Online Appendix for Passive Ownership and Price Informativeness

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1 Model Details

1.1 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:

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

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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:

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

1.2 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 1.14.2 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:

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

1.3 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.

1.4 Supply shocks to the ETF

The supply shocks to the ETF 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 (2019), 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: $\tilde{U} = (\Gamma')^{-1} \sigma_x^2 \mathbf{I}_{n+1} (\Gamma')^{-1}$.

1.5 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.

1.6 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 section.

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 that an equilibrium would exist.

1.7 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 supply: few have short interest equal to 100% or more of their AUM[1]. 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.

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.

1.8 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.

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. In Section 1.18.1 of the Online Appendix I calibrate a version of the model to match the empirical effects of introducing sector ETFs in the late 1990's.

[1]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%.

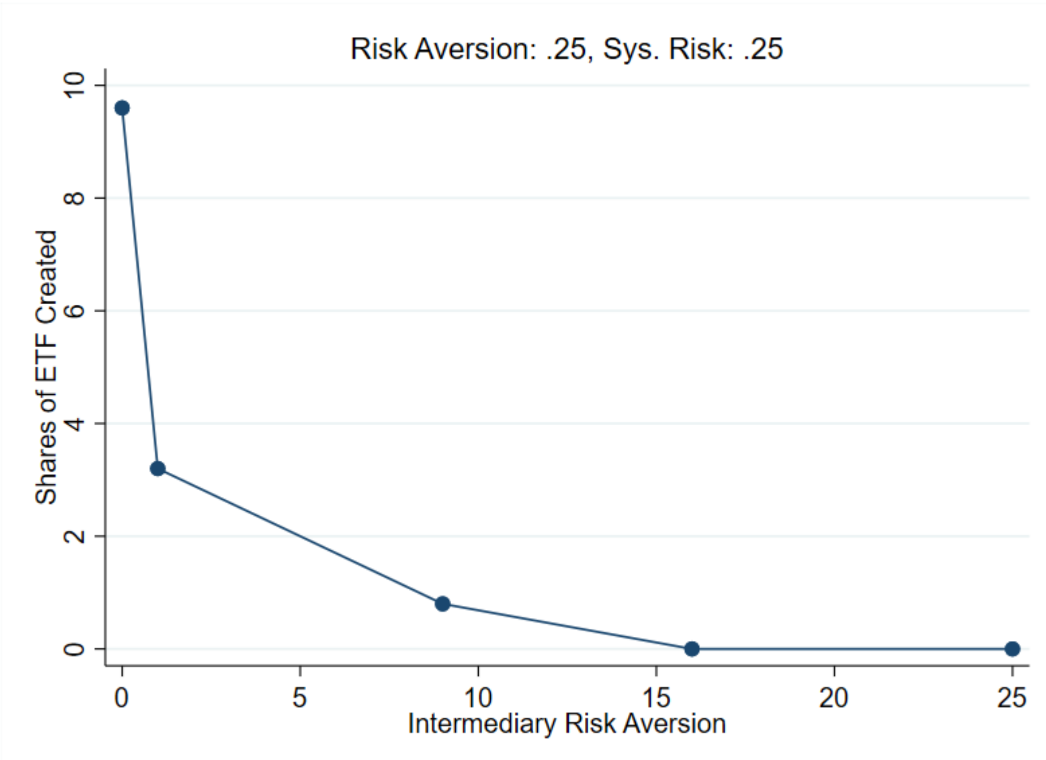

Figure 1. Relationship between size of the ETF and the intermediary's risk aversion. Risk aversion of informed/uninformed investors $\rho = 0.25$. Volatility of the systematic risk factor $\sigma_f = 0.25$ The share of informed investors is set to 50%. If the ETF owned all the shares of the underlying stocks, it would have 20 shares outstanding.

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.

My simplified ETF creation technology does not exactly match the real world. 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

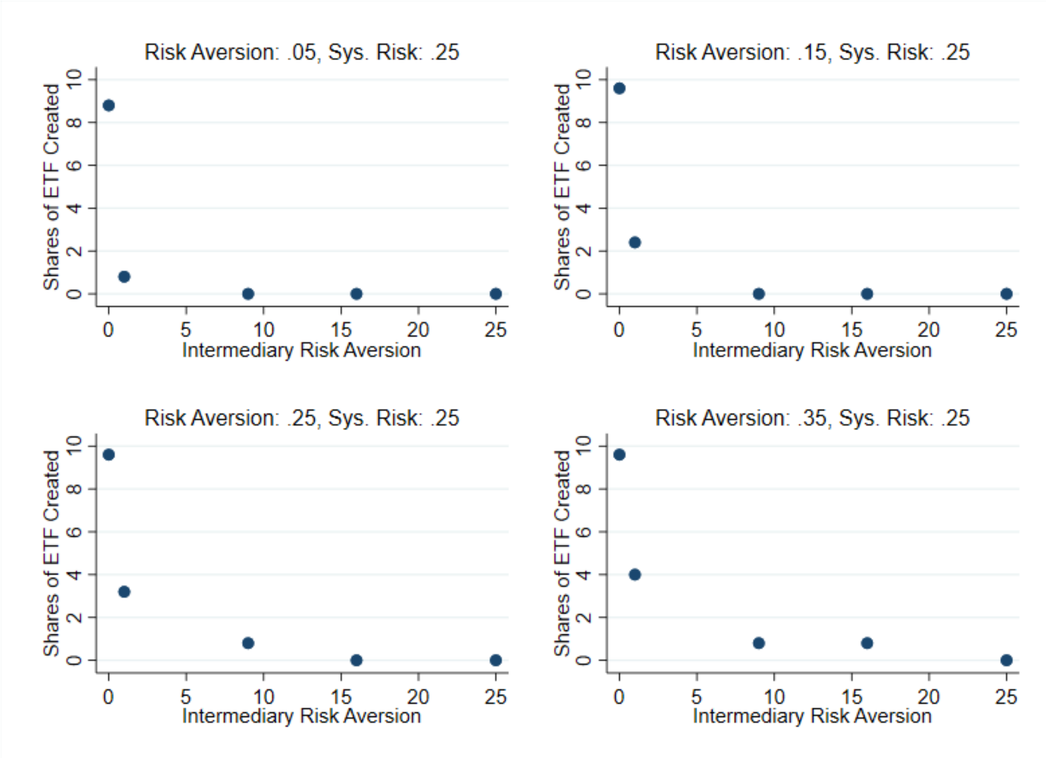

Figure 2. Relationship between the size of the ETF and informed/uninformed investors' risk avesrion. The share of informed investors is set to 50%. The volatility of the systematic risk-factor $\sigma_f = 0.25$. If the ETF owned all the shares of the underlying stocks, it would have 20 shares outstanding.

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. The reason I do not use this alternative setup is because with this ETF creation technology, the intermediary would be able to remove idiosyncratic risk from the economy by creating more shares of the ETF.

1.9 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.

$t = 0$	∘ 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.

1.10 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.

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.

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, 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.

1.11 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.

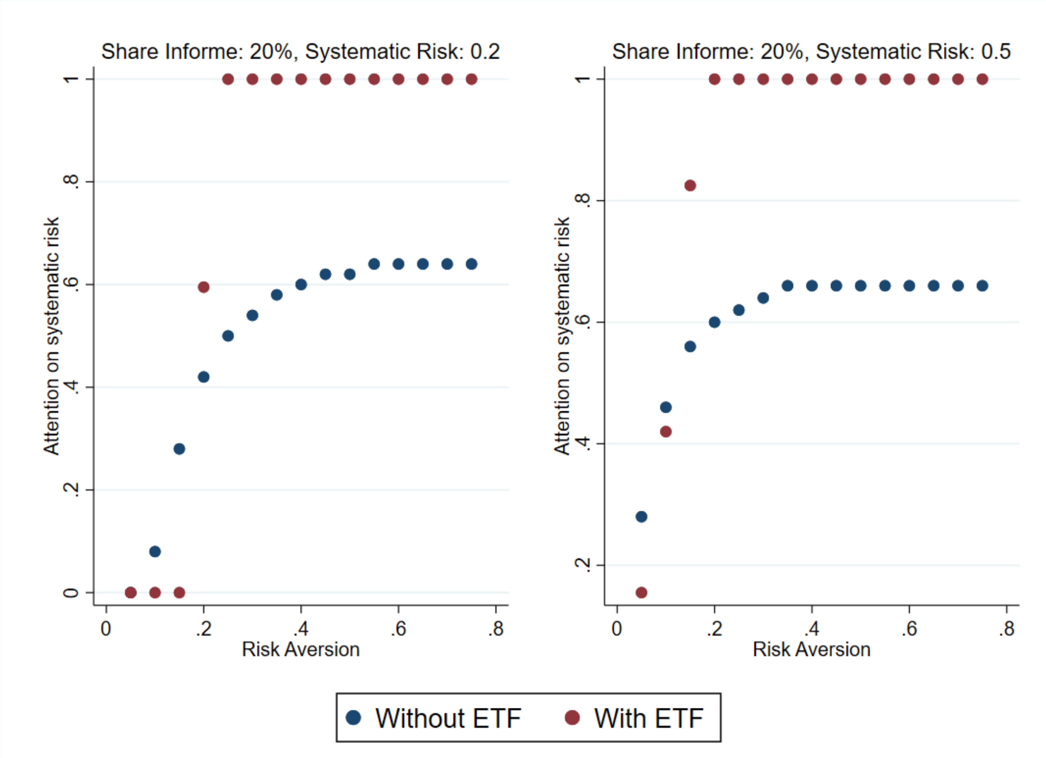

Figure 3. Relationship between risk aversion and attention to systematic risk-factor. In the left panel, σ_n^2 is set to 0.2, while in the right panel, σ_n^2 is set to 0.5. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

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.

1.12 Discussion of numerical method for solving 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.

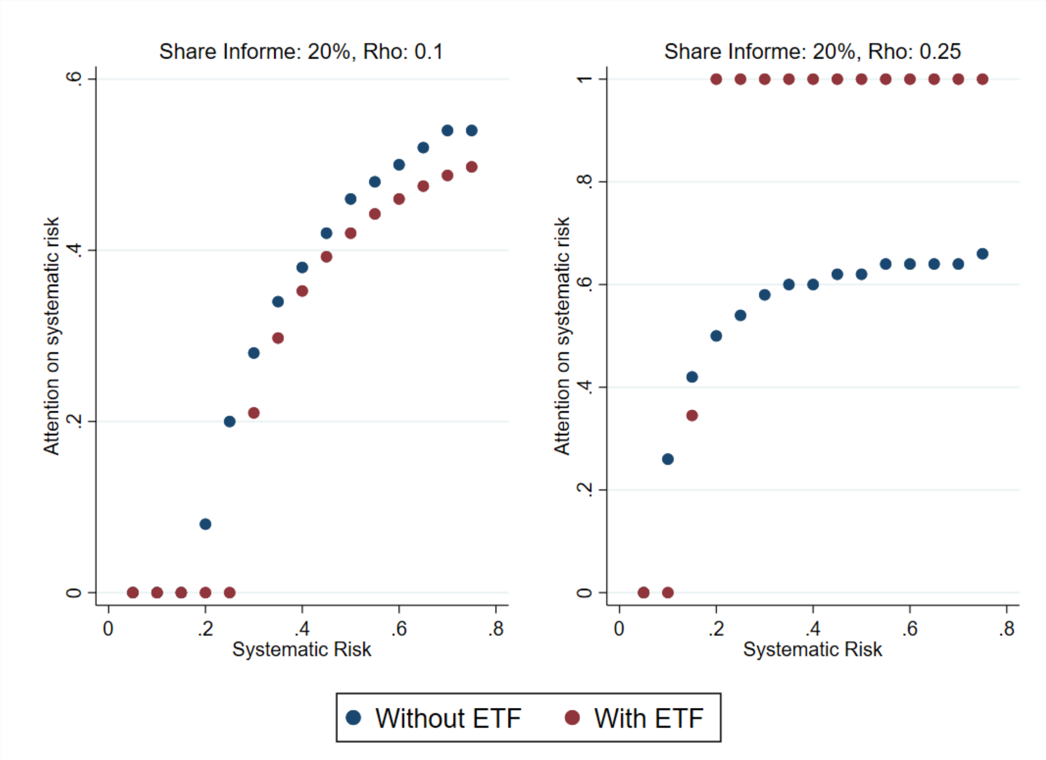

Figure 4. Relationship between systematic risk and attention to systematic risk-factor. In the left panel, risk aversion, ρ is set to 0.1, while in the right panel, risk aversion is set to 0.25. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

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 et al. (2016). While this is possible, it still relies 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 1.16 for more details.

Solving for the share of informed investors

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

Solving for the size of the ETF

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

1.13 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)).

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

Putting in our 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 we can derive their utility function 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: $V_0 = -E_0(ln[-V_1])$

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

Why early resolution of uncertainty matters

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

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

A more nuanced argument requires a discussion of why learning about particular risks is useful. Expected excess portfolio return achieved through learning depends on the covariance between your portfolio q and asset payoffs $f - p$, $cov(q, f - p)$. Specializing in learning about one asset leads to a high covariance between payoffs and holdings of that asset. The actual portfolio investors end up holding, however, can deviate substantially from the time 0 expected portfolio. Learning a little about every risk leads to smaller deviations between the realized and time 0 expected portfolio, but also lowers $cov(q, f - p)$.

With expected utility, investors are averse to time 1 portfolio uncertainty (i.e. risk that signals will lead them to take aggressive bets), so do not like portfolios that deviate substantially from $E_0[q]$. The utility cost of higher uncertainty from specialization offsets the utility benefit of higher portfolio returns, removing the "planning benefit" experienced by the mean-variance specification.

Recursive utility investors are not averse to risks resolved before time 2, so specialization is a low-risk strategy. They lower their time 2 portfolio risk by loading their portfolios heavily on assets whose payoff risk will be reduced by learning.

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

1.14 Extensions

1.14.1 Extension 1: Endogenous capacity choice

In the main body of the paper, the exogenous 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.

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 $c(K)$.

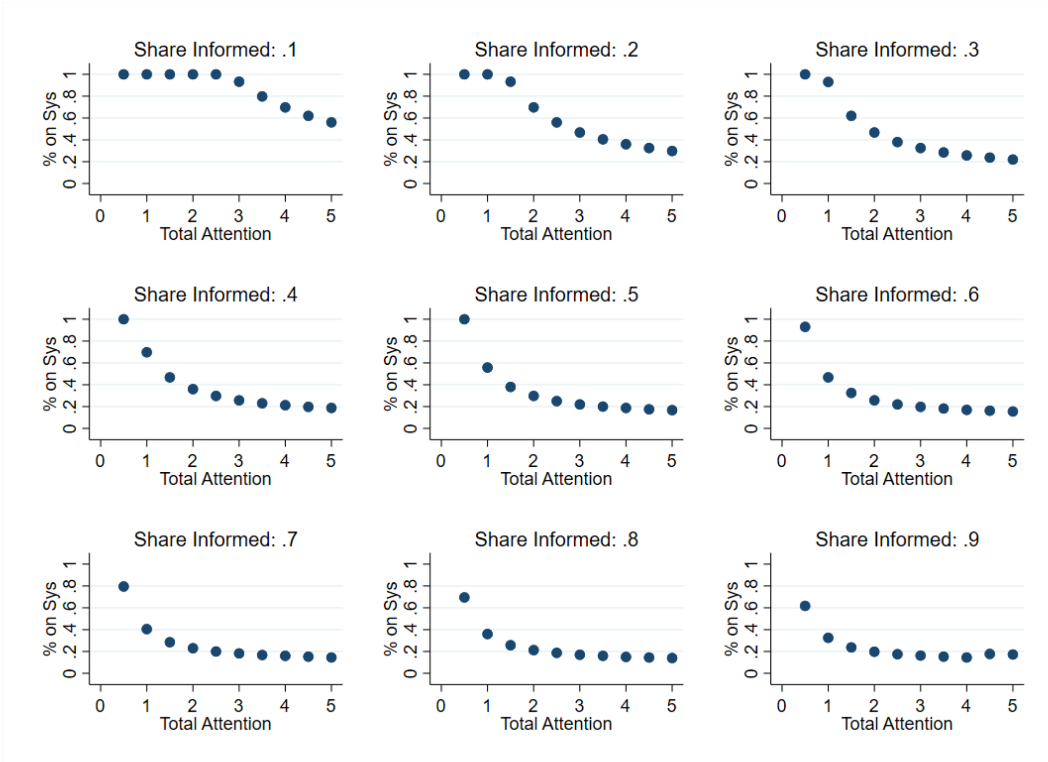

Figure 5. Effect of Varying K and Share Informed. x-axis is total attention K, y-axis is the share of total attention allocated to systematic risk. Parameters: $\rho = 0.25$, $\sigma_n = 0.25$. ETF is present in zero average supply.

1.14.2 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.

1.15 Additional theoretical results

1.15.1 Learning Trade-Offs

To illustrate this trade-off, 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).

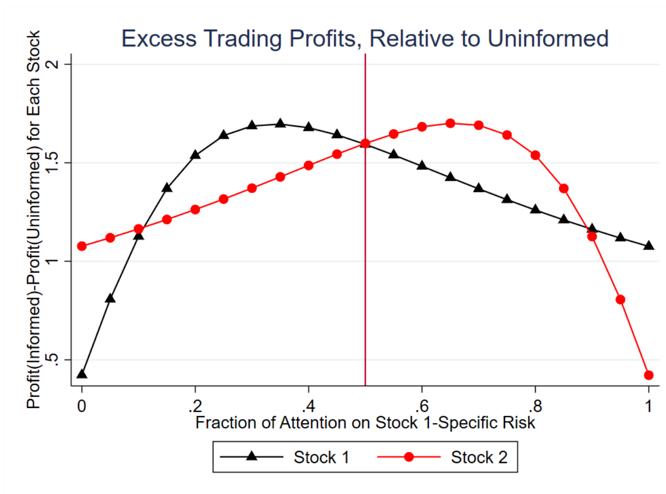

Figure 6. Two Stock Example, No Systematic Risk. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on Stock 2-specific risk. $\rho = 0.1$, $\sigma^2 = 0.55$

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.

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.

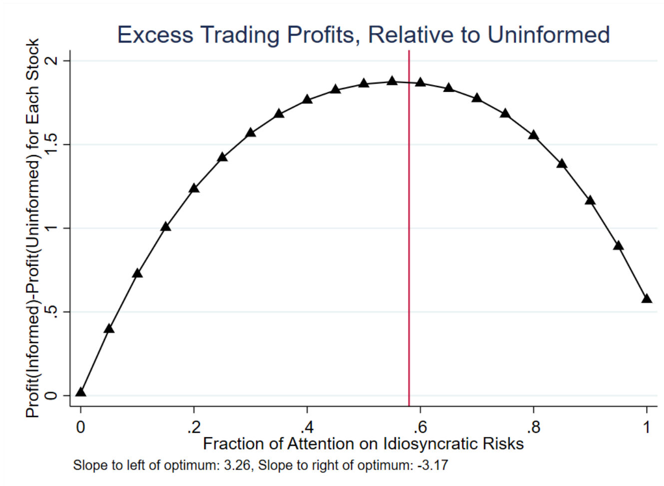

Figure 7. .Two stock example, systematic risk, no ETF Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Attention on stock-specific risks is equal. Residual attention is on systematic risk-factor. $\rho = 0.1$, $\sigma_f^2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

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.

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

Introducing the ETF changes the way investors form beliefs about asset payoffs. Define $\mathbf{s_p} = \mathbf{z} + \epsilon_\mathbf{p}$ as the signal about asset payoffs contained in prices. From the price function, this can be written as: $\mathbf{s_p} = A_1^{-1}(\mathbf{p} - A_0)$, which implies that $\epsilon_\mathbf{p} = A_1^{-1}A_2(\overline{\mathbf{x}} + \mathbf{x})$ and $\Sigma_p = A_1^{-1}A_2U$ where U is the variance-covariance matrix of supply shocks. This implies that $\mathbf{s_p} \sim N(0, \Sigma_p)$. Without the ETF:

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

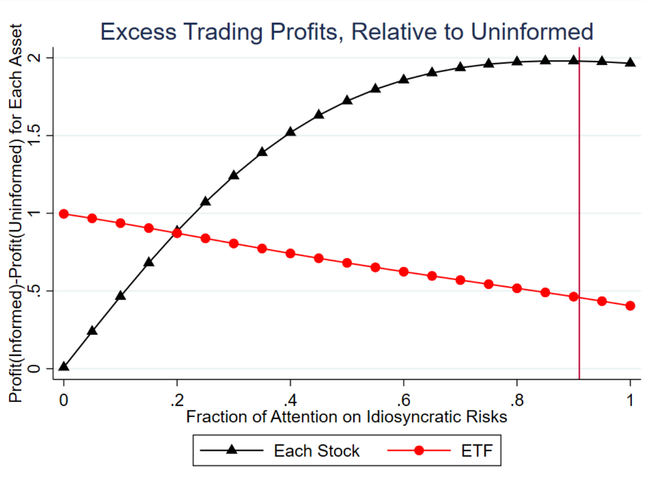

Figure 8. Two stock example, systematic risk, ETF present. Vertical red line denotes optimal attention allocation. All other points are not equilibrium outcomes. 20% of investors are informed. Residual attention is on systematic risk-factor. ETF is in zero average supply. $\rho = 0.1$, $\sigma_f^2 =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

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:

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

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)[2], 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.

1.15.3 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-

[2] 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.

to-apples comparison. The results are unaffected if the market is defined as the return of the ETF when it is present.

Panel A: Fix Share Informed

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.

1.15.4 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.

ρ	σ_n^2	Share Informed no ETF	Share Informed ETF	Diff. in EU no ETF	Diff. in EU ETF
Panel A: Matching Cost of Becoming Informed					
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%					
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%					
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.

1.15.5 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 fixes the cost of becoming informed. Table 8 fixes the share of investors becoming informed.

				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.

1.15.6 Effect of varying baseline learning α

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

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

Figure 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-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.

1.16 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

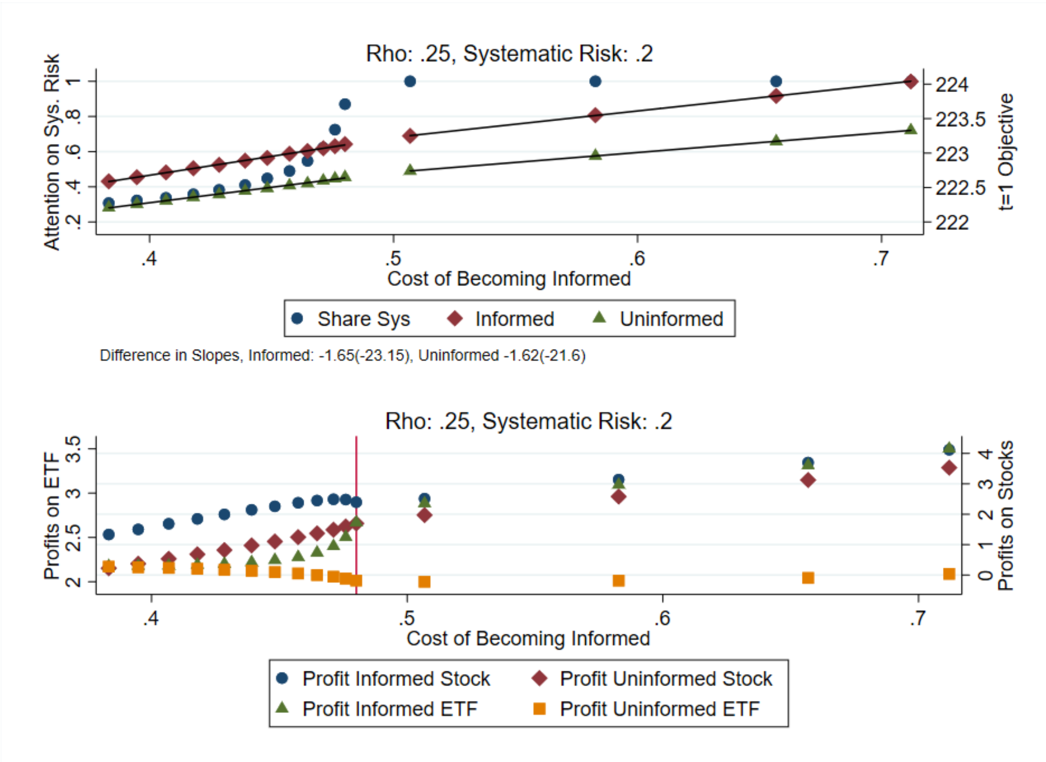

Figure 9. Effect of larger α. Top panel: Effect of the cost of becoming informed on the share of attention on systematic risk. Bottom panel: Effect of the cost of becoming informed on trading profits. $\alpha = 0.05$. In both panels, ρ^i is set high enough that the ETF is in zero average supply.

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.

1.17 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[3]. This note explains why my solution method preserves total attention, and shows examples where the rotation method may not.

1.17.1 General Mapping

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

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

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

1.17.2 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 $K = 1$.

[3] 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 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.

1.17.3 Numerical Examples

There is no guarantee that the sum of the $K_i^{\prime}s$ in L^* (the optimal attention allocation in the rotated economy) are the same as the sum of the $K_i^{\prime}s$ 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.

1.18 Effects of Introducing the ETF vs. Effect of Growing Passive Ownership

Introducing the ETF, even in zero average supply, completes the market. As shown in other parts of this Online Appendix, introducing the ETF has effects on investors' demand functions, posterior beliefs, and expected utility. In this subsection, I outline an empirical exercise which better maps to the *introduction* of ETFs, rather than the growth of passive ownership.

1.18.1 Introduction of sector ETFs

Sector ETFs are ETFs that track specific industries, rather than the market as a whole. While there are many sector ETFs, the most well known are State Street's Sector SPDR Funds. Table 9 contains a list of the all the sector SPDRs. These funds were introduced in waves: The first set was introduced in 1999. The second wave, which were all sub-sects of the S&P 500 were introduced in 2005 and 2006. The third wave, also subsets of the S&P 500 was introduced in 2011, while the final few were introduced in 2015 and later. As of June 2020 there is over \$170 Billion invested in these products.

The introduction of sector ETFs captures some of the features of introducing the ETF in the model. These are low fee products (expense ratios less than 50 basis points), so they make it easier to trade on systematic risk. These are also heavily used by hedge funds to short/hedge sector risks. According to Goldman Sachs Hedge Fund Monitor (2016), hedge funds are net short XRT, XLY, XBI, XOP, XLI, XLF, XLV, XLU and XLE – and this is only among sector ETFs they explicitly listed in their report. Further, these net short positions are not due to small long positions. For example, in XLF (the Financial Select Sector SPDR), hedge funds have net \$712 million long and \$2.4 *billion* short. The large short interest in many ETFs by hedge funds may be due to the ETFs relatively low borrowing cost. According to Deutsche Bank, shorting SPY (the largest S&P 500 ETF) usually costs about 40 basis points, while shorting something riskier like the US consumer staples sector ETF (XLP) can run up to 72 basis points.

I examine the effect of the introduction of the original set of sector ETFs in 1999 on price informativeness. There are three groups of firms to compare (1) firms which were in the ETFs (2) firms in the same sector as the ETF, but were not part of the ETF basket (3) firms in sectors without ETFs.

The firms which were added to the sector ETFs are mostly firms in the largest 20% of each industry. To construct a better control group, I split firms up into quintiles of market capitalization by industry. The two groups of treated firms are (1) those in the ETF (2) those in the same 3-digit SIC industry as firms in the ETF and in the top 20% of market capitalization for these industries, but not in the ETF. The control group is going to be firms in 3-digit SIC industries that do not have sector ETFs, but are still in the top 20% of market capitalization for their own industry.

The empirical estimates I am trying to match are from the following regression:

$$Outcome_{i,t} = \alpha + \beta \times Treated_{i,t} \times Post_t + \gamma_t + \epsilon_{i,t} \tag{17}$$

where *Outcome* is pre-earnings volume, pre-earnings drift, or share of volatility on earnings days. $Post_t = 1$ for all year/quarters after the first quarter of 1999. I omit the second quarter of 1999 for the volume/drift regressions (which use quarterly data) in case of a temporary liquidity shock to these stocks as the result of the ETFs being introduced. For the volatility regression (which uses annual data), I omit all of 1999 for the same reason. *Treated* equals 1 if a firm was in one of the ETFs, or in a sector with an ETF. It is equal to zero otherwise. The regression also includes time fixed effects, γ_t, and because of these time fixed effects, there is no uninteracted $Post_t$. Observations are weighted by lagged market capitalization. Standard errors are clustered at the firm-level.

Table 10 contains the regression results. After the introduction of sector ETFs, the treated firms had a decrease in pre-earnings volume, a decrease in pre-earnings drift, and an increase in the share of annual volatility on earnings days. The effect is slightly stronger among the treated firms that were members of the new sector ETFs. Figure 10 has a visual version of these regressions. This is consistent with the sector ETFs decreasing stock-level price informativeness. A calibration is in the row below the regression results. The calibrated parameters are: (1) informed share before ETF introduction at 90%, after ETF introduction 70% (2) Risk aversion ρ at 0.15, and (3) volatility of systematic risk σ_n^2 at 0.3. In the calibration, the ETF is in zero average supply, designed to capture the fact that these ETFs were small when they were first introduced.

The calibration is able to quantitatively match the changes in volume and volatility, but can only qualitatively match the results for the pre-earnings drift. Part of this is due to the fact that in the data, I am using returns over 22 trading days to construct the drift, while in the model, there is only 1 day before the earnings announcement. The concept of information being slowly incorporated into prices might be better suited to a Kyle (1985)-style model, than the model in this paper.

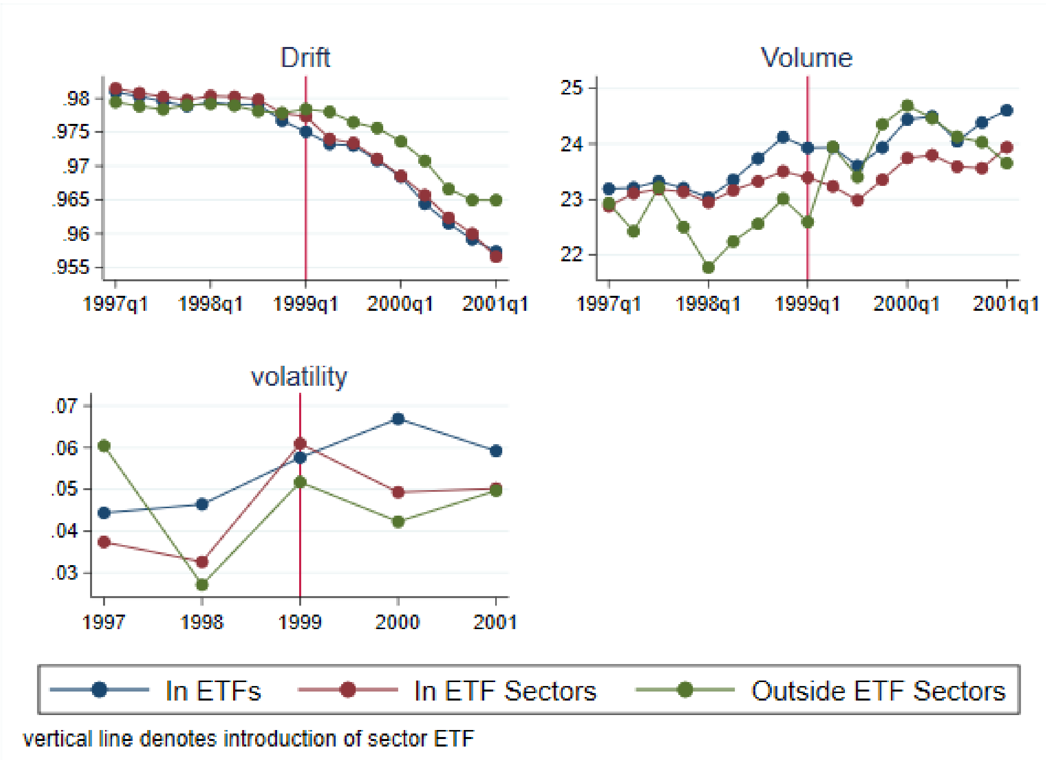

Figure 10. Sector ETF Trends. Trends in pre-earnings drift, pre-earnings trading volume and share of volatility on earnings days around the introduction of Sector ETFs by State Street in Q1 1999 (vertical red line).

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

2 Robustness of Stylized Facts

2.1 Data details

I/B/E/S: 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 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 (2) For the pre-earnings drift, and pre-earnings volume, I am measuring returns/volume leading up to an earnings announcement. These missing earnings times could only move the effective earnings date *earlier* in time, which would bias both of my measures toward finding nothing. If volume dropped significantly on the last trading day before the earnings announcement, this would not be included in my pre-earnings volume measure for observations with a missing announcement time. For the pre-earnings drift, and the earnings day share of volatility, 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 1.6%.

2.2 Alternative definitions of pre-earnings volume

Rather than look at the 22 days before an earnings announcement, I expand the analysis to 60 trading days before the earnings announcement. 60 trading days roughly corresponds to the time between earnings announcements. A concern with the regression of cumulative abnormal volume on days-before-earnings-announcement indicator variables is that average earnings day volume has increased, so the relative volume on the days leading up to the earnings days would appear to *mechanically* decrease in a regression with year fixed effects. Figure 11 shows the cross-sectional median pre-earnings volume, which exhibits the same decline in pre-earnings volume as the average.

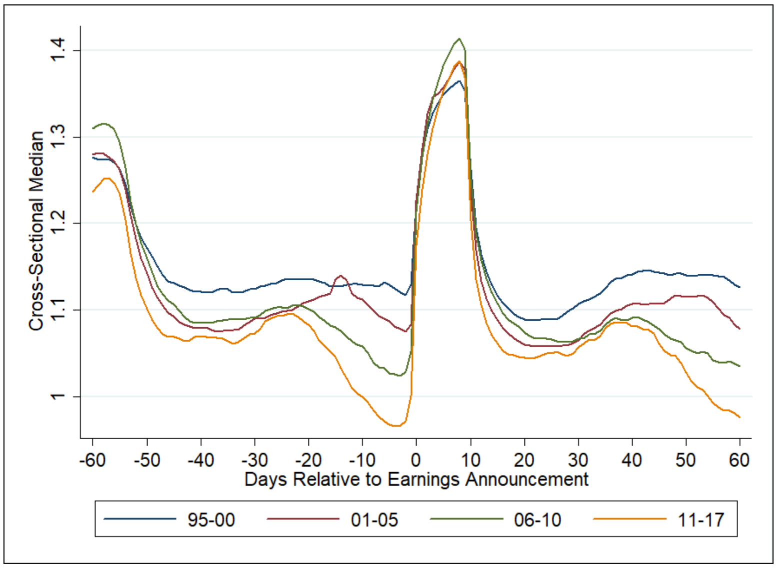

Figure 11. Decline of Pre-Earnings Volume, Expanded Window. Plot of 10-day moving average of abnormal volume. Abnormal volume is volume relative to the historical average over the past year. Average historical volume is fixed at the beginning of each 10-day moving-average window to avoid mechanically amplifying drops in volume.

The figure also motivates my choice of a 22 trading-day window for the drop in pre-earnings volume: This is where there are differences across years. This is a case of looking where the *average* effect is, but nothing in this figure suggests that this trend is driven by changes in passive ownership.

Another explanation for decreased pre-earnings volume is that informed trading before earnings announcements has moved to dark pools. This could occur 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.

2.3 Alternative definitions of the pre-earnings drift

One alternative way to define a pre-earnings drift measure is using squared returns, rather than signed returns. Define the drift volatility, DV, as the ratio of the squared earnings day return to the squared return on all days since last earnings announcement plus squared earnings day return. This is similar to QVS, but is defined for each individual earnings announcement, rather than a whole year.

If DV is near one, almost all volatility occurs on earnings days, while if it is near zero, almost all volatility happens between earnings days. In a Kyle (1985)-type model, DV would decrease with the precision of the insider's signal[4]. All my baseline pre-earnings drift results are robust to switching any drift magnitude measure for DV.

2.4 Value weights vs. equal weights

2.5 Trends in Pre-Earnings Volume and Pre-Earnings Drift

Figure 15 shows the value-weighted average of $CAV_{i,t}$ by year. Between the 1990's and 2010's, average $CAV_{i,t}$ declined by about 1. This can be interpreted as as a loss of about 1 trading-day's worth of volume over the 22-day window before earnings announcements.

Figure 16 shows the cross-sectional average value of $DM_{i,t}$ by year. The pre-earnings drift decreased by about -0.02 between 1990 and 2018.

2.6 Placebo tests for stylized facts

In this subsection, I conduct two placebo tests for the stylized test (1) Using days between earnings announcements as placebo announcement dates (2) Using FOMC meetings as placebo announcement dates.

[4]I thank Alex Chinco for making his two-period Kyle code available on his website.

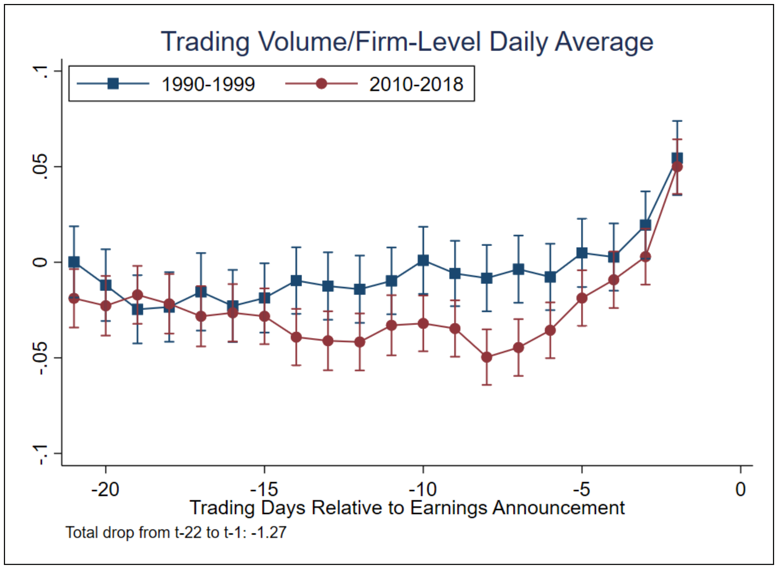

Figure 12. Decline of Pre-Earnings Volume (Value Weighted). Plot of β_k estimated from the regression:

$$AV_{i,t+\tau} = \alpha + \sum_{k=-21}^{22} \beta_k \mathbf{1}_{\{\tau=k\}} + e_{i,t+\tau}$$

Bars represent a 95% confidence interval around the point estimate. Standard errors are clustered at the firm level. Observations are weighted by a firm's 1-year lagged market capitalization.

2.6.1 Days between earnings announcements

This section replicates Figures for the decrease in pre-earnings volume, the decrease in pre-earnings drift and the increase in earnings day volatility, except replaces the true earnings dates with placebo earnings dates 22 days before the actual announcements. In all three cases, there is no trend toward decreased informativeness on the placebo earnings dates.

2.6.2 Systematic Information Announcement Days

The other set of placebo announcement days I focus on are FOMC announcement dates. I obtain FOMC announcement dates from Gorodnichenko and Weber (2016). To create an apples-to-apples comparison with the anticipated nature of earnings announcements, I restrict the sample to scheduled FOMC meetings. I compute versions of pre-earnings volume, and pre-earnings drift for these FOMC dates. The only difference is that I use a $\pm$ 10 day

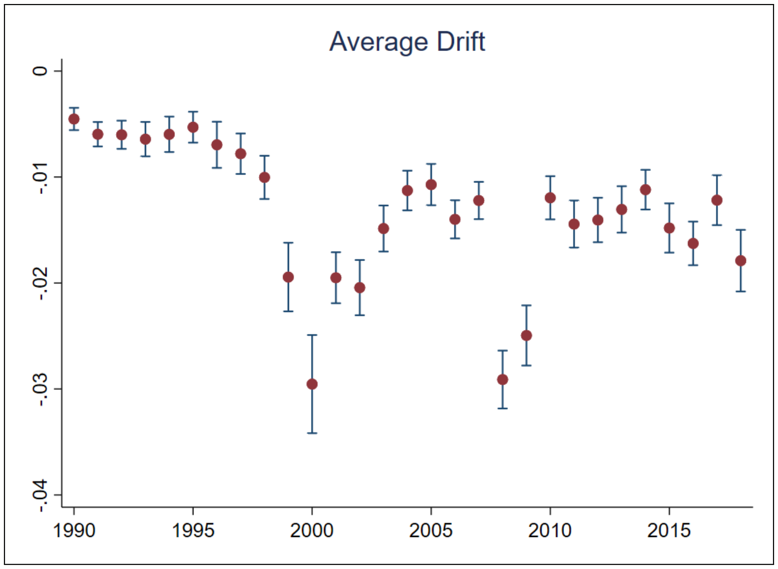

Figure 13. Decline of Average Pre-Earnings Drift (Value Weighted). This figure plots coefficients from a regression of pre-earnings drift on a set of year dummy variables where $DM_{it} = \begin{cases} \frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} & \text{if } r_t > 0 \\ \frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} & \text{if } r_t < 0 \end{cases}$. A value near 1 implies most earnings information is incorporated in prices before the announcement date, while lower values denote less informative pre-earnings announcement prices. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level. Observations are weighted by a firm's 1-year lagged market capitalization.

around each announcement, instead of ± 22 days, to avoid overlap as there are 8 scheduled meetings per year. Share of volatility on FOMC meeting dates is the sum of squared returns on those dates, divided by the sum of squared returns on all dates.

Figure 19 shows the trends in volume around FOMC announcement dates. There is no drop before the announcement in the last third of the sample. Figure 20 shows the pre-FOMC announcement drift. There is no upward/downward trend throughout the sample. Figure 21 shows a slight trend toward increased volatility on FOMC announcement dates, but this may be due to the increased importance of FOMC meetings during the global financial crisis.

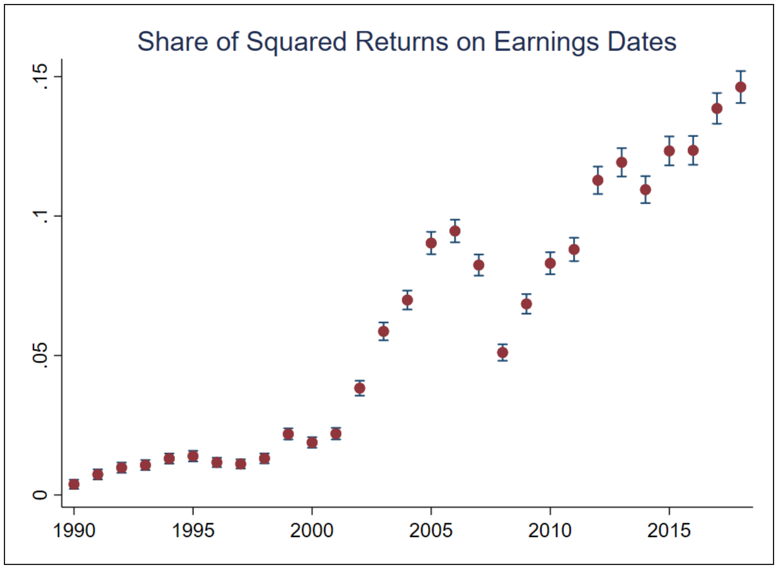

Figure 14. Increase in Earnings Day Volatility (Value Weighted). This figure plots coefficients from a regression of QVS on a set of year dummy variables. For firm i in year t the quadratic variation share (QVS) is defined as: $QVS_{i,t} = \sum_{\tau=1}^{4} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, where r denotes a market-adjusted daily return. The numerator sums over the 4 quarterly earnings days in year t, while the denominator includes all days in calendar year t. Standard errors are clustered at the firm level. Observations are weighted by a firm's 1-year lagged market capitalization.

3 Robustness of Cross-Sectional Regression Results

3.1 Levels vs. First Differences

To better understand why the levels and first-differences specifications yield different results, I simulate the distribution of β. To this end, I simulate an economy 1,000 times. Within each economy, there are 10,000 firms and 30 years of data. I have three scenarios for trends in the right-hand-side and left-hand-side variables as follows: (1) No trend in passive ownership or price informativeness (2) Aggregate trends in passive ownership and/or price informativeness (3) Firm-specific trends in passive ownership and/or price informativeness.

Under each of these three scenarios, I have two sub-scenarios: One where there is no relationship between price informativeness and passive ownership, and another where they are linearly related with a coefficient of one. In all cases, I add noise to both the right-hand-side and left-hand-side variables, so the R-squared will not be equal to one.

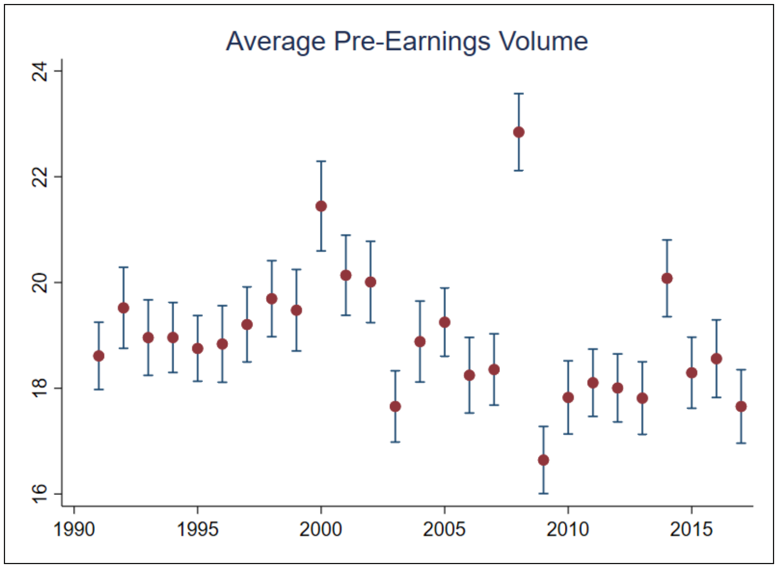

Figure 15. Average Cumulative Abnormal Pre-Earnings Volume by Year. This figure plots coefficients from a regression of $CAV_{i,t}$ on a set of year dummy variables where

$$CAV_{i,t} = \sum_{\tau=-22}^{-1} AV_{i,t+\tau}$$

the sum of abnormal trading volume from $t-22$ to $t-1$ for firm i around earnings date t. Observations are weighted by 1-month lagged market capitalization. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level.

Under scenarios 1 and 2, there is almost no difference between using levels and first differences. In scenario 3, however, differences arise when there is no relationship between passive ownership and price informativeness. Figure 23 shows the distribution of β's from regressions of price informativeness on passive ownership. In the left panel, the true $\beta = 0$ and in the right panel the true $\beta = 1$. The distributions of β are significantly different when the true $\beta = 0$: The spread of β's is wider with the levels, which could lead to more false positives in terms a relationship between the two quantities. If there is a strong relationship between the two, the distributions are almost identical in levels and first-differences.

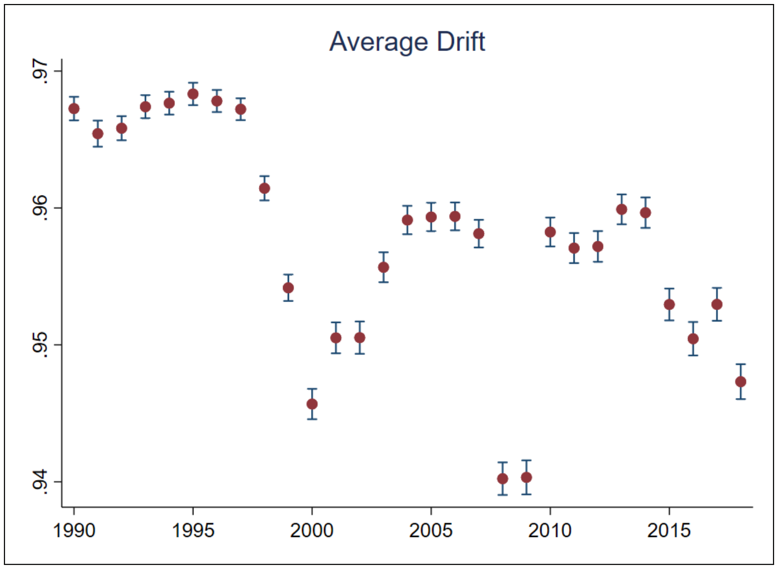

Figure 16. Decline of Average Pre-Earnings Drift. This figure plots coefficients from a regression of pre-earnings drift on a set of year dummy variables where $DM_{it} = \begin{cases} \frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} & \text{if } r_t > 0 \\ \frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} & \text{if } r_t < 0 \end{cases}$. A value near 1 implies most earnings information is incorporated in prices before the announcement date, while lower values denote less informative pre-earnings announcement prices. Observations are weighted by 1-month lagged market capitalization. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level.

3.2 Placebo tests for cross-sectional regressions

Table 12 contains placebo tests for the cross-sectional regressions. The "Baseline" columns use actual earnings dates, while the "Placebo" results are the coefficient estimates when selecting dates between the actual earnings days $t = -22$, or the FOMC meeting dates.

3.3 Alternative explanations for the decline of price informativeness

In this subsection, I discuss three threats to identification in my main baseline regressions (1) Regulation Fair Disclosure (2) The rise of algorithmic trading (3) Omitted variables.

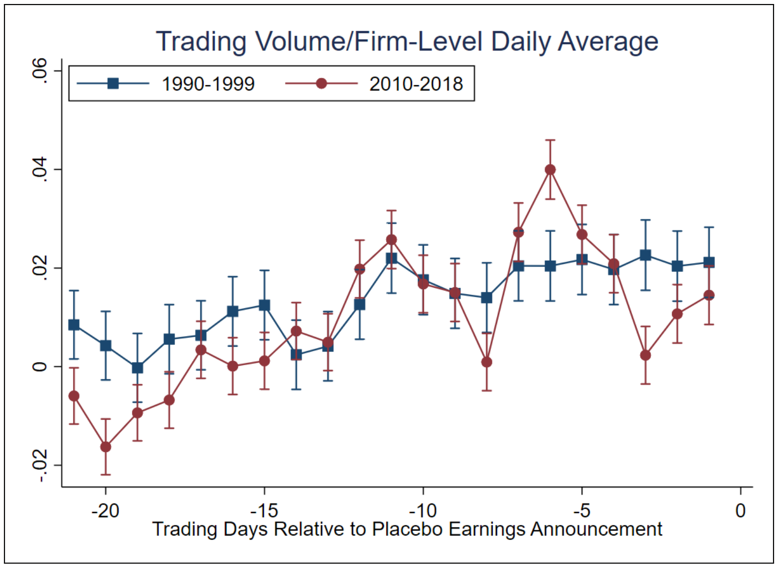

Figure 17. Placebo Test: Pre-Earnings Volume. Plot of β_k estimated from the regression:

$$AV_{i,t+\tau} = \alpha + \sum_{k=-21}^{22} \beta_k \mathbf{1}_{\{\tau=k\}} + e_{i,t+\tau}$$

where t represents a placebo earnings date, 22 days before the actual earnings announcement date. Bars represent a 95% confidence interval around the point estimate. Standard errors are clustered at the firm level.

3.3.1 Regulation Fair Disclosure (Reg FD)

Before Reg FD was passed in August, 2000, firms would disclose earnings information to selected analysts before it became public. This information leakage could increase the share of earnings information incorporated into prices before it was formally announced. After Reg FD, firms were no longer allowed 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.

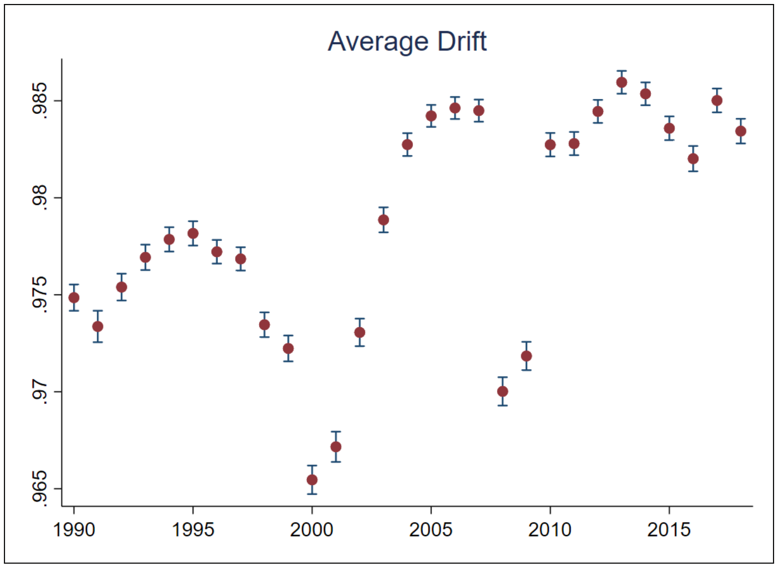

Figure 18. Placebo Test: Pre-Earnings Drift. This figure plots coefficients from a regression of pre-earnings drift on a set of year dummy variables where $DM_{it} = \begin{cases} \frac{1+r_{(t-22,t-1)}}{1+r_{(t-22,t)}} & \text{if } r_t > 0 \\ \frac{1+r_{(t-22,t)}}{1+r_{(t-22,t-1)}} & \text{if } r_t < 0 \end{cases}$. except t is a placebo earnings date 22 days before the actual earnings announcement date. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level.

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. 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 i.e. before Reg FD. 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 between increases in passive ownership and changes in insider buys/sells before or after earnings announcements.

Finally, if Reg FD totally explained the decreased pre-earnings informativeness, I would

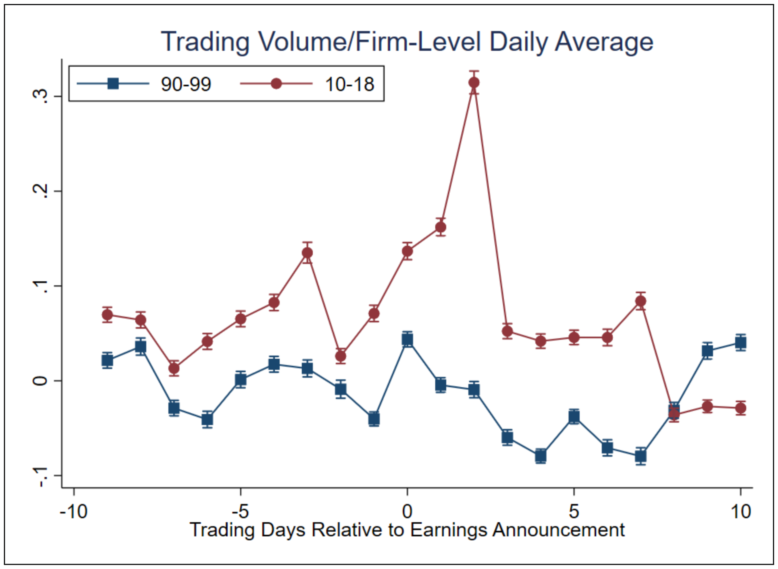

Figure 19. FOMC Meeting Dates: Pre-Earnings Volume. Plot of β_k estimated from the regression:

$$AV_{i,t+\tau} = \alpha + \sum_{k=-10}^{10} \beta_k \mathbf{1}_{\{\tau=k\}} + e_{i,t+\tau}$$

Bars represent a 95% confidence interval around the point estimate. Standard errors are clustered at the firm level. t represents a scheduled FOMC meeting date. The firm-level daily average is computed over the previous quarter. Observations are weighted by a firm's 1-year lagged market capitalization.

expect the trends in decreased informativeness to level out in the early 2000's. In the data, however, this leveling out does not happen for any of the three measures.

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 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 13, 14 and 15. The results are qualitatively similar, which alleviates concerns of the results being driven by time trends resulting from Reg FD, which was passed in August 2000.

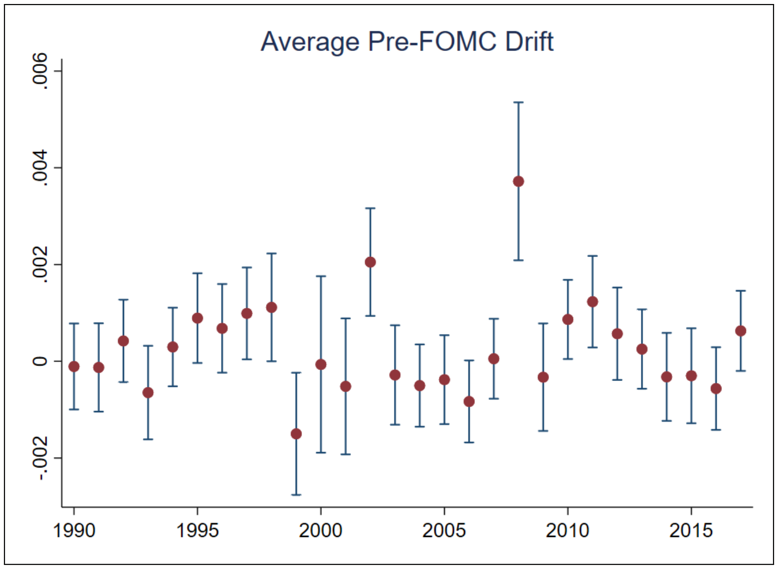

Figure 20. FOMC Meeting Dates: Pre-Earnings Drift. This figure plots coefficients from a regression of pre-earnings drift on a set of year dummy variables where $DM_{it} = \begin{cases} \frac{1+r_{(t-10,t-1)}}{1+r_{(t-10,t)}} & \text{if } r_t > 0 \\ \frac{1+r_{(t-10,t)}}{1+r_{(t-10,t-1)}} & \text{if } r_t < 0 \end{cases}$. Standard errors represent 95% confidence intervals around the point-estimates. Standard errors are clustered at the firm level. t denotes a scheduled FOMC meeting date. Observations are weighted by a firm's 1-year lagged market capitalization.

3.3.2 The Rise of algorithmic trading (AT) activity

Weller (2017) shows that Algorithmic Trading (AT) activity is negatively correlated with pre-earnings price informativeness. His 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 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 reasonable AT activity measures between 2012-2018. I can, however, measure the effect of AT activity on the cross-sectional 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

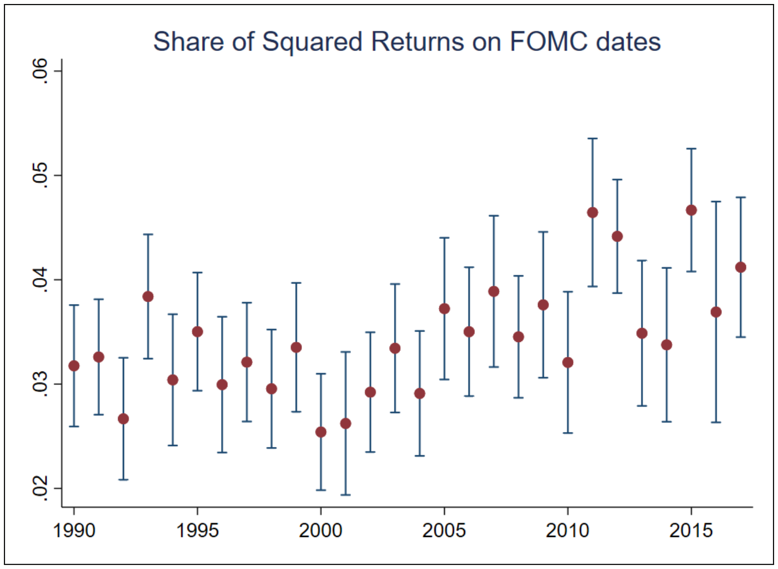

Figure 21. FOMC Meeting Dates: Earnings Day Volatility. This figure plots coefficients from a regression of QVS on a set of year dummy variables. For firm i in year t the quadratic variation share (QVS) is defined as: $QVS_{i,t} = \sum_{\tau=1}^{8} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, where r denotes a market-adjusted daily return. The numerator sums over the 8 scheduled FOMC meeting days in year t, while the denominator includes all days in calendar year t. Standard errors are clustered at the firm level. Observations are weighted by a firm's 1-year lagged market capitalization.

regressions (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 (2017) 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 (2017), 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 87% drop in sample size relative to previous regressions is almost entirely the result of

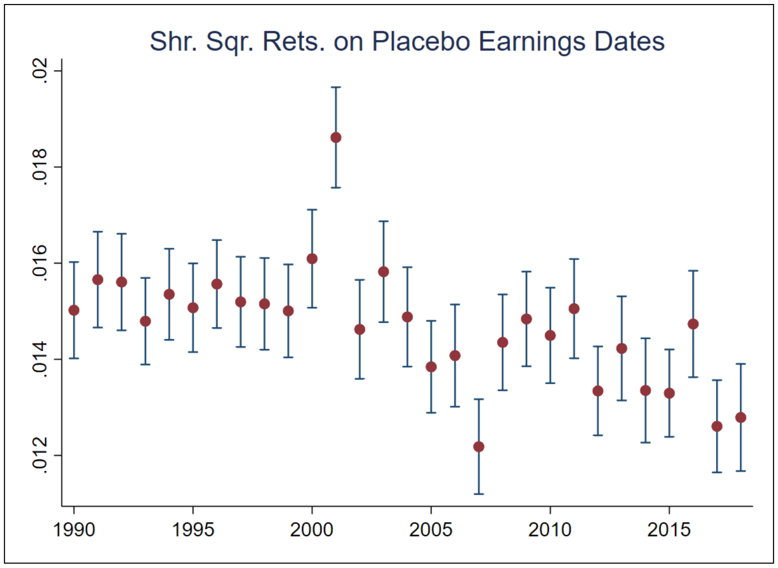

Figure 22. Placebo Test: Earnings Day Volatility. This figure plots the share of market-adjusted quadratic variation occurring on placebo earnings days. For firm i in year t the quadratic variation share (QVS) is defined as: $QVS_{i,t} = \sum_{\tau=1}^{4} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, where r denotes a market-adjusted daily return. The numerator is the sum of squared returns on the 4 placebo earnings dates, each of which are 22 days before the actual earnings announcement dates, while the denominator is the sum of squared returns on all trading days in calendar year t.

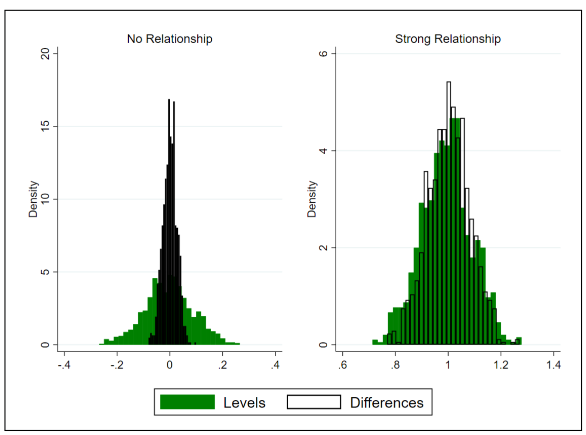

Figure 23. Simulated Distribution of β: Levels vs. First Differences. Distribution of β from a regression of price informativeness on passive ownership. In the left panel, the true β is zero. In the right panel, the true β is one.

the year restrictions.

I re-run all the reduced form regressions, but restrict to the matched sample with MIDAS, and include the 4 measures of HFT activity. As a sanity check, I first re-run the baseline regressions on the sub-sample matched to the MIDAS data – these regressions are labeled "Baseline" in the corresponding tables. The regressions with all the AT measures included are labeled "+ AT Controls".

Tables 16, 17 and 18 contain the regressions with AT controls. All the results in this matched sub-sample are qualitatively unchanged from Tables the cross-sectional regression results. For the pre-earnings drift, and earnings day share of volatility, adding the AT activity controls does not significantly change the coefficient on change in passive ownership. For volume, the value-weighted results are robust to including the AT controls, while the equal weighted result is the right sign, but insignificant. This could imply (1) The equal-weighted volume result has become weaker over time, as the coefficient in column 2 of Table 16 is 1/3 the size of the same coefficient in the main body of the paper. Given that I can only include the AT controls in the matched subsample, it is hard to fully disentangle this effect (2) Part of the AT activity measure is mechanically correlated with passive ownership because, for example, ETFs attract algorithmic traders implementing ETF arbitrage. I show AT activity and passive ownership are positively correlated in Table 19 (described in detail below) (3) Increased AT activity may partially explain the observed decrease in market efficiency, but increasing passive ownership is still an important factor in decreased pre-earnings price informativeness.

One possible reason for the drop in statistical significance when including the AT activity measures is a strong correlation between passive ownership and AT activity. To test this, I calculate an AT activity score as the first principal component of the 4 AT measures in Weller (2017). Table 19 runs a regression of the AT activity score on the level of and changes in passive. Across almost all specifications, the relationship is positive and statistically significant. In unreported results, I find AT activity also increases in stocks after they are added to the S&P 500.

3.4 Possible omitted variables

In addition to identification concerns, the cross-sectional regressions could suffer from omitted variable bias. Most of passive ownership is determined by mechanical rules derived from observable signals like market capitalization and past returns. This implies that it may be possible to select a large set of stock/firm characteristics to explain all of the variation in passive ownership.

My results would be biased if these underlying characteristics were driving the changes in pre-earnings price informativeness. I find this unlikely, as a significant amount of the differences in passive ownership across stocks is determined by index membership, which is sticky for some indices, and hard to predict for others. Firms that have been in the S&P 500 index for many years would not necessarily be added to the index today, even if they meet all the criteria for index addition. For other indices like the Russell 1000, there is a sharp size cutoff in the index addition rule[5], which makes it difficult to predict index membership around the cutoff. The difficulty of predicting index membership, and as a result predicting passive ownership, reduces the likelihood that my results are driven by an omitted variables problem.

Another possibly omitted variable is the quantity of ETF rebalancing. The changes in pre-earnings volume could be driven by mechanical changes in systematic trading rules by ETFs, as in Chinco and Fos (2019). I find this unlikely, as ETFs typically rebalance on a calendar frequency, not around particular firms' earnings announcements, which may be scattered throughout a calendar quarter. In unreported results, I find that the drop in volume before earnings announcements is robust to including the ETF rebalancing or imbalance measures of Chinco and Fos (2019) on the right-hand-side of the cross-sectional regression.

It is also possible that firms with high passive ownership anticipate increased volatility on earnings days, or amplified responses to earnings news (as I show in Section 3.5 of the Online Appendix) and as a result, release earnings information when the market is closed. To test this, I form three groups of earnings announcements (1) Weekday, before 4PM EST (2) Weekday, after 4PM EST (3) Weekend or trading holiday. I then run a multinomial logistic regression of these categories on passive ownership. Passive ownership does not have

[5]There was a sharp size cutoff before the rule change in 2006, see e.g. Wei and Young (2017).

significant predictive power in this regression, once I control for time trends, and differences in firm characteristics correlated with passive ownership like market capitalization.

A final omitted variable is the composition and importance of systematic and idiosyncratic information in the economy. The growth of passive management could be a response to a secular increase in the importance of systematic risks, and increased demand for exposure to these factors. If this were true, it might be rational to focus on learning about factor risk, rather than firm-specific risk, which could explain my results. I find this unlikely for several reasons.

Figure 24 replicates the volatility decomposition in Campbell et al. (2001), extending the analysis to 2017. Between 1990 and 2017, there does not appear to have been a significant increase in the market or industry components of total risk. It is still possible, however, that this does not fully account for changes in systematic risk, if those changes occur on a small number of days, like FOMC announcements, as the figure is composed of slow-moving averages. Figure 25 re-constructs the patterns in trading volume, but using FOMC announcement dates instead of earnings announcement dates. Between the 1990's and 2010's there was no major change in returns or trading volume around these systematic information release dates at the stock level, also inconsistent with an increase in importance of systematic risk.

3.5 Additional Result 1: Stock 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.

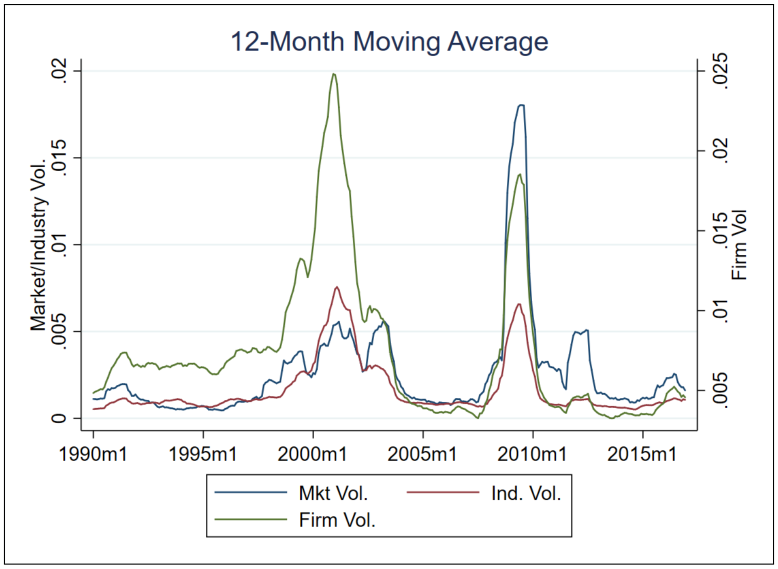

Figure 24. Replication and Expansion of Campbell et al. (2001). This figure plots a 12-month moving average for the 3 components of total volatility. The market component in period t is $\sum_{s\in t}(R_{ms}-\mu_m)^2$, where R_{ms} is the return on the market at time s and μ_m is the mean return on the market over the sample. Industry returns are assumed to follow $R_{it} = R_{mt} + \epsilon_{it}$, so the industry component is the sum of squared ϵ_{it}'s. The firm component is any residual volatility not explained by the industry and market components.

3.5.1 Trends in earnings responses

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

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

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

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

$$\beta_2 \times |SUE_{i,t}| \times \mathbf{1}_{SUE_{i,t}<0} + controls + \epsilon_{i,t} \tag{20}$$

The results of running these regressions year-by-year, and taking a 5-year moving average of the β's are in Figure 26. Over the past 30 years, earnings responses have increased.

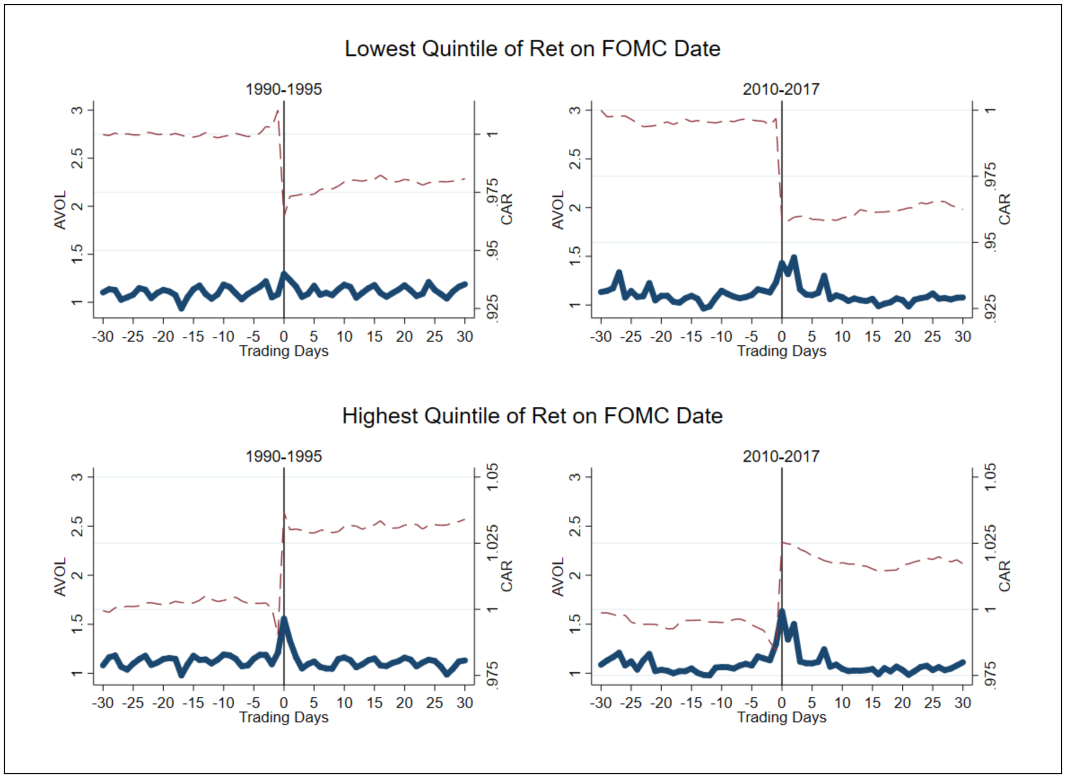

Figure 25. Returns and Trading Volume around FOMC meeting dates. Each plot represents the cross-sectional average for each quintile of Return on FOMC dates over the specified years. Abnormal returns are defined as returns relative to the returns on the CRSP value-weighted index, as in Campbell et al. (2001). Cumulative abnormal returns (CAR) are calculated by compounding net abnormal returns. Cumulative abnormal volume is volume relative to the firm-level average over the past year.

3.5.2 Effect of passive ownership on earnings responses

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

$$\begin{aligned} r_{i,t} = \alpha + \beta_1 SUE_{i,t} + \phi_1 Passive_{i,t} + \gamma_1 \left(SUE_{i,t} \times Passive_{i,t}\right) \\ + \xi X_{i,t} + \text{Fixed Effects} + e_{i,t} \end{aligned} \tag{21}$$

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 $X_{i,t}$ include 1-year lagged passive ownership, market capitalization, growth of market capitalization from $t-1$ to t, idiosyncratic volatility, calculated as the sum of squared market-adjusted returns over the past year, and total institutional

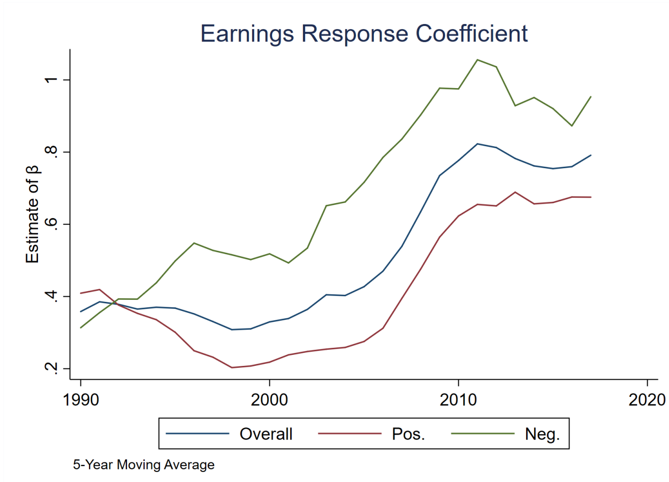

Figure 26. Trends in Earnings Response. This table contains the results of the following regression:

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

and

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

Here, $r_{i,t}$ denotes the market-adjusted return on the effective quarterly earnings date. *Overall* is coefficient from baseline earnings-response regression. *Pos.* and *Neg.* are coefficients from the earnings-response regression which allows for asymmetric effects of positive and negative earnings surprises.

ownership. Fixed effects include year/quarter and firm. Results are similar when calculating SUE relative to IBES estimates using the method in Anson et al. (2012).

I also run a version of Equation 21, breaking SUE into two variables: They are equal to SUE if SUE is positive (negative), and zero otherwise. I then interact these variables with passive ownership, to account for a possibly asymmetric effect of passive ownership on positive and negative news.

Table 20 contains the regression results. 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. An alternative explanation is that passive ownership, in particular ETFs, has reduced short sale constraints, as in Palia and Sokolinski (2019). In unreported results, I calculate the shorting of individual stocks through ETFs, and I find this cannot explain the larger response of stocks with high passive ownership to negative earnings news.

3.6 Additional result 2: Effects 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.

3.6.1 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 (See e.g. Eberly et al. (2008) for details.).

To test this, I run the following regression

$$\frac{CAPX_{i,t}}{Assets_{i,t-1}} = \alpha + \beta_1 Q_{i,t} + \beta_2 Passive_{i,t} + \beta_3 Q_{i,t} \times Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t} \quad (22)$$

where $CAPX$ is capital expenditures and $Assets$ is total assets, both obtained from the CRSP/Compustat merged quarterly firm fundamentals database. Q is the market-to-book ratio, the inverse of the book-to-market ratio from the WRDS financial ratios suite. I include both firm and time fixed effects. Results are similar using $CAPX_{i,t}/Capital_{i,t-1}$ as the left-hand-side variable, where capital is defined as in Salinger and Summers (1983). Results are also similar when $CAPX$ is replaced with $R\&D$ or $SG\$A$. Standard errors are double clustered at the firm/time level.

If passive ownership makes investment less sensitive to market-based information, β_3 should be negative. Table 21 contains the regression results. In columns 1 and 3, I confirm that there is a positive relationship between investment and Q in my sample. In columns 2 and 4, I add in passive ownership and the interaction between passive ownership and Q. A 15% increase in passive ownership, the average in my sample between 1990 and 2018, would lead to a net zero relationship between investment and Q. This suggests that passive ownership has real effects on managers' decisions. When passive ownership is high, they essentially ignore the market value of the firm when making investment decisions.

3.7 Additional result 3: Price of options that span earnings announcements

Given the increase in volatility on earnings days, especially for stocks with high passive ownership, it is natural to believe that ex-ante measures of uncertainty, like options prices, should also reflect this change. To quantify the change in option prices around earnings announcements, I follow the method in Kelly et al. (2016). For each earnings announcement τ, I select 3 expiration dates, a, b, and c, where a the last expiration before the earnings announcement date, b is the first expiration after the announcement and c is expiration after b. For each of these dates, I average implied volatility (IV) across all options with $|\Delta| \in (0.4, 0.5)$ in a 20-day window starting 1 day before τ. I also choose corresponding 20-day windows before a and c to match time to expiration.

This measure was originally designed for S&P 500 options, so I have to modify it to be comparable across firms:

$$IVD_\tau = \frac{\overline{IV}_b}{0.5\left(\overline{IV}_a + \overline{IV}_c\right)} \tag{23}$$

I also calculated the *Variance Risk Premium* and *Slope* measures from Kelly et al. (2016), but given that I am using individual equity options, I had the longest/most reliable sample using the *IVD* measure.

I constructed a second measure of ex-ante uncertainty based on Dubinsky et al. (2006). Suppose there is one predictable announcement before an option expires:

$$\text{Before event IV} = \sigma^2 + \frac{1}{T_i}(\sigma_j^{\mathbb{Q}})^2 \tag{24}$$

I estimate earnings uncertainty using two options with different maturities, $T_1 < T_2$, on the day before earnings are released:

$$(\sigma_{term}^{\mathbb{Q}})^2 = \frac{\sigma_{t,T_1}^2 - \sigma_{t,T_2}^2}{T_1^{-1} - T_2^{-1}} \tag{25}$$

For each firm/earnings announcement, I average this measure over the 3 strikes closest to the money. To make this comparable across firms, I divide by average IV: $\frac{(\sigma_{term}^{\mathbb{Q}})^2}{\overline{IV}_b}$:

To construct these option-based measures of earnings uncertainty, I used daily implied volatility data from OptionMetrics. To make sure I am working with reliable data, I restrict to S&P 500 firms, discard all options with $\frac{ask}{bid} > 5$, or zero open interest and filter for firms which have at least 15 years of non-missing options data.

3.7.1 Trends

Figure 27 shows that both measures of option prices around earnings announcements increased substantially between the 1990's and 2010's.

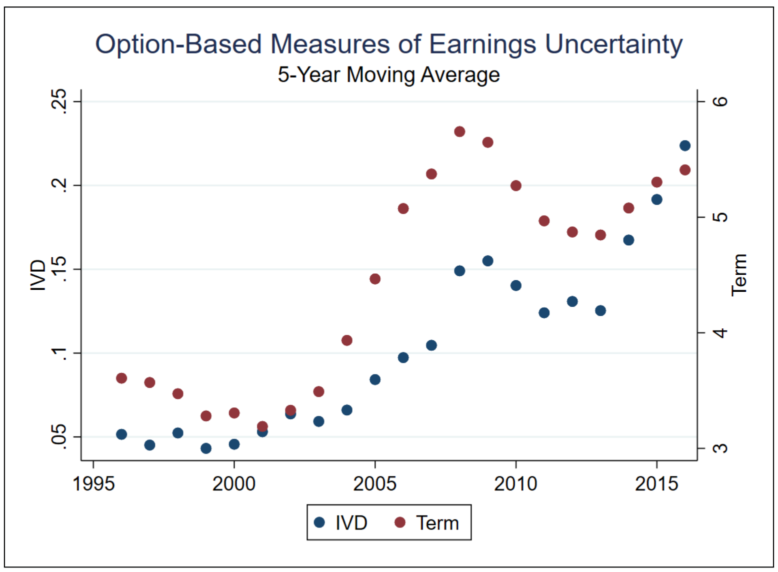

Figure 27. Option-Based Measures of Earnings Uncertainty. Each point represents the cross-sectional average of each option-based measure of earnings uncertainty. For earnings date τ, $IVD = \frac{\overline{IV}_b}{0.5(\overline{IV}_a + \overline{IV}_c)}$ and Term$= \frac{(\sigma^{\mathbb{Q}}_{term})^2}{\overline{IV}_b}$. Sample includes 306 S&P 500 firms with options that meet the filters described in Kelly et al. (2016), and have at least 16 years with 4 non-missing earnings announcements.

3.7.2 Effect of passive ownership on options that span earnings announcements

I run the following regression to see if changes in passive ownership can explain the increases in IVD and $Term$:

$$\Delta_{(t,t-5)} Outcome_{i,t} = \alpha + \beta \Delta_{(t,t-5)} Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t} \tag{26}$$

Controls in $X_{i,t}$ include institutional ownership, lagged institutional ownership, market capitalization, lagged market capitalization. Fixed effects include industry, year and firm. The results are in Table 22. Although the effects are not always statistically significant, increases in passive ownership are correlated with increases in both the IVD and $Term$ measures of earnings uncertainty.

4 Appendix D: Robustness of quasi-experimental results

4.1 Effect of passive ownership vs. effect of index inclusion

One concern is that the quasi-experimental results are driven by index inclusion effects (see e.g. Elliott et al. (2006)), rather than the increase in passive ownership associated with index inclusion. For example, the general consensus is that when a firm is added to an index, its stock returns become more correlated with the stock returns of other firms in that index. If this changed the distribution of stock returns on non-earnings announcement dates, it could bias my results for the pre-earnings drift, and share of annual volatility on earnings dates.

To rule out this channel, I examine the effect of index additions/rebalancing on CAPM beta, CAPM R-squared, idiosyncratic volatility and total volatility. For the S&P 500 experiment, the results are in Figure 28. I find that when a firm is added to the S&P 500 index, its CAPM beta increases (marginally statistically significant) and its CAPM R-squared increases (statistically significant). There is no effect on the magnitude of CAPM residuals (i.e. idiosyncratic volatility), but there is an increase in total volatility (statistically significant). This last fact is consistent with Ben-David et al. (2018) and Chinco and Fos (2019), where being a member of an ETF basket leads to additional volatility.

For the Russell experiment, the results are in Figure 29. Firms which switch have a significant increase in CAPM beta, and a marginally significant decrease in CAPM R-squared. Switching firms also have significant increases in idiosyncratic volatility and total volatility. Firms which switch from the Russell 1000 to the 2000 are shrinking, so these last two facts are consistent with bad news usually being associated with increased volatility.

These facts imply that index inclusion effects are likely working against my results on the share of volatility on earnings days. If total volatility increases after index addition/rebalancing, the denominator of QVS should increase, and shrink QVS. This may explain why the volatility results are insignificant for the Russell experiment: In the post period, treated firms have an increase in total volatility that was two times as large as the increase in total volatility for the corresponding firms in the S&P 500 experiment.

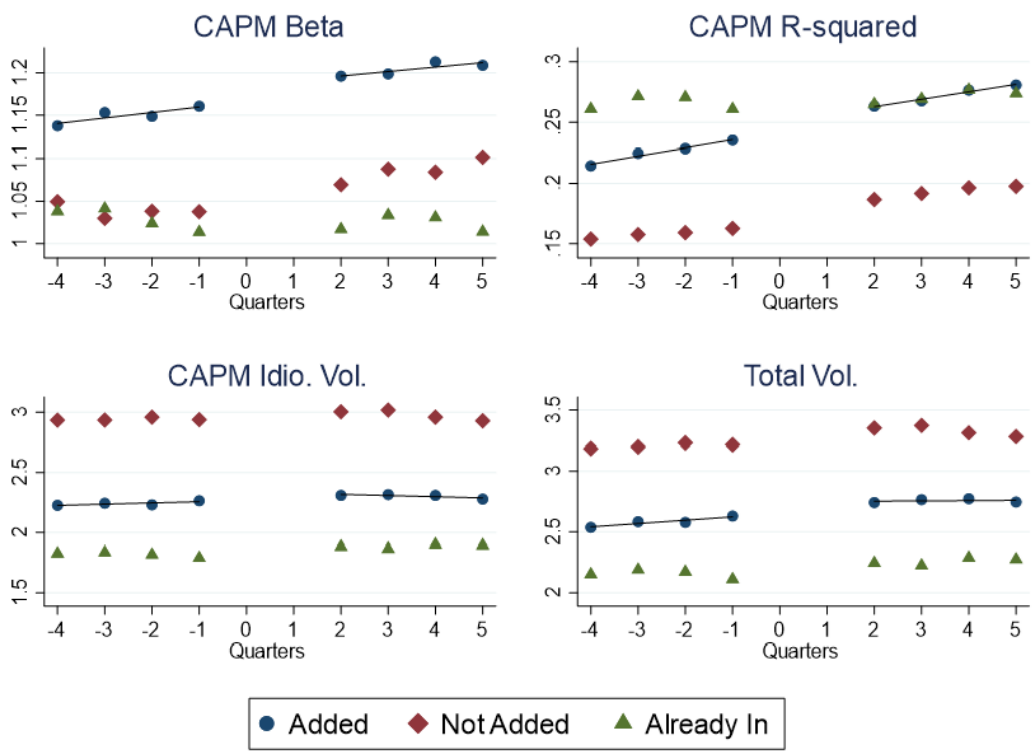

Figure 28. Effect of S&P 500 Index Addition on CAPM β, CAPM R^2, Idiosyncratic Volatility and Total Volatility. Quarters are quarters relative to index addition.

4.2 Alternative quasi-exogenous changes in passive ownership

4.2.1 S&P 500 index deletions

In the main body of the paper, I use S&P 500 index additions to identify plausibly exogenous increases in passive ownership. A natural extension is to run a similar difference-in-differences regression, but use the decrease in passive ownership associated with index

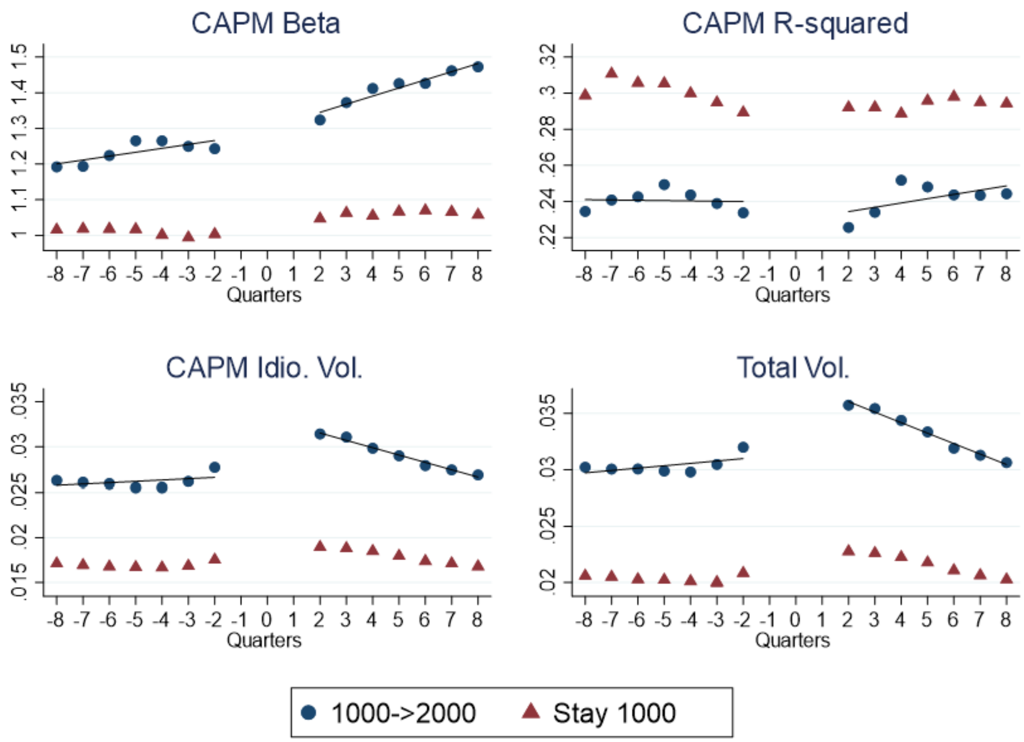

Figure 29. Russell 1000/2000 rebalancing on CAPM β, CAPM R^2, Idiosyncratic Volatility and Total Volatility. Quarters are quarters relative to index rebalancing.

deletion as the treatment. In this DID setup, the exogeneity assumption is likely violated, because index deletion is always about firm fundamentals.

The next challenge is identifying the control group, which should consist of firms with a similar likelihood of being dropped from the index as the treated firms. Three major reasons for S&P 500 index deletion are small market capitalization, poor performance and lack of liquidity. To facilitate a direct comparison with the index addition results, I sort on industry, size and growth rate to identify control firms, even though removing the industry filter and replacing it with a measure of liquidity would probably yield a more appropriate control group.

In the index deletion setup, the treatment group is all firms dropped from the S&P 500 index. The control group is all firms in the same 2-digit SIC industry, in the same size and growth rate quintiles that were initially in the S&P 500 index, and remained there over the next two years. All the index deletion results are similar if the control group only includes firms were initially not in the S&P 500 index, and remained out of the index over the next two years. Results are also similar when choosing the treatment period to be the year immediately after index deletion, instead of skipping a year.

Figure 30 shows the changes in passive ownership around the index deletion date. There is a drop in passive ownership in the quarter of deletion, and the quarter after deletion. Unlike the increase in passive ownership after index addition, however, the decrease after index deletion is only temporary, as can be seen in the levels plot. One explanation is that stocks on the margin are still relatively large. Passive ownership increased for all stocks over my sample, especially the larger ones. The weak and temporary treatment effect suggests that index deletion would be a weak instrument for change in passive ownership.

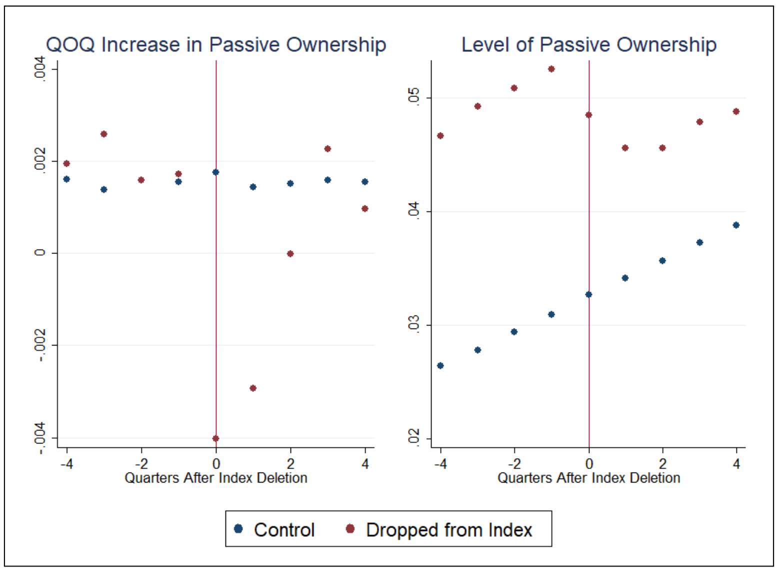

Figure 30. S&P 500 Index Deletions: Testing Parallel Trends. Average level and increase in passive ownership for control firms and firms dropped from the S&P 500. Control firms are all firms in the same 2-digit SIC industry, in the same size and growth rate quintiles that were initially in the S&P 500 index, and remained there over the next two years.

4.2.2 Moving from the Russell 2000 to the Russell 1000

Similar to S&P 500 index deletion, 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. Unlike the S&P 500 deletions, however, this DID setup still satisfies the exogeneity assumption, as moving from firm 1001 to 999 may have nothing to do with firm fundamentals.

I choose the control firms to be all Russell 3000 firms, with June ranks between 900 and 1100 that did not switch from the 1000 to the 2000, or from the 2000 to the 1000. Figure 31 shows the problem with this setup: the treatment is small and temporary. The common pattern between moving from the Russell 2000 to the 1000, and S&P 500 index deletion suggests that the general upward trend in passive ownership for almost all stocks drowns out the temporary change in passive ownership associated with index rebalancing.

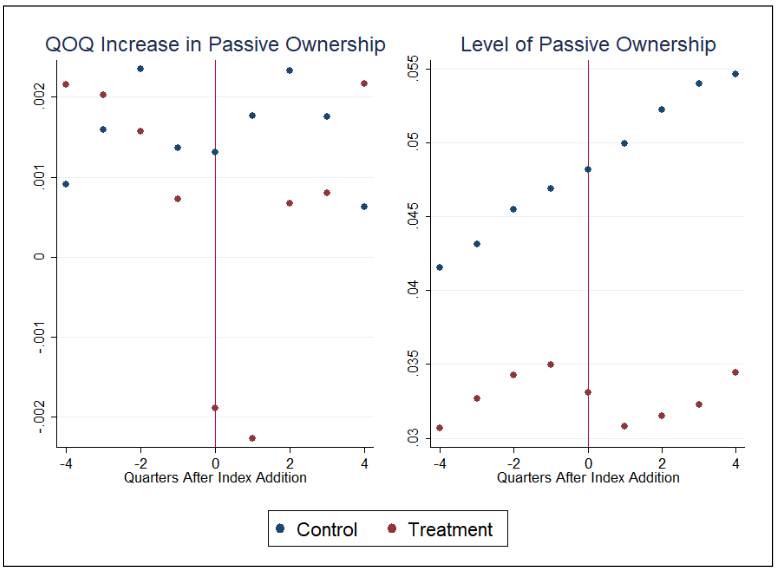

Figure 31. Russell 2000/1000 Reconstitution: Checking Parallel Trends. Average level and change in passive ownership for control firms and firms moved from the Russell 2000 to the Russell 1000. Control firms are all firms in the Russell 3000 ranked 900 to 1100 that did not move from the 1000 to the 2000 or from the 2000 to the 1000.

4.2.3 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. (2018)) (2) While there may have been a *relative* increases in flows to iShares ETFs, relative to all other ETFs (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	Share Informed ETF	No ETF Present Own	No ETF Present Stock Hedge	ETF Present Own	ETF Present Stock Hedge	ETF Present ETF Hedge
0.1	0.2	0.1	0.1	4.096	-0.036	4.040	0.000	-4.040
0.1	0.5	0.1	0.1	4.899	-0.528	7.656	0.000	-7.656
0.25	0.2	0.1	0.1	4.884	-0.464	6.270	0.000	-6.270
0.25	0.5	0.1	0.1	4.976	-0.601	6.270	0.000	-6.270

Informed

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

Panel B: Share Informed Fixed at 30%

Uninformed

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

Informed

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

Table 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.

Name	Ticker	Founded	Expense Ratio	NAV	AUM
The Consumer Discretionary Select Sector Fund	XLY	3/31/1999	0.13%	$132.26	$14,012.89 M
The Consumer Staples Select Sector Fund	XLP	3/31/1999	0.13%	$60.54	$14,241.29 M
The Energy Select Sector Fund	XLE	3/31/1999	0.13%	$45.09	$12,164.02 M
The Financial Select Sector Fund	XLF	3/31/1999	0.13%	$26.16	$21,849.83 M
The Health Care Select Sector Fund	XLV	3/31/1999	0.13%	$102.82	$26,580.85 M
The Industrial Select Sector Fund	XLI	3/31/1999	0.13%	$74.39	$10,293.96 M
The Materials Select Sector Fund	XLB	3/31/1999	0.13%	$59.18	$5,209.07 M
The Technology Select Sector Fund	XLK	3/31/1999	0.13%	$102.42	$30,947.40 M
The Utilities Select Sector Fund	XLU	3/31/1999	0.13%	$61.55	$11,819.93 M
Bank ETF	KBE	12/30/2005	0.35%	$36.90	$1,666.27 M
Capital Markets ETF	KCE	12/30/2005	0.35%	$59.82	$25.42 M
Insurance ETF	KIE	12/30/2005	0.35%	$30.36	$629.94 M
Biotech ETF	XBI	3/31/2006	0.35%	$104.56	$4,577.23 M
Homebuilders ETF	XHB	3/31/2006	0.35%	$45.13	$857.47 M
Semiconductor ETF	XSD	3/31/2006	0.35%	$115.13	$518.10 M
Metals & Mining ETF	XME	6/30/2006	0.35%	$23.39	$457.38 M
Oil & Gas Equipment & Services ETF	XES	6/30/2006	0.35%	$43.91	$121.41 M
Oil & Gas Exploration & Production ETF	XOP	6/30/2006	0.35%	$66.61	$2,337.89 M
Pharmaceuticals ETF	XPH	6/30/2006	0.35%	$43.79	$249.63 M
Regional Banking ETF	KRE	6/30/2006	0.35%	$44.87	$1,503.21 M
Retail ETF	XRT	6/30/2006	0.35%	$44.21	$362.53 M
Health Care Equipment ETF	XHE	3/31/2011	0.35%	$88.00	$521.40 M
Telecom ETF	XTL	3/31/2011	0.35%	$73.55	$53.32 M
Transportation ETF	XTN	3/31/2011	0.35%	$57.37	$174.97 M
Aerospace & Defense ETF	XAR	9/30/2011	0.35%	$98.20	$1,571.20 M
Health Care Services ETF	XHS	9/30/2011	0.35%	$71.93	$90.64 M
Software & Services ETF	XSW	9/30/2011	0.35%	$110.64	$236.77 M
The Real Estate Select Sector Fund	XLRE	12/31/2015	0.13%	$37.43	$4,641.12 M
Internet ETF	XWEB	6/30/2016	0.35%	$98.83	$21.74 M
The Communication Services Select Sector Fund	XLC	6/29/2018	0.13%	$56.41	$9,803.64 M

Table 9List of Sector SPDR ETFs. The expense ratio, Net Asset Value per share (NAV) and Assets Under Management (AUM) are as of 6/9/2020.

	Volume	Drift	Volatility
$Treated \times Post$	-0.0776	-0.00715**	0.0128*
	(0.435)	(0.003)	(0.008)
Model	-0.0881	-0.00006	0.0112
In ETFs	343	343	343
In ETF Sectors	3316	3316	3316
Outside ETF Sectors	866	866	866
Time FE	YES	YES	YES

Table 10Effect of Introducing Sector ETFs. Coefficients from: $Outcome_{i,t} = \alpha + \beta \times Treated_{i,t} \times Post_t + \gamma_t + \epsilon_{i,t}$ Observations are weighted by lagged market capitalization. Standard errors, clustered at the firm level, in parenthesis.

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 11 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.

	Baseline	Placebo t=-22	Placebo FOMC	Baseline	Placebo t=-22	Placebo FOMC
Inc. Passive	0.106***	-0.00474	0.00709	0.382**	-0.0501	0.0159
	(0.036)	(0.013)	(0.009)	(0.180)	(0.042)	(0.023)
Observations	126,319	157,769	126,654	126,319	157,769	126,654
R-squared	0.03	0.031	0.03	0.035	0.035	0.034
Controls/FE	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Equal	Equal	Equal	Value	Value	Value

Table 12 Placebo Test: Earnings Day Share of Volatility. Table with estimates of β from:

$$\Delta QVS_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

$QVS_{i,t} = \sum_{\tau=1}^{4} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, which is the ratio of the squared returns on the 4 quarterly earnings announcement days, relative to the squared returns on all days in year t. Controls in $X_{i,t-1}$ include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, calculated as the sum of squared market-adjusted returns over the past year, and total institutional ownership. I also condition on the growth in market capitalization from $t-1$ to t. Fixed effects are year and firm. Standard errors are computed using panel Newey-West with 2 lags. The "Baseline" columns use actual earnings dates, while the "Placebo" results are the coefficient estimates when selecting dates between the actual earnings days $t = -22$, or the FOMC meeting dates. Standard errors in parenthesis.

	(1)	(2)	(3)
Inc. Passive	-12.26***	-13.97***	-15.91**
	(1.923)	(2.214)	(6.207)
Observations	151,068	151,064	151,064
R-squared	0.03	0.031	0.181
Controls	No	Yes	Yes
Firm FE	No	No	Yes
Weight	Eq.	Eq.	Val.

Table 13 Post-2000: Pre-Earnings Volume. Estimates of β from:

$$\Delta CAV_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

$CAV_{i,t}$ is cumulative abnormal pre-earnings trading volume. Δ is a year-over-year change, matching on fiscal quarter. Change in passive ownership is expressed as a decimal, so $0.01 = 1\%$ increase. Controls, $X_{i,t-1}$, include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, total institutional ownership and growth in market capitalization from $t-1$ to t. Standard errors are computed using panel Newey-West with 8 lags. Column 1 is a univariate regression, while column 2 includes the controls, as well as year/quarter and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-quarter lagged market capitalization relative to other firms that quarter. Standard errors in parenthesis.

	(1)	(2)	(3)
Inc. Passive	-0.0282**	-0.0273**	-0.0660**
	(0.012)	(0.014)	(0.029)
Observations	151,023	151,020	151,020
R-squared	0.022	0.023	0.072
Controls	No	Yes	Yes
Firm FE	No	No	Yes
Weight	Eq.	Eq.	Val.

Table 14 Post-2000: Pre-Earnings Drift. Table with estimates of β from:

$$\Delta DM_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

Where $DM_{i,t}$ is a measure of the pre-earnings drift. Passive ownership is expressed as a decimal, so 0.01 = 1% of shares outstanding held by passive funds. Controls, $X_{i,t-1}$, include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, total institutional ownership and growth in market capitalization from $t-1$ to t. Standard errors are computed using panel Newey-West with 8 lags. Column 1 is a univariate regression, while column 2 includes the controls, as well as year/quarter and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-quarter lagged market capitalization relative to other firms that quarter. Standard errors in parenthesis.

	(1)	(2)	(3)
Inc. Passive	0.216***	0.140***	0.365**
	(0.032)	(0.035)	(0.172)
Observations	68,142	68,126	67,224
R-squared	0.012	0.013	0.037
Controls	No	Yes	Yes
Firm FE	No	No	Yes
Weight	Eq.	Eq.	Val.

Table 15 Post-2000: Earnings Day Share of Volatility. Table with estimates of β from:

$$\Delta QVS_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

$QVS_{i,t} = \sum_{\tau=1}^{4} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, which is the ratio of the squared returns on the 4 quarterly earnings announcement days, relative to the squared returns on all days in year t. Controls in $X_{i,t-1}$ include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, calculated as the sum of squared market-adjusted returns over the past year, and total institutional ownership. I also condition on the growth in market capitalization from $t-1$ to t. Fixed effects are year and firm. Standard errors are computed using panel Newey-West with 2 lags. Column 1 is a univariate regression, while column 2 includes the controls, as well as year and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-year lagged market capitalization relative to other firms that year. Standard errors in parenthesis.

	Baseline			AT Measures	
	(1)	(2)	(3)	(4)	(5)
Ch. Passive	-7.602***	-7.261**	-19.28***	-1.651	-13.59**
	(2.313)	(3.385)	(6.339)	(3.289)	(6.338)
Ch. Oddlot				-3.428***	-2.596***
				(0.272)	(0.712)
Ch. Trade/Order				6.009***	3.371***
				(0.245)	(0.479)
Ch. Trade/Cancel				-1.941***	-4.248***
				(0.245)	(0.595)
Ch. Tradesize				1.247***	2.789***
				(0.452)	(1.015)
Obs	44,544	44,542	44,542	44,542	44,542
R-squared	0.053	0.078	0.171	0.19	0.262
Controls	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Weight	Eq.	Eq.	Vw.	Eq.	Vw.

Table 16 AT Activity: Pre-Earnings Volume. Estimates of β from:

$$\Delta CAV_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

$CAV_{i,t}$ is cumulative abnormal pre-earnings trading volume. Δ is a year-over-year change, matching on fiscal quarter. Change in passive ownership is expressed as a decimal, so $0.01 = 1\%$ increase. Controls, $X_{i,t-1}$, include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, total institutional ownership and growth in market capitalization from $t-1$ to t. Standard errors are computed using panel Newey-West with 8 lags. Only uses data that can be matched to MIDAS from 2012-2018. Column 1 is a univariate regression, while column 2 includes the controls, as well as year/quarter and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-quarter lagged market capitalization relative to other firms that quarter. Columns 4 and 5 add the AT activity measures from Weller (2017). Standard errors in parenthesis.

	Baseline			AT Measures	
	(1)	(2)	(3)	(4)	(5)
Ch. Passive	-0.0531***	-0.0770***	-0.0994***	-0.0790***	-0.103***
	(0.017)	(0.024)	(0.037)	(0.024)	(0.037)
Ch. Oddlot				0.00408***	0.00158
				(0.001)	(0.003)
Ch. Trade/Order				0.0012	0.00128
				(0.001)	(0.003)
Ch. Trade/Cancel				0.00328***	0.00781***
				(0.001)	(0.003)
Ch. Tradesize				0.00202	0.00551
				(0.002)	(0.005)
Obs	44,527	44,525	44,525	44,525	44,525
R-squared	0.013	0.059	0.05	0.06	0.053
Controls	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Weight	Eq.	Eq.	Vw.	Eq.	Vw.

Table 17 AT Activity: Pre-Earnings Drift. Table with estimates of β from:

$$\Delta DM_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

Where $DM_{i,t}$ is a measure of the pre-earnings drift. Passive ownership is expressed as a decimal, so $0.01 = 1\%$ of shares outstanding held by passive funds. Controls, $X_{i,t-1}$, include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, total institutional ownership and growth in market capitalization from $t-1$ to t. Standard errors are computed using panel Newey-West with 8 lags. Column 1 is a univariate regression, while column 2 includes the controls, as well as year/quarter and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-quarter lagged market capitalization relative to other firms that quarter. Standard errors in parenthesis.

		Baseline		AT Measures	
	(1)	(2)	(3)	(4)	(5)
Ch. Passive	0.312***	0.255***	0.789**	0.237***	0.805**
	(0.050)	(0.077)	(0.328)	(0.077)	(0.334)
Ch. Oddlot				-0.00439	-0.00685
				(0.005)	(0.030)
Ch. Trade/Order				-0.00875	-0.0384
				(0.006)	(0.043)
Ch. Trade/Cancel				-0.0106**	-0.0653
				(0.005)	(0.053)
Ch. Tradesize				-0.0223**	0.0211
				(0.009)	(0.067)
Obs	19,220	18,815	18,815	18,815	18,815
R-squared	0.006	0.065	0.084	0.066	0.087
Controls	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Weight	Eq.	Eq.	Vw.	Eq.	Vw.

Table 18 AT Activity: Earnings Day Share of Volatility. Table with estimates of β from:

$$\Delta QVS_{i,t} = \alpha + \beta \Delta Passive_{i,t} + \gamma X_{i,t-1} + \text{Fixed Effects} + e_{i,t}$$

$QVS_{i,t} = \sum_{\tau=1}^{4} r_{i,\tau}^2 / \sum_{j=1}^{252} r_{i,j}^2$, which is the ratio of the squared returns on the 4 quarterly earnings announcement days, relative to the squared returns on all days in year t. Controls in $X_{i,t-1}$ include 1-year lagged passive ownership, market capitalization, idiosyncratic volatility, calculated as the sum of squared market-adjusted returns over the past year, and total institutional ownership. I also condition on the growth in market capitalization from $t-1$ to t. Fixed effects are year and firm. Standard errors are computed using panel Newey-West with 2 lags. Only uses data that can be matched to MIDAS from 2012-2018. Column 1 is a univariate regression, while column 2 includes the controls, as well as year/quarter and firm fixed effects. Column 3 is the same as column 2, except firms are weighted by their 1-quarter lagged market capitalization relative to other firms that quarter. Columns 4 and 5 add the AT activity measures from Weller (2017). Standard errors in parenthesis.

	AT Activity Score		1-Year Ch. In Score		3-Year Ch. In Score	
Level of Passive Ownership	1.585***	0.318**				
	(0.155)	(0.158)				
1-Year Inc. in Passive			0.736***	0.369*		
			(0.199)	(0.212)		
3-Year Inc. in Passive					0.619***	0.462
					(0.211)	(0.290)
Observations	17,210	17,210	17,068	17,068	12,783	12,783
R-squared	0.3	0.086	0.093	0.098	0.125	0.108
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry/Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes	No	Yes

Table 19 Relationship Between Passive Ownership and AT Activity I calculate the AT activity score as the first principal component of the 4 AT measures in Weller (2017). This score is normalized to have mean zero and standard deviation one. The effect in levels of moving from the 25th percentile (0.0) to 75th percentile (0.1) of passive ownership is a 0.15 standard deviation increase in AT activity score. Although a 0.15 standard deviation increase may seem small, this is about half the mean for firms with high passive ownership. Controls include firm market capitalization, institutional ownership, idiosyncratic volatility and market cap. growth. Standard errors in parenthesis.

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

Table 20 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 $X_{i,t}$ include 1-year lagged passive ownership, market capitalization, growth of market capitalization from $t-1$ to t, idiosyncratic volatility, calculated as the sum of squared market-adjusted returns over the past year, and total institutional ownership. Fixed effects include year/quarter and firm. Columns 1 and 2 are equal weighted, while Columns 3 and 4 are value weighted. Standard errors in parenthesis.

	LHS: CAPX/Assets			
	(1)	(2)	(3)	(4)
Q	0.0147***	0.020***	0.0121*	0.032***
	(0.003)	(0.003)	(0.007)	(0.010)
Passive		-4.638***		-1.252
		(0.766)		(2.641)
Passive x Q		-0.133***		-0.241***
		(0.030)		(0.088)
Observations	511,744	511,744	511,744	511,744
R-squared	0.494	0.495	0.597	0.598
Weight	Equal	Equal	Value	Value
Firm/Quarter FE	YES	YES	YES	YES
Firm-Level Controls	NO	YES	NO	YES

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

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

Standard errors are double clustered at the firm/time level.

		1-year		3-year		5-year	
		IVD					
Increase in Passive Ownership	1-year	0.325	0.334*				
		(0.225)	(0.191)				
	3-year			0.173	0.100		
				(0.154)	(0.158)		
	5-year					0.328**	0.300*
						(0.141)	(0.157)
Observations		4,519	4,519	3,979	3,979	3,496	3,496
		Term					
		1-year		3-year		5-year	
Increase in Passive Ownership	1-year	9.375	9.155**				
		(5.873)	(4.495)				
	3-year			8.789*	8.278**		
				(4.758)	(4.000)		
	5-year					5.489	7.653*
						(4.547)	(4.121)
Observations		4,457	4,457	3,916	3,916	3,441	3,441
Firm Controls		Yes	Yes	Yes	Yes	Yes	Yes
Year FE		Yes	Yes	Yes	Yes	Yes	Yes
Industry FE		Yes	Yes	Yes	Yes	Yes	Yes
Firm FE		No	Yes	No	Yes	No	Yes

Table 22 Option Regressions. Estimates of β from:

$$\Delta_{(t,t-5)}Outcome_{i,t} = \alpha + \beta\Delta_{(t,t-5)}Passive_{i,t} + \gamma X_{i,t} + \text{Fixed Effects} + e_{i,t}$$

Where the outcomes are $IVD = \frac{\overline{IV}_b}{0.5\left(\overline{IV}_a+\overline{IV}_c\right)}$ and Term= $\frac{(\sigma^{\mathbb{Q}}_{term})^2}{\overline{IV}_b}$. Sample includes 306 S&P 500 firms with options that meet the filters described in Kelly et al. (2016), and have at least 16 years with 4 non-missing earnings announcements. Controls in $X_{i,t}$ include institutional ownership, lagged institutional ownership, market capitalization, lagged market capitalization. Fixed effects include industry, year and firm. Standard errors in parenthesis.

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