z}|\mathbf{s_j}, \mathbf{p}] &= B_{0,in} + B_{1,in}\mathbf{s_j} + B_{2,in}\mathbf{p} \\
V_{in}^a &= \left(V^{-1} + QU^{-1}Q + S^{-1}\right)^{-1} \\
B_{0,in} &= \rho V_{in}^a G_0 \\
B_{1,in} &= \rho V_{in}^a G_0 \\
B_{2,in} &= \mathbf{I}_n - \rho V_{in}^a G'_{2,in}
\end{aligned}
\tag{4}
$$

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

$$
\begin{aligned}
E_{1,j}[\mathbf{z}|\mathbf{p}] &= B_{0,in} + B_{2,un}\mathbf{p} \\
V_{un}^a &= \left(V^{-1} + QU^{-1}Q\right)^{-1} \\
B_{0,un} &= \rho V_{un}^a G_0 \\
B_{2,un} &= \mathbf{I}_n - \rho V_{un}^a G'_{2,un}
\end{aligned}
\tag{5}
$$

1.3 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:

$$
\Gamma = \begin{bmatrix} 1 & 0 & \dots & 0 & 1 \\ 0 & 1 & \dots & 0 & 1 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 1 & 1 \end{bmatrix} \tag{6}
$$

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 1.15.2 of the Online Appendix.

Define the variance of stock payoffs, V as:

$$V = \Gamma \begin{bmatrix} \sigma_1^2 & 0 & \dots & 0 & 0 \\ 0 & \sigma_2^2 & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \sigma_n^2 & 0 \\ 0 & 0 & \dots & 0 & \sigma_f^2 \end{bmatrix} \Gamma' \tag{7}$$

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

$$S_j = \Gamma \begin{bmatrix} \frac{1}{\alpha+K_{1,j}} & 0 & \dots & 0 & 0 \\ 0 & \frac{1}{\alpha+K_{2,j}} & \dots & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{1}{\alpha+K_{n,j}} & 0 \\ 0 & 0 & \dots & 0 & \frac{1}{\alpha+K_{n+1,j}} \end{bmatrix} \Gamma' \tag{8}$$

1.4 Model Timeline

Table 1 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 1 Model Timeline.

1.5 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: $\tilde{U} = (\Gamma')^{-1} \sigma_x^2 \mathbf{I}_{n+1} (\Gamma')^{-1}$.

1.6 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.

1.7 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.

1.8 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[2]. 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 1 shows that as the intermediary's risk aversion increases, the number of shares of the ETF decreases.

[2]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%.

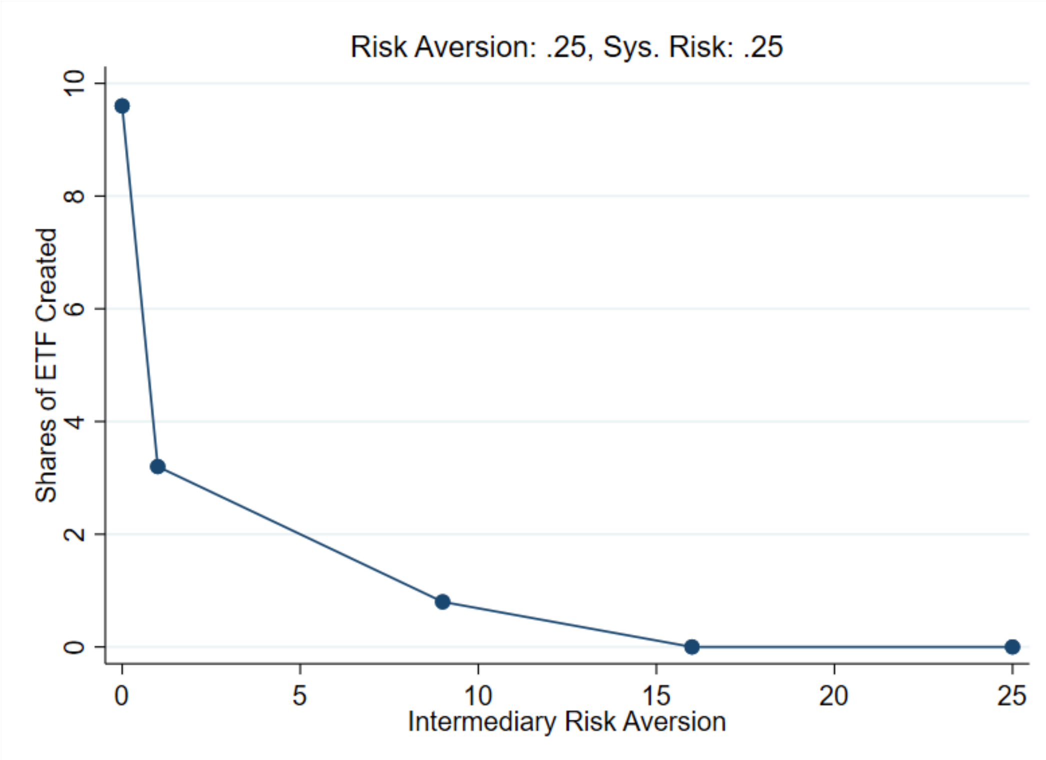

Figure 1. Relationship between size of the ETF and the intermediary's risk aversion. Risk aversion of informed/uninformed investors $\rho = 0.25$. Volatility of the systematic risk factor $\sigma_f = 0.25$ The share of informed investors is set to 50%. If the ETF owned all the shares of the underlying 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 2 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.

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

In the main body of the paper, 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.

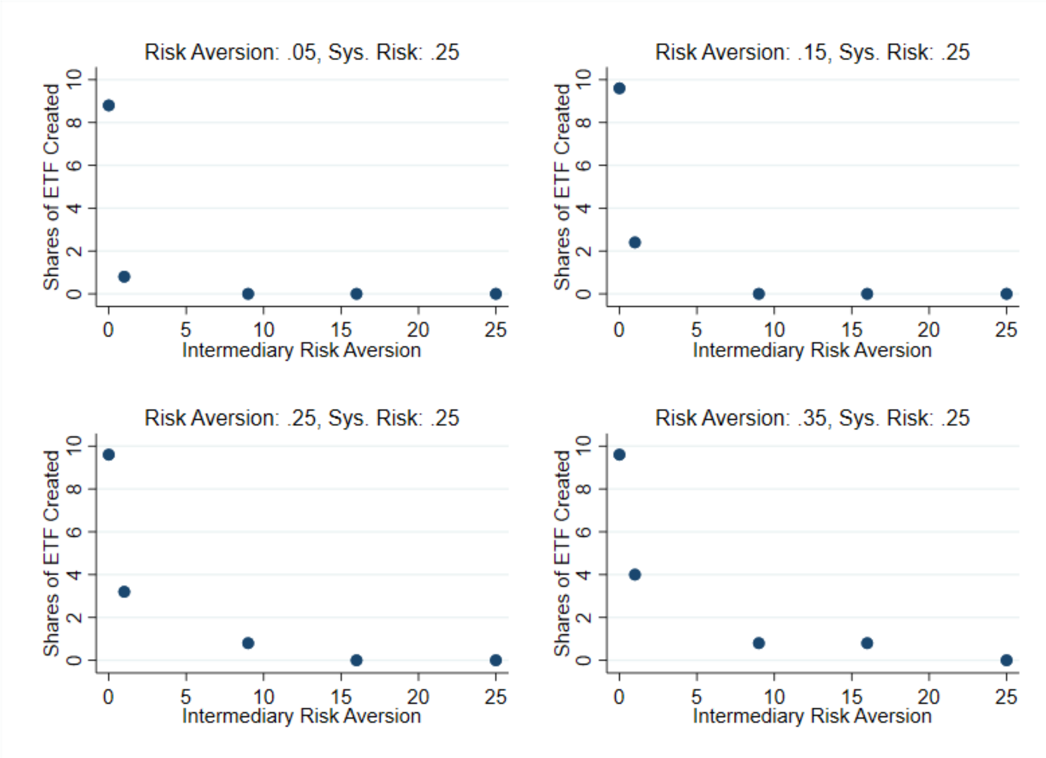

Figure 2. Relationship between the size of the ETF and informed/uninformed investors' risk avesrion. The share of informed investors is set to 50%. The volatility of the systematic risk-factor $\sigma_f = 0.25$. If the ETF owned all the shares of the underlying stocks, it would have 20 shares outstanding.

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.

1.10 Model timeline with ETF intermediary

The model timeline for the economy with the intermediary is in Table 2. The differences from the original timeline 1 are in bold.

1.11 Discussion of baseline parameters

Table 3 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 2 New Model Timeline. Differences from original timeline in bold.

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
# idiosyncratic assets	n	8
Total supply of idiosyncratic assets	$\overline{x}$	20

Table 3 Baseline Parameters.

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.

1.12 Sensitivity to Parameter Choice

In this sub-section, I examine how sensitive the model is to varying risk aversion and systematic risk. In Figure 3 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.

In Figure 4, 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.

1.13 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 the technique in Kacperczyk

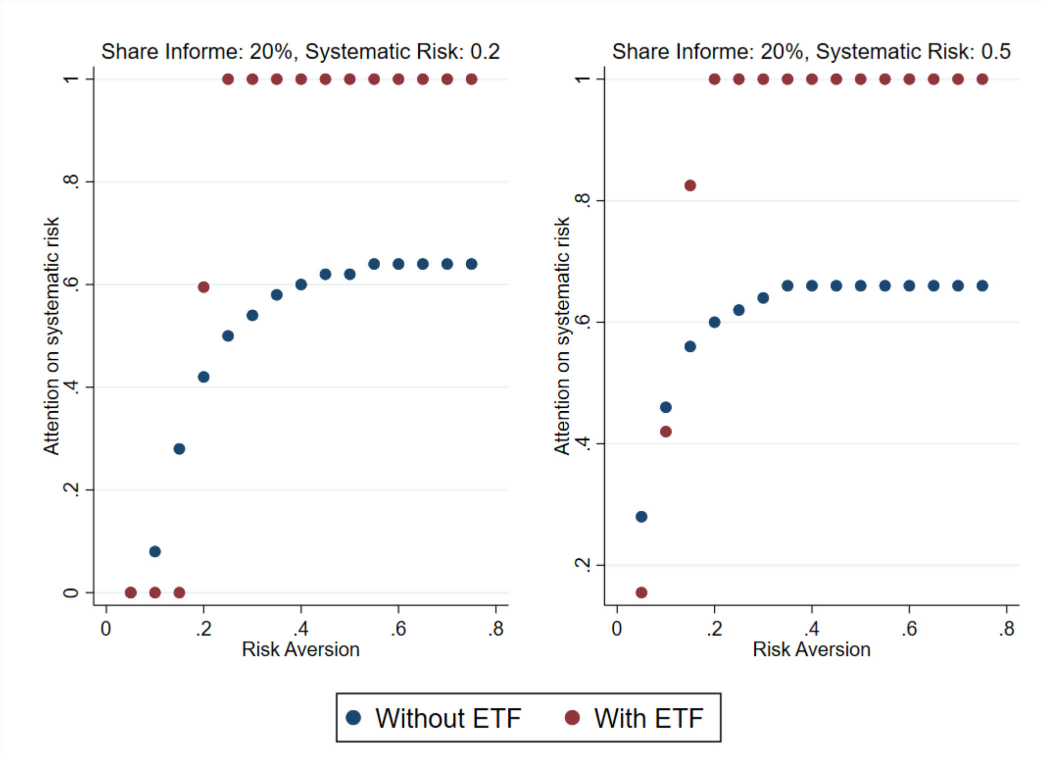

Figure 3. Relationship between risk aversion and attention to systematic risk-factor. In the left panel, σ_n^2 is set to 0.2, while in the right panel, σ_n^2 is set to 0.5. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

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 Online Appendix section 1.17 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

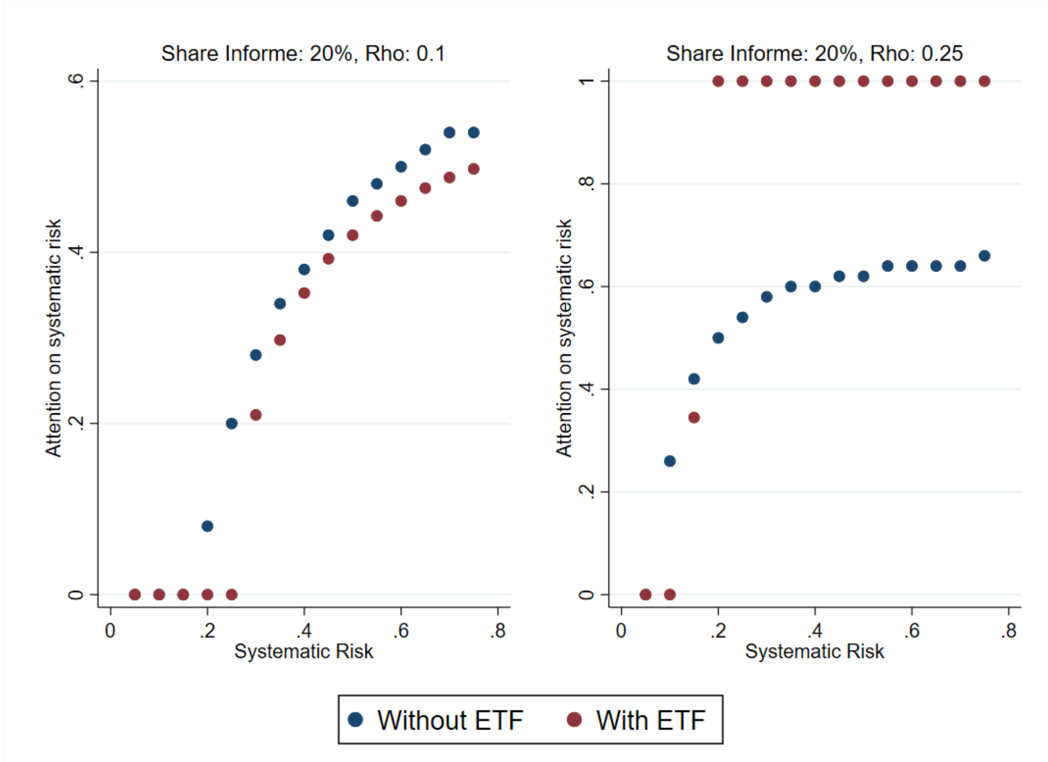

Figure 4. Relationship between systematic risk and attention to systematic risk-factor. In the left panel, risk aversion, ρ is set to 0.1, while in the right panel, risk aversion is set to 0.25. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

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.

1.14 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)).

1.14.1 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 $E_0\left[q\right]$. 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.

1.15 Extensions

1.15.1 Extension 1: Endogenous capacity choice

In the main body of the paper, 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 5 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.

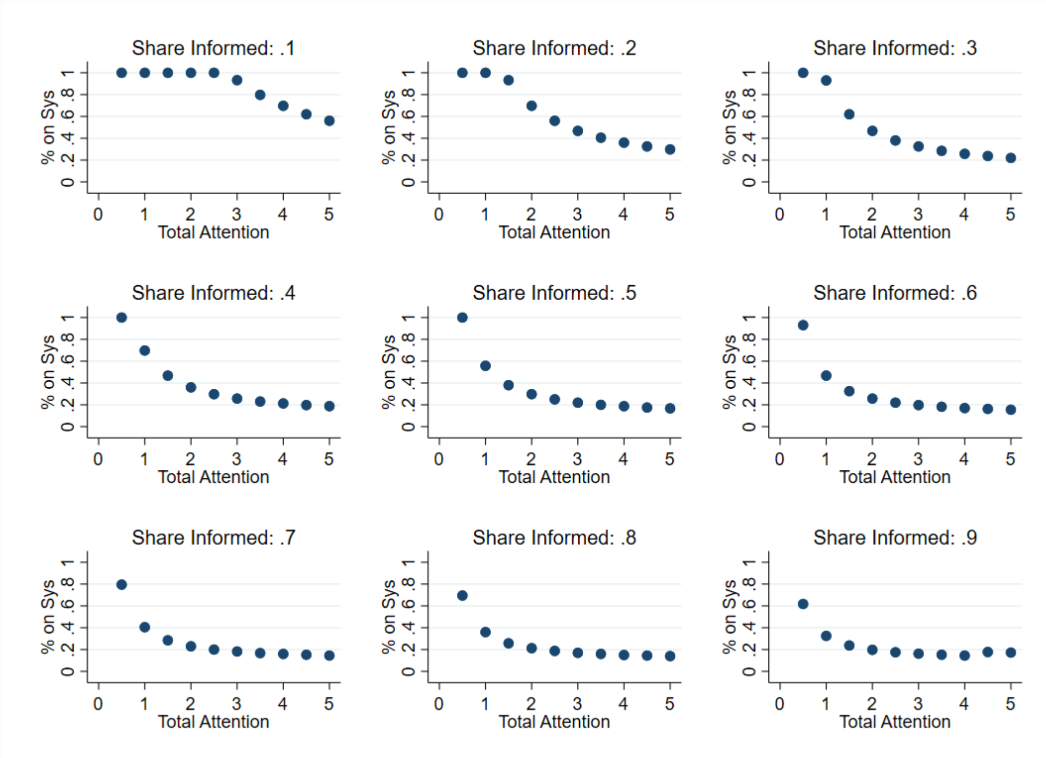

Figure 5. Effect of Varying K and Share Informed. x-axis is total attention K, y-axis is the share of total attention allocated to systematic risk. Parameters: $\rho = 0.25$, $\sigma_n = 0.25$. ETF is present in zero average supply.

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 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 $c(K)$.

1.15.2 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:

$$z_i = a_i + \beta_i f + \eta_i \tag{9}$$

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 the main body of the paper.

1.16 Additional theoretical results

1.16.1 Two-Asset Examples of Learning Trade-Offs

To illustrate the learning trade-offs, I present a few examples with only two stocks. Figure 6 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).

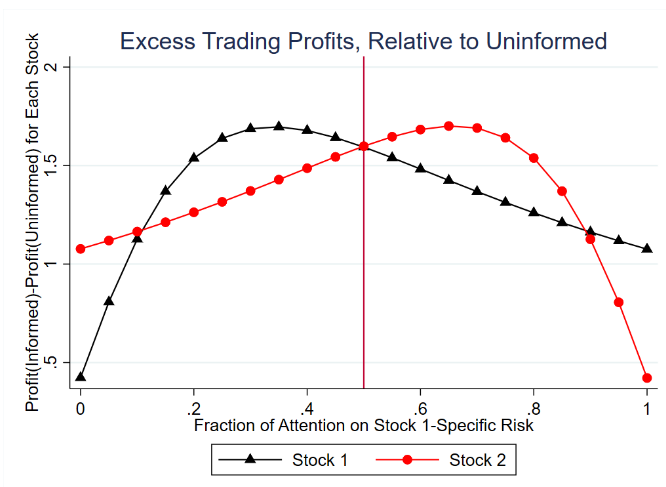

Figure 6. Two Stock Example, No Systematic Risk. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on Stock 2-specific risk. $\rho = 0.1$, $\sigma^2 = 0.55$

Compare this to Figure 7, 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 6, where there is no systematic risk, which ensures this is not entirely driving the results in Figure 7.

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.

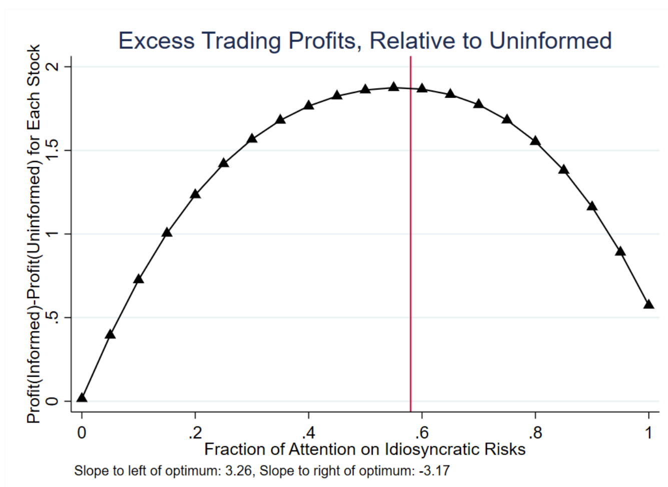

Figure 7. Two stock example, systematic risk, no ETF Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Attention on stock-specific risks is equal. Residual attention is on systematic risk-factor. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$

Finally, Figure 8 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.

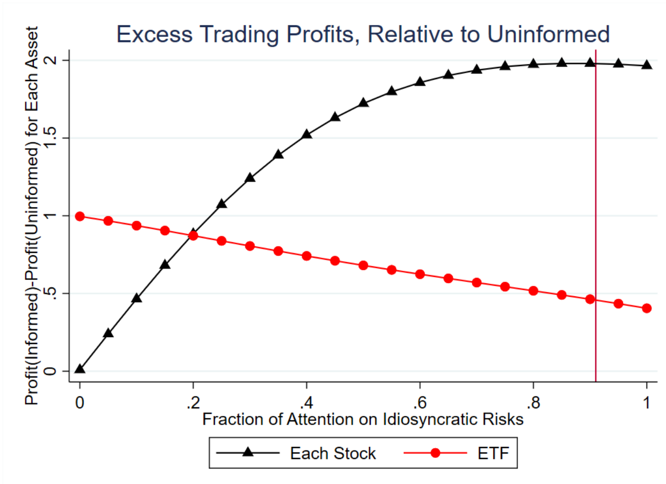

Figure 8. Two stock example, systematic risk, ETF present. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on systematic risk-factor. ETF is in zero average supply. $\rho = 0.1$, $\sigma_f^2 = 0.2$, $\sigma^2 = 0.55$

1.16.2 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 $\epsilon_\mathbf{p} = A_1^{-1}A_2(\bar{\mathbf{x}} + \mathbf{x})$ and $\Sigma_p = A_1^{-1}A_2U$ where U is the variance-covariance matrix of supply shocks. This implies that $\mathbf{s_p} \sim N(0, \Sigma_p)$. Without the ETF:

$$\underbrace{\widehat{\Sigma_j^{-1}}}_{\text{Posterior Precision}} = \underbrace{V^{-1}}_{\text{Prior Precision}} + \underbrace{\Sigma_p^{-1}}_{\text{Price Precision}} + \underbrace{S_j^{-1}}_{\text{Signal Precision}} \tag{10}$$

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:

$$\underbrace{E_{1,j}[\mathbf{z}]}_{\text{Posterior Mean}} = \underbrace{\hat{\Sigma}_j}_{\text{Posterior Variance}} \times \left(\underbrace{S_j^{-1}}_{\text{Precision on Asset Signals}} \mathbf{s_j} + \underbrace{\Sigma_p^{-1}}_{\text{Price Precision}} \mathbf{s_p} \right) \tag{11}$$

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

$$\underbrace{E_{1,j}[\mathbf{z}]}_{\text{Posterior Mean}} = \underbrace{\hat{\Sigma}_j}_{\text{Posterior Variance}} \times \left(\color{red}{\underbrace{S_j^{-1}}_{\text{Precision on Risk-Factor Signals}}} \mathbf{s_j} + \color{blue}{\underbrace{\Sigma_p^{-1}}_{\text{Price Precision}}} \mathbf{s_p} \right) \tag{12}$$

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:

$$\begin{aligned} \mathbf{z} = \mu + \Gamma\eta \leftrightarrow \tilde{\mathbf{z}} = \Gamma^{-1}\mu + \eta \\ \tilde{s}_i = \eta_i + \tilde{\epsilon}_i \text{ for } i = 1, \ldots, n \end{aligned} \tag{13}$$

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)[3], 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 4 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]I would like to thank the authors for sharing their solution code with me.

Panel A: Matching Cost of Becoming Informed

				Precision			
		Share Informed		Informed		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%

				Precision			
		Share Informed		Informed		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%

				Precision			
		Share Informed		Informed		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 4 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.

1.16.3 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 5 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 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.

1.16.4 Expected utility of informed and uninformed investors

Table 6 contains information on the percentage difference in expected utility between informed and uninformed investors when the ETF is and is not present.

1.16.5 Sensitivity of demand to prices

As shown in main body of the paper, 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 7 shows this is true in examples where the cost of becoming informed is fixed. Table 8 shows this is also true in examples where the share of investors becoming informed is fixed.

1.16.6 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

Panel A: Fix Share Informed

ρ	σ_f^2	Shr. Inf.	Risk Premium 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

ρ	σ_f^2	Risk Premium 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 5 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.

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

Panel A: Matching Cost of Becoming Informed

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	Diff. in EU no ETF	Diff. in EU 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%

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	Diff. in EU no ETF	Diff. in EU 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%

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	Diff. in EU no ETF	Diff. in EU 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 6 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.

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 9 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-

		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 7 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.

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.

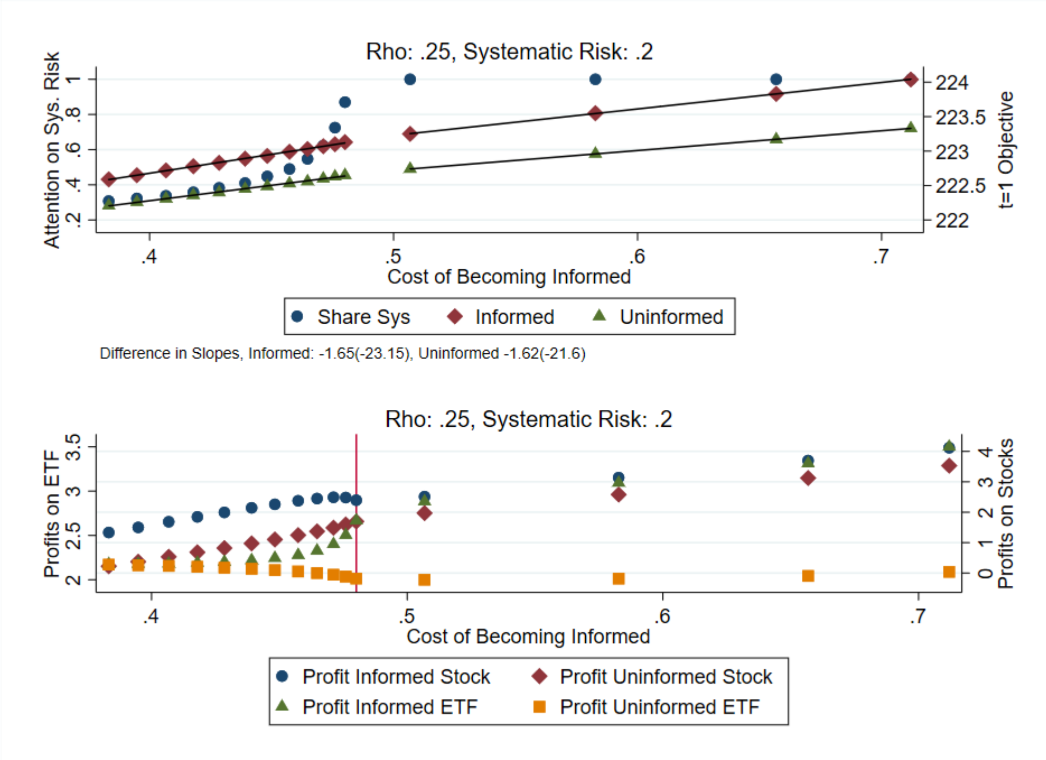

Figure 9. Effect of larger α. Top panel: Effect of the cost of becoming informed on the share of attention on systematic risk. Bottom panel: Effect of the cost of becoming informed on trading profits. $\alpha = 0.05$. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

1.17 Representation as economy with independent assets

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

$$z_i = a_i + \eta_i \tag{14}$$

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 strcture of the payoffs with a systematic component. This model can be solved the same way as the baseline version of the model in the main body of the paper.

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):

$$\begin{aligned}
\text{Define: } \Sigma^{1/2} &= \text{Square root of } V\text{, the variance-covariance matrix of payoffs} \\
\text{Define: } \Sigma_s &= S\text{, the variance-covariance matrix of signals} \\
\text{Define: } \Sigma_s^1 &= \Sigma^{-1/2} \times \Sigma_s \times \Sigma^{-1/2} \\
\text{We can re-write: } \Sigma_s &= \Sigma^{1/2} \times G \times L \times G \times \Sigma^{1/2} \\
\text{where } G \text{ and } L &\text{ come from the eigen-decomposition of } \Sigma_s^1 \\
\text{Define orthogonal signal matrix: } \tilde{\Sigma}_s &= G' \times \Sigma^{-1/2} \times \Sigma_s \times \left(\Sigma^{-1/2}\right)' \times G
\end{aligned} \tag{15}$$

This implies that:

$$\tilde{\Sigma}_s = \begin{bmatrix} 1/(\alpha + \tilde{K}_1) & 0 \\ 0 & 1/(\alpha + \tilde{K}_2) \end{bmatrix} \tag{16}$$

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.

1.18 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[4]. This note explains why my solution method preserves total attention, and shows examples where the rotation method may not.

1.18.1 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 $\overline{K}$.

[4] 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.

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.
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.

1.18.2 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 GL^*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.

1.18.3 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.

1.19 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 the main body of the paper, 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 9 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.

2 Data details

2.1 Missing announcement times in IBES

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%.

2.2 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.

3 Robustness of Stylized Facts

3.1 Decomposition of earnings days' share of volatility

Figure 10 decomposes the rise 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.

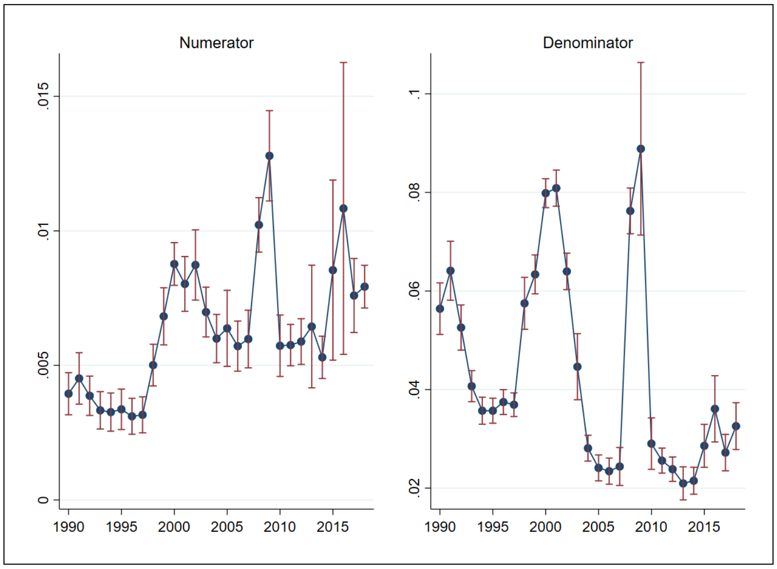

Figure 10. Decomposition of QVS. This figure plots coefficients from a regression of the numerator and denominator of QVS on a set of year dummy variables. The constant term for the omitted year (1989) is added to each coefficient. For firm i around earnings announcement τ the quadratic variation share (QVS) is defined as: $QVS_{i,\tau} = r^2_{i,\tau} / \sum_{k=0}^{22} r^2_{i,\tau-k}$, where r denotes a market-adjusted daily return. The numerator is the squared earnings-day return, while the denominator is the sum of squared returns from $\tau - 22$ to τ. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level.

3.2 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.

3.2.1 22 Days before each earnings announcement

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

$$Outcome_{i,t} = \alpha + \sum_{k=1990}^{2018} 1_{year(t)=k} + \phi_q + \epsilon_{i,t} \tag{17}$$

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 11 shows that there is no trend toward decreased price informativeness before these placebo earnings dates.

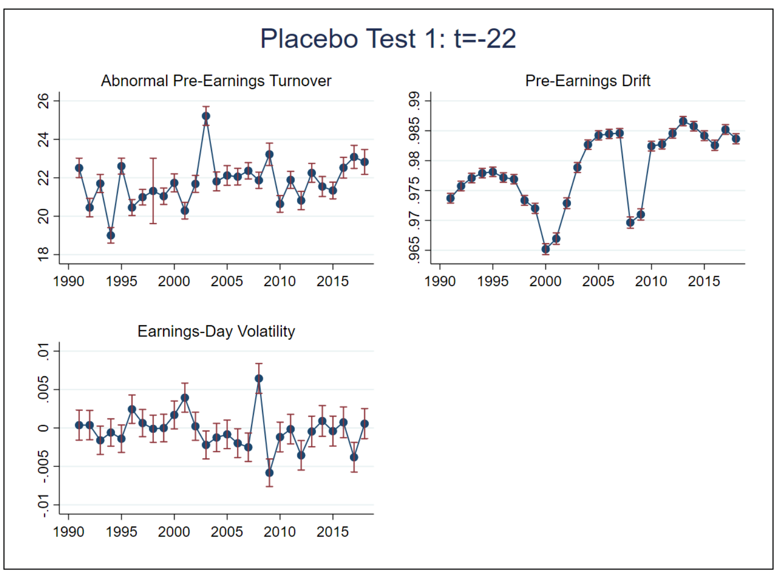

Figure 11. Placebo Test 1: 22 trading days before each earnings announcement. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

3.3 Random days

In this sub-section, I randomly select 4 days each year to be placebo earnings announcements, and re-run regression 17. 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 12 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 12.

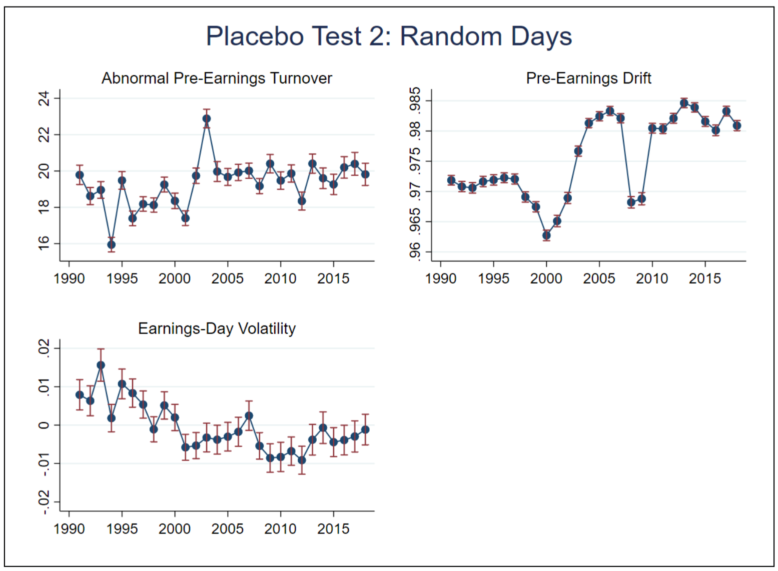

Figure 12. Placebo Test 2: Randomly selected dates. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

3.3.1 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 13 plots coefficients on the year fixed effects from regression 17. 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, but the magnitude is significantly smaller than the upward trend for actual earnings announcement dates documented in the main body of the paper (0.25% vs. nearly 20%).

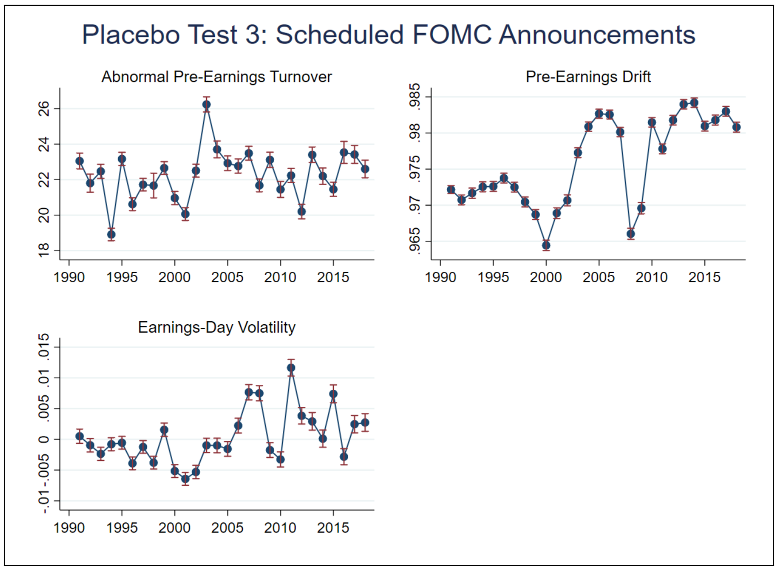

Figure 13. Placebo Test 3: Scheduled FOMC announcement dates. Each panel presents coefficients from a regression of each of the price informativeness measures on a set of year fixed effects. These regressions also include quarter-of-year fixed effects to account for seasonality. The red bars represent 95% confidence intervals. Standard errors are clustered at the security level.

4 Robustness of Cross-Sectional Regression Results

4.1 Placebo tests for cross-sectional regressions

Table 10 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 positive 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 share of informed investors. The magnitude of these coefficients, however, is small, at about 1/20th the size of the baseline cross-sectional estimates.

4.2 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.

4.2.1 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 11, 12 and 13. The results are qualitatively similar, which alleviates concerns that my results being driven by Reg FD.

4.2.2 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 14, 15 and 16 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 earnings-day volatility 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.

4.3 Stock price responses to earnings surprises

Buffa et al. (2014) propose a model where stocks with a higher share of "buy and hold" investors are more responsive to cash flow news. In their model, buy and hold investors distort prices, so informed investors underweight these stocks. When the good cashflow news arrives, the informed investors were previously underweight these stocks, so their diversification motive is weak, and they buy. In relating this model to my empirical setup, I treat buy and hold investors as passive owners and the cashflow news as earnings announcements.

4.3.1 Trends in earnings responses

To measure trends in earnings responses, I run two types of regressions. The baseline comes from Kothari and Sloan (1992):

$$r_{i,t} = \alpha + \beta \times SUE_{i,t} + controls + \epsilon_{i,t} \tag{18}$$

where $SUE_{i,t} = \frac{E_{i,t} - E_{i,t-4}}{\sigma_{(t-1,t-8)}(E_{i,t} - E_{i,t-4})}$, and the controls are lagged market capitalization, firm fixed effects and quarter-of-year fixed effects. Results are similar when calculating SUE relative to IBES estimates using the method in Anson (2009).

I also design an earnings-response regression which allows for asymmetry between positive and negative surprises:

$$r_{i,t} = \alpha + \beta_1 \times SUE_{i,t} \times 1_{SUE_{i,t}>=0} + \beta_2 \times SUE_{i,t} \times 1_{SUE_{i,t}<0} + controls + \epsilon_{i,t} \tag{19}$$

The results of running these regressions in 5-year rolling windows are in Figure 14. Over the past 30 years, earnings responses have increased by a factor of almost 3×. Most of this increase is coming from increased responsiveness to SUEs which are greater than zero.

4.3.2 Effect of passive ownership on earnings responses

To test the predictions in Buffa et al. (2014), I run the following regression:

$$\begin{aligned} r_{i,t} = \alpha + \beta_1 SUE_{i,t} + \phi_1 Passive_{i,t} + \gamma_1 \left(SUE_{i,t} \times Passive_{i,t} \right) \\ + \xi X_{i,t} + \text{Fixed Effects} + e_{i,t} \end{aligned} \tag{20}$$

Here, $r_{i,t}$ denotes the market-adjusted return on the effective quarterly earnings date i.e., the first day investors could trade on earnings information. Controls in $X_{i,t}$ are total institutional ownership and lagged market capitalization. The regression also includes, firm, year/quarter and quarter-of-year fixed effects.

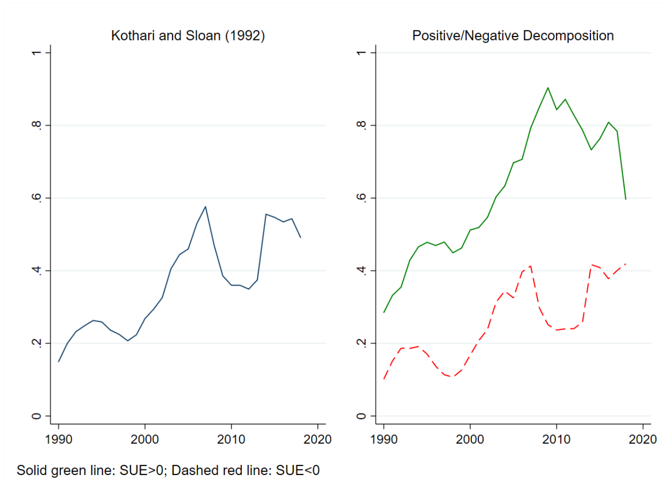

Figure 14. Trends in Earnings Response. Left panel has estimates of β from:

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

Right panel has estimates of β_1 and β_2 from:

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

The controls in each regression are lagged market capitalization, firm fixed-effects and quarter-of-year fixed effects.

I also run a version of Equation 20, breaking SUE into positive and negative components, and taking the *absolute value*. I then interact these variables with passive ownership, to account for a possible asymmetric effect of passive ownership on positive and negative news. Finally, I decompose the earnings news into a systematic and idiosyncratic component using the method in Glosten et al. (2021). This is done by regressing SUE on market-wide SUE and industry-wide SUE in five year rolling windows. The systematic component of earnings is the predicted value from this regression, while the idiosyncratic component is the residual.

Table 17 contains the regression results. Columns 1-3 are a sanity check and do not include the interaction terms with passive ownership. Everything is consistent with common-sense intuition: (1) SUE is positively correlated with earnings-day returns (2) this is true individually both for the positive and negative components of SUE[5] and (3) This is also true

[5]In this table, I take the absolute value of SUE, so the coefficient on the negative part of SUE should be negative.

individually for the positive/negative components of SUE when decomposing earnings news into systematic and idiosyncratic components.

Columns 4-6 add the interaction terms with passive ownership to columns 1-3. Consistent with the Buffa et al. (2014) model, firms with a high share of passive ownership are more responsive to earnings news, especially if that news is negative. Further, the response is especially strong to negative idiosyncratic news. This increased responsiveness to earnings news is one explanation for why QVS is relatively higher for firms with more passive ownership.

4.4 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.

4.4.1 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:

$$\frac{CAPX_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_1 Q_{i,t} + \beta_2 Passive_{i,t} + \beta_3 Q_{i,t} \times Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t} \quad (21)$$

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 18 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.

5 Robustness of quasi-experimental results

5.1 S&P Index Addition Details

The treatment effect of being added to the S&P 500 index has been increasing over time. Figure 15 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%.

5.2 Russell Details

5.2.1 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

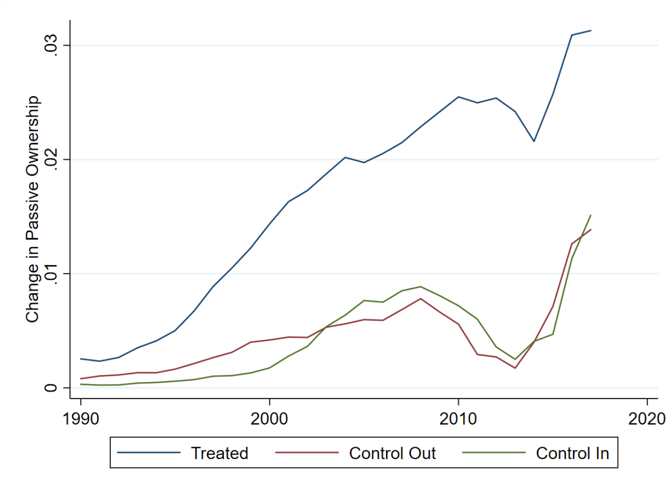

Figure 15. Increase in Passive Ownership from S&P 500 Index Addition. 5-year moving average of increase in passive ownership associated with index addition. Increase in passive ownership is computed from 6 months before index addition to 6 months after index addition.

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.[6]
- 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):

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

  - 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 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 ± 2.5% of the total market capitalization of the Russell 3000.[7]
- 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 ± 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.

[7]In reality, the bands are ± 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.

– 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

5.3 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 16 shows the average increase in passive ownership by year. In 2007, firms switching to the 2000 experienced a less than 2% increase in passive ownership, while now the increase is over 4%.

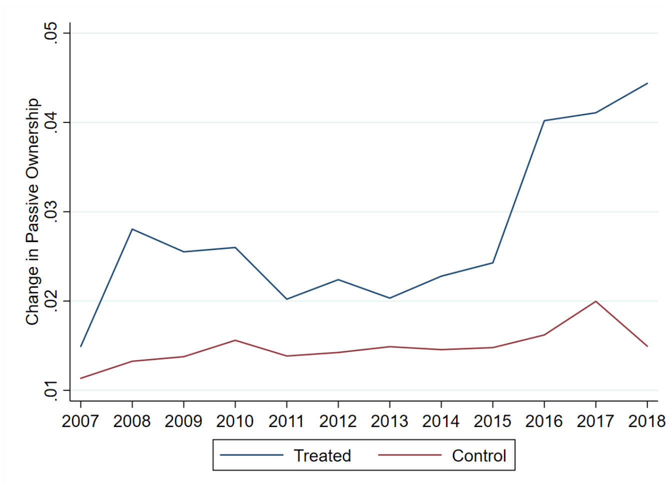

Figure 16. Increase in Passive Ownership from Russell 1000/2000 Reconstitution. 5-year moving average of increase in passive ownership associated with switching from the Russell 1000 to the Russell 2000. Increase in passive ownership is computed from 6 months before index rebalancing to 6 months after index rebalancing.

5.4 Alternative quasi-exogenous changes in passive ownership

5.4.1 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 17 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.

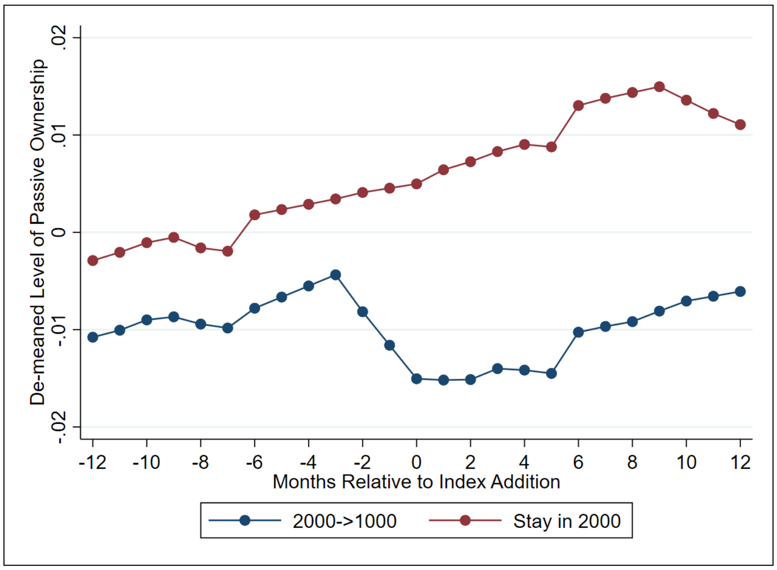

Figure 17. Russell 1000/2000 Reconstitution and Changes in Passive Ownership. Average level of passive ownership for firms that stay in the Russell 2000 (control firms) and firms that moved from the Russell 2000 to the Russell 1000 (treated firms). Passive ownership is demeaned within each cohort.

5.4.2 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 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.

Panel A: Share Informed Fixed at 10%

Uninformed

ρ	σ_n^2	Share Informed no ETF	ETF	No ETF Present Own	Stock Hedge	ETF Present Own	Stock Hedge	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	ETF	No ETF Present Own	Stock Hedge	ETF Present Own	Stock Hedge	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	ETF	No ETF Present Own	Stock Hedge	ETF Present Own	Stock Hedge	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	ETF	No ETF Present Own	Stock Hedge	ETF Present Own	Stock Hedge	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 8 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	0.706	0.6	0.34
9	0%	0.614	0.963	0.783	0.35	0.35
1	12%	0.505	0.963	0.810	0.3	0.41
0	48%	0.256	0.963	0.875	0.2	0.65

Table 9 Counterfactual Analysis. All parameters are chosen to match the value-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	-0.00309	0.00104	0.00397	0.0221	0.030
	(0.009)	(0.009)	(0.009)	(0.025)	(0.027)
Observations	386,739	352,868	352,868	352,868	352,868
R-Squared	0.038	0.038	0.039	0.032	0.034
	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 10 Cross-Sectional Regression Placebo Tests: Earnings-Day Volatility. Table with estimates of β from:

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

$QVS_{i,\tau} = r^2_{i,\tau} / \sum\limits_{k=0}^{22} r^2_{i,\tau-k}$, where τ 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.

	(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 11 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 12 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 13 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 14 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 15 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***	0.317***	0.306	0.410***
	(0.047)	(0.047)	(0.049)	(0.199)	(0.128)
Observations	92,159	83,667	83,667	83,667	83,667
R-Squared	0.24	0.242	0.246	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 16 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)	(6)
Sys. SUE>0			0.360*			0.602***
			(0.1910)			(0.1810)
Sys. SUE<0			-0.241**			-0.285**
			(0.1040)			(0.1310)
Idio. SUE>0			0.647***			0.653***
			(0.0350)			(0.0362)
Idio. SUE<0			-0.282***			-0.214***
			(0.0231)			(0.0233)
SUE>0		0.642***			0.660***	
		(0.0367)			(0.0367)	
SUE<0		-0.291***			-0.225***	
		(0.0194)			(0.0213)	
SUE	0.400***			0.355***		
	(0.0219)			(0.0238)		
SUE x Passive				0.859*		
				(0.4460)		
SUE>0 x Passive					-0.348	
					(0.8010)	
SUE<0 x Passive					-1.335***	
x Passive					(0.3550)	
Sys. SUE>0						-3.002
x Passive						(2.3620)
Sys. SUE<0						1.043
x Passive						(1.8820)
Idio. SUE>0						-0.143
x Passive						(0.7580)
Idio. SUE<0						-1.390***
x Passive						(0.3990)
Observations	344,237	344,237	344,237	344,237	344,237	344,237
R-squared	0.061	0.062	0.062	0.061	0.062	0.062

Table 17 Passive Ownership and Response to Earnings News. This table contains the results of the following regression:

$$r_{i,t} = \alpha + \beta_1 SUE_{i,t} + \phi_1 Passive_{i,t} + \gamma_1 \left(SUE_{i,t} \times Passive_{i,t}\right) + \xi X_{i,t} + \text{Fixed Effects} + e_{i,t}$$

Here, $r_{i,t}$ denotes the market-adjusted return on the effective quarterly earnings date. $SUE_{i,t} = \frac{E_{i,t}-E_{i,t-4}}{\sigma_{(t-1,t-8)}(E_{i,t}-E_{i,t-4})}$. Controls in $X_{i,t}$ are total institutional ownership and lagged market capitalization. The regression also includes, firm, year/quarter and quarter-of-year fixed effects. Columns 1 and 2 are equal weighted, while Columns 3 and 4 are value weighted. 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 18 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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