Stock-Specific Price Discovery From ETFs

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Abstract

Conventional wisdom warns that exchange traded funds (ETFs) harm stock price discovery, either by "stealing" single-stock liquidity or forcing stock prices to co-move. Contra this belief, I develop a theoretical model and present empirical evidence which demonstrate that investors with stock-specific information trade both single stocks and ETFs. Single-stock investors can access ETF liquidity by means of this tandem trading, and stock prices can flexibly adjust to ETF price movements. Using high-resolution data on SPDR and the Sector SPDR ETFs, I exploit exchange latencies in order to show that investors place simultaneous, same-direction trades in both a stock and ETF. Consistent with my model predictions, effects are strongest when an individual stock has a large weight in the ETF and a large stock-specific informational asymmetry. I conclude that ETFs can provide single-stock price discovery.

Keywords: Exchange Traded Fund, ETF, Liquidity, Asymmetric Information, Market Microstructure, Trading Costs, Comovement, Cross Market Activity, High-Frequency Data, Microsecond TAQ Data

JEL Classification: G12, G14

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I. Introduction

Do exchange traded funds (ETFs) harm price discovery? With an average trading volume of \$90 billion per day, ETFs now comprise 30% of total US equities trading volume. This ascendancy has raised two primary concerns about the impact of ETFs on the price discovery process. The first is that ETFs—with their promise of diversification, ease, and safety—lure noise traders away from individual stocks. Consequently, informed traders lose profits, and thus lose incentives to acquire stock-specific information. The second, related concern is that ETF trading could lead to excessive co-movement. Given the high volume of ETF trading, a liquidity shock in an ETF could trigger arbitrage activity that forces a symmetric price movement in all the underlying securities, regardless of stock fundamentals. Underlying both concerns is the implicit assumption that investors with stock-specific information either never trade ETFs, or that the two assets function as separate markets.

This paper is the first to theoretically model and empirically document how investors with stock-specific information strategically trade both stocks and ETFs. This trading behavior attenuates the concerns mentioned in the previous paragraph: stock-specific investors can access ETF liquidity, and stock prices can flexibly adjust to ETF price movements. My model shows that ETF-based price discovery of single-stock information occurs whenever a stock is a sufficiently large or sufficiently volatile constituent of the ETF, or both. The predictions of the model are supported by a series of empirical tests using high frequency transactions data of single stocks and ETFs.

Formally, the model is an extension of Glosten and Milgrom (1985) with three assets: stock A, stock B, and an ETF AB which combines ϕ shares of A and $(1-\phi)$ shares of B. There is a single market maker who posts quotes for all three assets. Each asset has some level of noise trading. In the simplest formulation of the model, there are informed investors only in stock A while the price of B remains fixed. The investors with information about stock A (hereafter referred to as "A-informed" traders) know the value of A exactly, and can trade both the stock and the ETF, subject to their position limit. While trading the ETF gives less exposure to stock A per unit of capital, the ETF is available at a lower bid-ask spread. This position limit induces a strategic choice of where to trade: the more investors capital investors commit to the ETF, the less capital they can commit to the individual stock. I normalize the capital limit to a single share, and model the trade-both behavior of traders by randomization between pure strategies of trading either the stock or the ETF. Two cases of equilibria obtain. The first case is a separating equilibrium in which A-informed traders only trade A and the ETF is available with a zero bid-ask spread. The second case is a pooling equilibrium in which A-informed traders randomize between trading A and trading the ETF, and equilibrium spreads leave informed investors indifferent between trading A or the ETF. In the pooling equilibrium, A-informed traders are able profit from market noise traders in the ETF, and the market maker learns about the value of stock A following an ETF trade.

When the ETF weight and informational asymmetry in stock A are sufficiently high, the pooling equilibrium prevails. As an example, consider the Technology Sector SPDR ETF, which trades under the ticker XLK. The Technology SPDR is value-weighted; hence Apple, being a large firm, comprises 19% of the ETF. Investors with a modest Apple-specific informational advantage also have an information advantage about XLK. As a result, trading both securities can offer more profit than trading Apple alone. On the other hand, Paypal, being a much smaller firm, comprises only 2% of the Technology SPDR. The portion of price movements in XLK explained by Paypal, however, can be much larger if the volatility of Paypal increases relative to other stocks. At times when the volatility of Paypal rises to three or four times that of other technology stocks, investors with Paypal-specific information also have an substantial information advantage about XLK.

The full model also has a class of traders with private information about stock B (hereafter "B-informed"). Both A-informed and B-informed traders have freedom over which asset to trade. This yields two additional equilibria: a partial separating equilibrium and a fully pooling equilibrium. In the fully pooling equilibrium, both A-informed and B-informed traders randomize between their respective stock and the ETF. In the partial separating equilibrium, only one class of informed trader trades the ETF. In both of these equilibria, different pieces of stock-specific information act as substitutes. If A-informed traders send more orders to the ETF, the market maker has to increase the ETF bid-ask spread. This increased ETF spread reduces the profit B-informed traders could make trading the ETF, so they reduce the probability with which they trade the ETF or stop trading the ETF altogether. Traders with small pieces of information or information about small stocks can be "excluded" from trading the ETF whenever the value of their information is less than cost of the adverse selection they face when trading the ETF.

This conflict between traders with different pieces of information creates the screening power of the ETF. As an example, consider the XLY Consumer Discretionary ETF. The ETF is value weighted, so the large retailer Amazon has a weight of 22% while the very small retailer Gap, Inc. has a weight of just 0.27%. An investor with Gap-specific information who attempts to exploit their informational advantage by trading XLY is unlikely to profit if traders with Amazon-specific information are also trading XLY. As a result, the partial separating equilibrium prevails and investors informed about Gap do not trade XLY.

In the fully pooling equilibrium the market maker learns about both stocks following an ETF trade. Dynamics between ETF trades and stock quotes depend on more than just the weight of each stock in the ETF. The population of informed traders and the market maker's prior both regulate the influence of ETF price movements on the underlying stocks. Following an ETF trade, stocks with certain priors or few informed traders undergo small adjustments in price, whereas stocks with uncertain priors or many informed traders undergo large adjustments in price. While both stock quotes change following an ETF trade in the fully pooling equilibrium, this movement is a flexible process of adjustment.

I test the predictions of the model with NYSE TAQ data from August 1, 2015 to December 31, 2018. I focus on the stocks of the S&P 500, and how the interact with SPDR and the ten Sector SPRD ETFs from State Street.The SPDR ETFs have the advantage of being very liquid, fairly concentrated, and representative of a broad set of securities. These ETFs have $30 billion per day in trading volume, accounting for one third of total ETF trading volume. Under the model, investors should trade both the stock and ETF whenever stock weight in the ETF is high and the stock-specific informational asymmetries are large. While TAQ data is anonymous, I exploit exchange latencies and precise timestamps to identify investors who trade both the stock and the ETF simultaneously. These simultaneous stock–ETF trades give a high resolution measure of how investors trade stocks and ETFs, and I examine how this relationship varies across stock-specific characteristics.

Consistent with the model predictions, I find that these simultaneous trades are driven by stock-specific information. When a stock has an earnings date, large absolute return, or stock-specific news article or press release published, that stock sees an increase in simultaneous stock–ETF trades. Effects are much stronger for large ETF-weight stocks than for small ETF-weight stocks, and are also much stronger for large absolute returns than for small absolute returns. When trades are signed according to Lee and Ready (1991), I find that the simultaneous trades are in the same direction: investors buy both the stock and the ETF at the same time, or they sell both at the same time. This same-direction trade-both behavior matches my model and is inconsistent with alternative explanations like hedging.

Simultaneous trades are a sizable portion of trading volume. Simultaneous trades from a single stock–ETF pairing can comprise 1% to 2% of Sector SPDR total volume, and 0.3% to 0.5% of total volume in SPDR. These simultaneous trades have larger price impacts than average trades, and earn negative realized spreads. A typical order pays a realized spread of one cent per share in stocks, and a fraction of a cent on ETFs. Simultaneous trades are the opposite, with simultaneous orders *earning* a realized spread of one cent per share on the stock side of the trade, and *earning* a half cent per share on the ETF side of the trade. Market makers appear to view these simultaneous trades as well informed.

The rest of the paper is organized as follows. Section II discusses the prior literature. Section III introduces the model. Section IV analyzes price discovery in one asset while Section V analyzes price discovery with multiple assets. Section VI presents empirical evidence on simultaneous trades. Section VII concludes.

II. Relation to Prior Literature

Early work on index funds focuses on the information shielding offered by basket securities. Gorton and Pennacchi (1991) argue that different pieces of private information get averaged out in an index fund, and thus liquidity traders can avoid informed traders by trading index funds. Subrahmanyam (1991) analyzes how introducing a basket changes the profits of traders, under the assumption that risk-neutral informed investors always trade both stocks and ETFs. Stocks and ETFs each have a separate market maker and independent price. As more liquidity traders choose the basket security, informed traders focus on common factors and acquire less security-specific information, though large traders are able to earn more from the ETF than small-stock traders. More recently, Cong and Xu (2016) study endogenous security design of the ETF while Bond and Garcia (2018) consider welfare effects from indexing.

A second line of the literature considers the information linkage between ETFs and the underlying assets. Bhattacharya and O'Hara (2016) construct herding equilibria, where the signal from the ETF overwhelms any signal from the underlying assets, or the signal from underlying assets overwhelms the ETF signal. Cespa and Foucault (2014) model illiquidity spillovers between two assets, like an ETF and the underlying stocks, where uncertainty in one market leads to uncertainty in another. Malamud (2016) constructs a model of risky arbitrage between an ETF and the underlying basket.

My model innovates on these foundational papers by giving investors a strategic choice between trading stocks and ETFs. I find conditions under which investors with stock-specific information trade stocks and ETFs in tandem, whereby prior concerns over ETFs are attenuated. Even if noise traders move to ETFs, I find that informed traders can follow them provided that the ETF weight or volatility of the stock is not too small. When the ETF weight and volatility of a stock are instead both small, however, I find that informed traders in that stock only trade the single stock. My model also combines this strategic choice with a single market maker across all securities, so that when ETF trades occur, market makers acquire stock-specific information, and update beliefs accordingly.

ETF prices are a natural setting for additive signals inasmuch as the ETF price is the weighted sum of several stocks. With additive signals, different pieces of information can act as complements or substitutes. When traders are not strategic—as in Goldstein, Li, and Yang (2013)—complementarities result, whereby more information acquisition about one signal encourages more information about a second signal. With strategic traders, pieces of information are substitutes. Foster and Viswanathan (1996) and Back, Cao, and Willard (2000) find imperfectly competitive traders may reveal even less information than a monopolist trader would. My model has strategic traders, and so substitutability of information results. According as traders with information about stock A send more orders to the ETF, adverse selection increases in the ETF, so traders who only have information about stock B want to send fewer orders. This substitutability leads to an asymmetric impact of changes in market structure. When the ETF is added, traders with information about large stocks can trade the ETF, but the substitutability means investors with information about small stocks rarely, if ever, trade the ETF.

ETFs are an important venue for price discovery. Hasbrouck (2003) compares price discovery in ETF markets with price discovery in futures markets and breaks down the share of price innovations that occur in each market. Sağlam, Tuzun, and Wermers (2019) present evidence from a rigorous difference-in-difference estimation which shows higher ETF ownership leads to improved liquidity for the underlying stocks under normal market conditions, though the effects may be reversed during periods of market stress. Dannhauser (2017) shows that bonds included in ETFs have higher prices, but decreased liquidity trader participation and potentially wider bid-ask spreads. Huang, O'Hara, and Zhong (2018) collect evidence that suggests industry ETFs allow investors to hedge risks, and thus pricing efficiency for stocks increases. Glosten, Nallareddy, and Zou (2016) show that ETFs allow more efficient incorporation of factor-based information in ETFs. Easley, Michayluk, O'Hara, and Putniņš (2018) show that many ETFs go beyond tracking the broad market, and instead offer portfolios on specific factors. Bessembinder, Spatt, and Venkataraman (2019) suggest that ETFs could help bond dealers hedge inventory risks. With trade and inventory data, Pan and Zeng (2016) confirm this. Holden and Nam (2019) find that ETFs lead to liquidity improvements in illiquid bonds. Evans, Moussawi, Pagano, and Sedunov (2019) suggest ETF shorting by liquidity providers improves price discovery.

However, a series of papers investigate potential harms from ETFs. Israeli, Lee, and Sridharan (2017) looks at the level of a company's shares owned by ETFs, and finds that when the level increases, the stock price begins to co-move more with factor news and co-move less with stock-specific fundamentals. Ben-David, Franzoni, and Moussawi (2018) argue ETFs can increase volatility and lead stocks to co-move beyond their fundamentals. While Sağlam et al. (2019) find that ETFs improve liquidity as discussed in the previous paragraph, they also find that during the 2011 US debt-ceiling crisis, stocks with high ETF ownership were associated with higher liquidation costs. Thus during periods of crisis, the effect of ETFs may impair rather improve liquidity. Cespa and Foucault (2014) investigate information spillovers between the SPY, E-Mini, and S&P 500 during the flash crash of May 6, 2010. From the same flash crash, Kirilenko, Kyle, Samadi, and Tuzun (2017) find that while market makers changed their behavior during the flash crash, high frequency traders did not. Hamm (2014), examining the relationship between ETF ownership and factor co-movement, finds that while companies with low quality earnings co-move more with factor returns when the level of ETF ownership rises, companies with high quality earnings do not show this effect.

The empirical methods of my paper build on techniques outlined in Dobrev and Schaumburg

(2017), who use trade time-stamps to identify cross-market activity. I utilize exchange-reported gateway-to-trade-processor latencies to identify simultaneous trades. At the daily level, I show that simultaneous stock–ETF trades are in the same direction, highly profitable, and driven by stock-specific information. The use of this novel empirical technique allows me to establish differences between the large-stock–ETF relationship and small-stock–ETF relationship. Traders with information about large stocks or large informational asymmetries can profitably trade the ETF, while traders with information about small stocks or small information asymmetries cannot.

Price discovery can happen across multiple assets or venues. Johnson and So (2012) study how informed traders use options as well as stocks. Holden, Mao, and Nam (2018) show how price discovery happens across both the stock and bonds of a company. Hasbrouck (2018) estimates the informational contribution of each exchange in equities trading. My paper demonstrates that ETFs contribute to the price discovery of individual stock information.

III. The Model

A. Assets

The model is in the style of Glosten and Milgrom (1985), with two stocks, A and B. Each stock in the economy pays a single per-share liquidating dividend from $\{0, 1\}$, and I assume the two dividends are independent. One share of the market portfolio contains ϕ shares of stock A and $(1 - \phi)$ shares of stock B.

The economy also has an ETF, which has the same weights as the market portfolio. Thus each share of the ETF contains ϕ shares of stock A and $(1 - \phi)$ shares of stock B. With market weights, no rebalancing is needed: should the value of stock A increase, the value of the ϕ shares of stock A within the ETF increases. I explore the differences between an economy where the ETF can be traded and an economy where only stocks A and B can be traded in Appendix B.

B. *Market Maker*

There is a single competitive market maker who posts quotes in all three securities. The market maker is risk neutral and has observable Bayesian prior beliefs:

$$\mathbb{P}(A = 1) = \delta, \qquad \mathbb{P}(B = 1) = \beta$$

In each security, the market maker sets an ask price equal to the expected value of the security conditional on receiving an order to buy, and a bid price equal to the expected value of the security conditional on receiving an order to sell. This expected value depends on both the population of traders and their trading strategies. Following an order arrival, the market maker updates beliefs about security value. Traders arrive according to a Poisson process, and the unit mass of traders can be divided up into informed and uninformed traders. Figure 1 presents an overview of the model timing.

Figure 1. Timeline of the Model. A single risk-neutral competitive market maker posts quotes in all three securities. A single trader arrives and trades against one of these quotes. Following an order, the market maker updates beliefs about the value of each of the three securities.

C. *Uninformed Traders*

Uninformed traders trade to meet inventory shocks from an unmodeled source. These uninformed, or noise, traders can be divided into three groups based on the type of shock they receive:

- Stock A noise traders of mass σ_A
- Stock B noise traders of mass σ_B
- Market-shock noise traders of mass σ_M

Uninformed traders who experience a stock-specific shock trade only an individual stock. Uninformed traders who experience the market shock could satisfy their trading needs with either the ETF or a combination of stocks A and B. Trading the ETF, however, allows market-based noise traders to achieve the same payoff at a potentially lower transaction cost. This possibility arises because the ETF offers some screening power. Trading at the ETF quote gives an investor the ability to buy or sell stocks A and B in a fixed ratio. Trading at the individual stock quotes, by contrast, allows an investor the ability to trade any ratio of stocks A and B. Thus for any information structure, the ETF quotes must be at least as good as a weighted sum of the individual quotes.[1] In all equilibria of my model, the ETF quotes turn out to be strictly better than the a weighted sum of the individual quotes.

Noise traders buy or sell the asset with equal probability. I also normalize the demand or supply of each noise trader to be a single share of the asset they choose to trade. The model could be extended as in Easley and O'Hara (1987) to have noise traders trading multiple quantities or multiple assets.

D. Informed Traders

Informed traders know the value of exactly one of the two securities. There is a mass μ_A of traders who know the value of stock A, and a mass μ_B of traders who know the value of stock B. Informed traders are limited to trading only a single unit of any asset, though they can randomize their selection. The single-unit limitation on trade can be thought of as a cost of capital or risk limit for their trading strategy. While investors could trade more aggressively in the ETF to obtain the same stock-specific exposure, this would require significantly higher capital or exposure to significantly more factor risk. Thus in the model, trading the ETF is not free for informed investors. If they choose to trade both the ETF and the stock via a randomization strategy, trading the ETF with higher probability means they must trade the single stock with a lower probability. Informed investors therefore face the following tradeoff: they can choose to trade A at a wide spread, or they can choose to trade the ETF (AB) at a narrow spread with the caveat that the ETF contains only $\phi < 1$ shares of A.

[1] One could reverse this result with a non-information friction. For example, one could add a trading friction so that investors would be willing to trade the ETF even if it had a wider information-based spread.

In addition to being conceptualized as the ETF weight of each stock, ϕ can be thought of in more general terms as the relevance of the investor's information. When an investor has information about security A, they could also trade a closely related security (AB). While the investor's information is less relevant to the price of (AB), the asset may be available at a lower trading cost. The lower ϕ, the less relevant the information, and thus the less appealing committing capital to this alternative investment becomes.

E. Equilibrium

The Bayesian-Nash equilibria between the traders and the market maker obtains as follows. Let A-informed traders μ_A submit orders to the ETF with probability ψ_A and B-informed traders μ_B submit orders to the ETF with probability ψ_B. A pair of strategies (ψ_A, ψ_B) is an equilibrium strategy when, for each stock, either ψ_i leaves the informed trader indifferent between trading the stock and the ETF, or when $\psi_i = 0$ and the informed trader strictly prefers to trade the single stock.

The effectiveness of the ETF for screening informed traders varies across the different equilibria. In a fully separating equilibrium, where investors with stock-specific information only trade specific stocks, there is no adverse selection in the ETF. ETF screening of stock-specific information is rarely complete, however. In a fully pooling equilibrium, traders from both stock A and stock B trade the ETF, while in a partial separating equilibrium, one class of informed investors trades both the stock and the ETF.

The direct modeling of bid-ask spreads, while allowing ETFs and underlying stocks to have different levels of adverse selection, means there are no law of one price violations. The word arbitrage is often used in reference to ETFs. In these industry applications of the term arbitrage, however, there are no true law of one price violations.[2] Consistent with observed behavior of ETF

[2] The creation/redemption mechanism is sometimes referred to as an "arbitrage" mechanism. After the close of the market, authorized participants (APs) can exchange underlying baskets of securities for ETF shares. The securities exchanged, however, had to have been acquired during trading hours. Positions in securities could be acquired for a variety of reasons, including regular market-making activities, so the use of the creation/redemption mechanism does not imply any previous violation of the law of one price.

Deviations from intraday net asset value (iNAV) are also sometimes referred to as "arbitrage" opportunities. They typically arise, however, from the technical details of the iNAV calculation, as discussed in Donohue (2012). iNAV is usually calculated from last prices of the components, so a deviation from iNAV is typically staleness in prices. iNAV can also be computed from bid prices; in this case, iNAV just confirms that the risk from placing one limit order for the ETF can differ from the risk of placing many limit orders in each of the basket securities. For some securities, the creation/redemption basket is different from the current ETF portfolio, so iNAV, which reflects the prices, the model has no law of once price violations.[3]

IV. Price Discovery in a Single Asset

In this section, I analyze the equilibria that result with price discovery in only stock A. Thus I set $\mu_B = 0 = \sigma_B$ and $\beta = \frac{1}{2}$. In this simplified setting, there are only two possible equilibria. The first is a separating equilibrium, where investors with information about A trade only security A and do not the ETF. In this equilibrium, the profits they make from single stock trading always dominate the profits they could make trading the ETF with no spread. The second is a pooling equilibrium, where investors with information about A mix their orders, randomly sending their order to either A or the ETF. In this equilibrium, investors are indifferent between trading the single stock and the ETF, as the profit from trading the single stock at a wide spread is the same as the profit from trading the ETF at a narrow spread. Note that it is not possible for an equilibrium to obtain where A-informed investors only trade the ETF. If this were the case, then security A would have no spread, and the A-informed investors would earn greater profits trading security A. The sequence of possible trades is illustrated in Figure 2, and key model parameters are reviewed in Table I.

A. Separating Equilibrium

PROPOSITION 1: *A separating equilibrium in which informed traders only trade A and do not trade the ETF, obtains if and only if:*

$$\phi \leq \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A + \frac{1}{2}\sigma_A} \qquad \textit{(bid condition)}$$

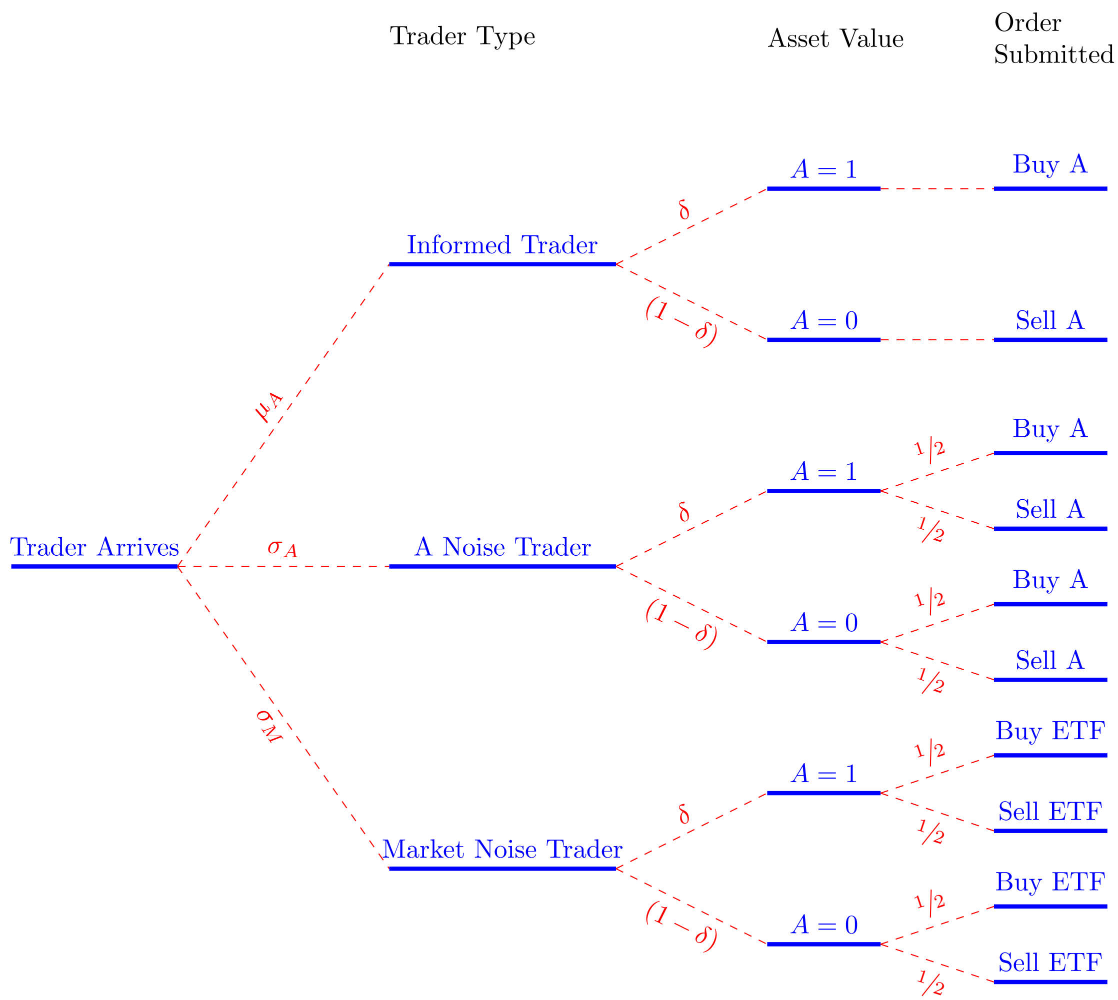
$$\phi \leq \frac{\frac{1}{2}\sigma_A}{\delta\mu_A + \frac{1}{2}\sigma_A} \qquad \textit{(ask condition)}$$

In the separating equilibrium, traders with information about security A only submit orders to stock A, and do not trade the ETF. Since no informed orders are submitted to the ETF, there

creation/redemption basket, can differ from the market price of the current portfolio. Finally, errors are common in the calculation and reporting of iNAV values.

[3] KCG analysis on trading for the entire universe of US equity ETFs finds that arbitrage opportunities occur in less than 10% ETFs. These arbitrages occurred in smaller, much less liquid ETFs, and were always less than \$5,000, which is “unlikely enough to cover all the trading, settlement, and creation costs.” Mackintosh (2014)

Figure 2. Potential Orders for Separating Equilibrium. In the separating equilibrium, only noise traders trade the ETF. The market maker can offer the ETF at zero spread. Informed traders only trade single stocks because the profits from trading the single stock at a wide spread exceed the profits from trading the ETF, even if the ETF has no spread.



is no information asymmetry and orders in the ETF reveal no information about the underlying value of the assets. Therefore, the ETF is offered at a zero bid-ask spread.

For the separating equilibrium to hold, the payoff to an informed trader from trading the individual stock must be greater than the payoff from trading the ETF. For the bid and the ask, these expression are:

$$\text{Payoff from trading ETF} \leq \text{Payoff from trading stock}$$

$$\phi(1-\delta) \leq 1 - ask_A \tag{1}$$

$$\phi\delta \leq bid_A \tag{2}$$

where the bid and ask prices are the expected value of the stock conditional on an order in the separating equilibrium, and ϕ is the proportion of shares of A in the ETF.

For the market maker to make zero expected profits, each limit order must be the expected value of A conditional on receiving a market order. The asking price is the expected value of A conditional on receiving a buy order in A. Since stock A pays a liquidating dividend from $\{0, 1\}$, the expected value of stock A is just the probability that A pays a dividend of 1. A similar logic holds for the bid price. The bid and ask are therefore given by:

$$\begin{aligned}
ask = \mathbb{P}(A = 1|\text{buy}_A, \delta) &= \frac{\mathbb{P}(A = 1\&\text{buy}_A|\delta)}{\mathbb{P}(\text{buy}_A|\delta)} \\
&= \delta \frac{\mu_A + \frac{1}{2}\sigma_A}{\delta\mu_A + \frac{1}{2}\sigma_A} \\
bid = \mathbb{P}(A = 1|\text{sell}_A, \delta) &= \frac{\mathbb{P}(A = 1\&\text{sell}_A|\delta)}{\mathbb{P}(\text{sell}_A|\delta)} \\
&= \delta \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A + \frac{1}{2}\sigma_A}
\end{aligned}$$

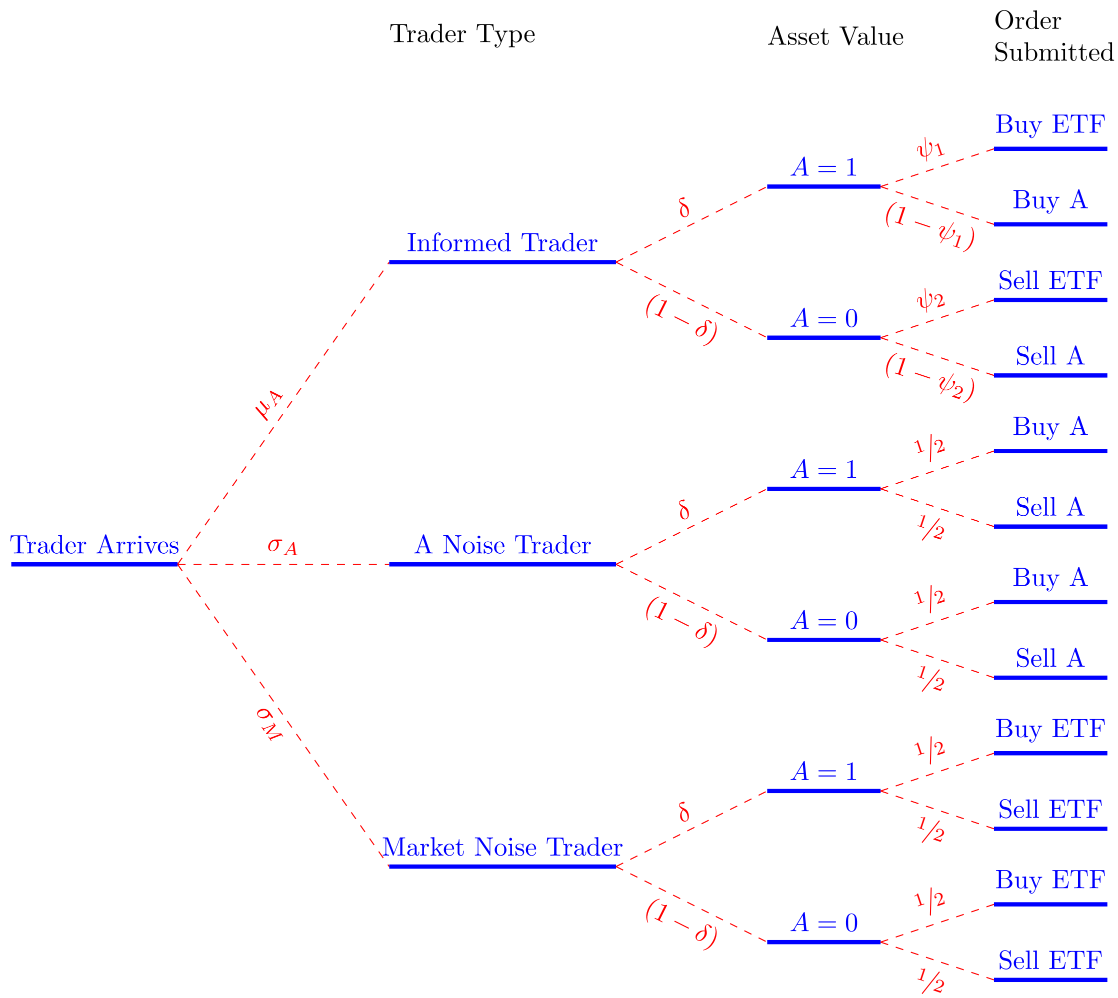
When spreads in the single stock become wide enough, either of (1) or (2) may no longer be satisfied. In this case, informed investors could make more profit trading the ETF than trading the individual stock. If they switched and only traded the ETF, then the single stock would have no spread, and trading the single stock would be more profitable. Thus for a non-separating equilibrium, informed traders must randomize between trading the ETF and the single stock.

B. Pooling Equilibrium

In the pooling equilibrium, informed traders randomize between trading stock A and trading the ETF. Figure 3 presents the possible trades for the pooling equilibrium. Informed traders trade the ETF with probability ψ and the stock with probability $(1 - \psi)$. The equilibrium value of ψ

leaves informed traders indifferent between trading either the stock or the ETF.

Figure 3. Potential Orders for Pooling Equilibrium. In the pooling equilibrium, informed traders randomize between trading the stock and the ETF. In equilibrium, informed traders trade the ETF with a probability ψ, which induces the market maker to quote a spread which leaves informed traders indifferent between trading stock A at a wide spread or trading the ETF at a narrow spread.



PROPOSITION 2: *A pooling equilibrium in which informed traders trade both A and the ETF exists so long as either of the following conditions hold:*

$$\phi > \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A + \frac{1}{2}\sigma_A} \qquad \textit{(bid condition)} \tag{3}$$

$$\phi > \frac{\frac{1}{2}\sigma_A}{\delta\mu_A + \frac{1}{2}\sigma_A} \qquad \textit{(ask condition)} \tag{4}$$

In a pooling equilibrium, informed investors mix between A and the ETF and submit orders to the ETF with the following probability:

$$\textit{ETF Buy Probability (A=1):}\ \psi_1 = \frac{\phi\delta\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{\delta\mu_A[\sigma_A + \phi\sigma_M]}$$
$$\textit{ETF Sell Probability (A=0):}\ \psi_2 = \frac{\phi(1-\delta)\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{(1-\delta)\mu_A[\sigma_A + \phi\sigma_M]}$$

Note that these conditions are determined independently. For example, there could be a pooling equilibrium for bid quotes while the ask quotes have a separating equilibrium. This asymmetry can occur when the market maker's prior δ is far from $\frac{1}{2}$, and therefore the market maker views either $\mathbb{P}(A = 1)$ or $\mathbb{P}(A = 0)$ as more likely.

In the pooling equilibrium, an informed trader with a signal about A randomizes between trading the ETF and trading the single stock. While the trader obtains fewer shares of A by trading the ETF, the ETF has a much narrower spread. Once it is more profitable for an informed trader to randomize between the stock and ETF, the market maker must charge a spread for ETF orders. The market noise traders in the ETF must pay this spread when they trade, and thus pay some of the costs of the stock-specific adverse selection.

For the informed trader to be willing to use a mixed strategy, he must be indifferent between buying the ETF or buying the individual stock. In the single stock, he trades one share of A at the single stock spread. In the ETF, he obtains only ϕ shares of A, but at the narrower ETF spread. Spreads in both markets depend on the probability ψ that he trades the ETF. Shifting more orders to the ETF increases the ETF spread and decreases the single stock spread. In equilibrium, ψ_1 (proportion of informed buy orders sent to the ETF) and ψ_2 (proportion of informed buy orders sent to the ETF) must solve:

$$[\phi \cdot 1 + (1-\phi) \cdot \frac{1}{2} - ask_{(AB)})] = 1 - ask_A$$
$$bid_{(AB)} - (1-\phi) \cdot \frac{1}{2} = bid_A$$

Solving for these expressions yields the mixing probabilities given in Proposition 2. A summary of the results is given in Table I. Note that for any $\phi > 0$, there exists a volume μ of informed traders and a proportion σ_M of noise traders in the ETF such that a pooling equilibrium exists.

Table I: Key Variables and Equilibrium Spreads. This table summarizes the equilibrium spreads for the separating and pooling equilibria. In the separating equilibrium, informed investors only trade stock A; the ETF has no informed trading and thus no bid-ask spread. In the pooling equilibrium, informed investors randomize their orders, trading the ETF with probability ψ and the stock with probability $(1-\psi)$.

Key Model Parameters

Parameter	Definition
ϕ	Weighting of A in the ETF
δ	Market Maker's prior about $P(A=1)$
μ_A	Fraction of traders who are informed about A
σ_A	Fraction of noise traders with stock-A specific shock (thus trade stock A)
σ_M	Fraction of noise traders with market shocks (thus trade the ETF)
ψ_1	Fraction of informed traders who trade the ETF when $A=1$
ψ_2	Fraction of informed traders who trade the ETF when $A=0$

Separating Equilibrium Spreads

Security	Bid-Ask Quotes
A	$A_{bid} = \delta \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A + \frac{1}{2}\sigma_A}$
	$A_{ask} = \delta \frac{\mu_A + \frac{1}{2}\sigma_A}{\delta\mu_A + \frac{1}{2}\sigma_A}$
ETF	$(AB)_{bid} = \phi\delta + (1-\phi)\frac{1}{2}$
	$(AB)_{ask} = \phi\delta + (1-\phi)\frac{1}{2}$

Pooling Equilibrium Spreads

Security	Bid-Ask Quotes
A	$A_{bid} = \delta \frac{\frac{1}{2}\sigma_A}{(1-\delta)(1-\psi_2)\mu_A + \frac{1}{2}\sigma_A}$
	$A_{ask} = \delta \frac{(1-\psi_1)\mu_A + \frac{1}{2}\sigma_A}{\delta(1-\psi_1)\mu_A + \frac{1}{2}\sigma_A}$
ETF	$(AB)_{bid} = \phi\delta \frac{\frac{1}{2}\sigma_M}{(1-\delta)\psi_2\mu_A + \frac{1}{2}\sigma_M} + (1-\phi)\frac{1}{2}$ where $\psi_2 = \frac{\phi(1-\delta)\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{(1-\delta)\mu_A[\sigma_A + \phi\sigma_M]}$
	$(AB)_{ask} = \phi\delta \frac{\psi_1\mu_A + \frac{1}{2}\sigma_M}{\delta\psi_1\mu_A + \frac{1}{2}\sigma_M} + (1-\phi)\frac{1}{2}$ where $\psi_1 = \frac{\phi\delta\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{\delta\mu_A[\sigma_A + \phi\sigma_M]}$

COROLLARY 1: *The portion of orders submitted to the ETF by A-informed traders is increasing in:*

1. *The number of informed traders, μ_A.*
2. *The number of noise traders in the ETF, σ_M.*
3. *The accuracy of the market maker's belief, $-|A - \delta|$.*
4. *The ETF weight of the stock, ϕ.*

The first three parameters determine the relative sizes of bid-ask spreads. If the are more informed traders, bid-ask spreads in stock A are wide. If there are more noise traders in the ETF, ETF spreads are narrower for a given level of informed trading. The accuracy of the market maker's belief, $|\delta - A|$, reflects both the sensitivity of the market maker's belief to order flow and the potential profits from trading. Suppose, for instance, that $A = 0$. If the market maker believes the value of A is close to zero, i.e. $\delta \sim 0$, then the market maker expects informed investors to sell. The bid price is be very close to zero, leaving informed traders with little potential profit. As a result, the probability ψ with which they trade the ETF is be very high. On the other hand, if the market maker believes $\delta \sim 1$, then the market maker does not expect informed traders to sell. The bid price is be close to one, so informed traders are content to trade the single stock. Trading the ETF is undesirable because the reduction in spread is small relative to the reduction in shares of A purchased.

The weight of the stock in an ETF, given by ϕ, determines the potential profit from using a mixed strategy. Investors with information about a large stock find themselves better informed about the ETF than they would with information about a smaller stock. The more informed a trader is about the ETF, the greater the profits they can make by trading against noise traders in the ETF.

Together, the weighting and spread create two dimensions along which stock–ETF interaction can vary. For most of the heavily traded ETFs, stock weights are determined by value weighting. Comparing stocks with a high ETF-weight against stocks with a low ETF-weight is therefore the same as comparing large market capitalization stocks with small market capitalization stocks. As Proposition 2 shows, however, the way in which stocks interact with the ETF also depends on informational asymmetries. For any fixed stock weight $\phi > 0$, there exists a pair of parameters (δ, μ_A) for which pooling is an equilibrium. When there are multiple informational asymmetries, this is no longer true. Section V explores how different pieces of information act as substitutes, and as a result investors with one piece of information may find that the ETF spread is always too wide for them to profit from trading the ETF.

V. Price Discovery with Multiple Assets

To develop the full model, I now add μ_B traders who are informed about the value of stock B. Stock B pays a liquidating dividend from $\{0, 1\}$, and the market maker has a prior belief $P(B = 1) = \beta$. I also assume that security B is uncorrelated with security A. Both classes of informed traders have a choice to trade one share of any of the securities. Given their stock-specific knowledge, A-informed investors consider trading stock A and the ETF (AB), while B-informed investors consider trading stock B and the ETF (AB). As before, investors can only trade a single share of any security, but they are allowed to randomize their selection.

Informed investors can now face adverse selection in the ETF. Each class of informed investors has information about only one stock; trading the ETF can exposes them to adverse selection from the other stock in the ETF. There are now four potential equilibria. The first is a fully separating equilibrium, in which no informed traders submit orders to the ETF. For this equilibrium, the cutoffs are the same as in the previous section. The second is a fully pooling equilibrium, where both traders in A and B mix between the underlying security and the ETF. The last two equilibria are partial separating, where investors from one security randomize between trading the ETF and their single stock while investors from the other security only trade their single stock.

A. *Partial Separating Equilibrium*

Without loss of generality, I examine the partial separating equilibrium where A-informed traders randomize and trade both A and the ETF (AB), while B-informed traders only trade stock B. In this equilibrium, A-informed traders behave just as they did in Section IV.B. The market maker must charge a non-zero bid-ask spread in the ETF to cover the costs of adverse selection from the A-informed traders. When the B-informed traders consider trading the ETF, they must now account for this non-zero bid-ask spread. For B-informed traders, the cutoff between using a pure strategy of just trading stock B and using a mixed strategy of trading both B and the ETF is be higher than it would be in the absence of the adverse selection from A-informed traders in the ETF.

PROPOSITION 3: *Partial Separating Equilibrium. If A traders mix between A and the ETF, B traders stay out of the ETF so long as:*

$$\text{If } B = 0\text{: } \phi \geq \frac{\beta\left(\frac{(1-\beta)\mu_B}{(1-\beta)\mu_B+\frac{1}{2}\sigma_B}\right)\left((1-\delta)\mu_A+\frac{1}{2}\sigma_A+\frac{1}{2}\sigma_M\right)-\frac{1}{2}\delta\sigma_A}{\delta\left((1-\delta)\mu_A+\frac{1}{2}\sigma_A\right)+\beta\left((1-\delta)\mu_A+\frac{1}{2}\sigma_A+\frac{1}{2}\sigma_M\right)} \tag{5}$$

$$\text{If } B = 1\text{: } \phi \geq \frac{(1-\beta)\left(\frac{\beta\mu_B}{\beta\mu_B+\frac{1}{2}\sigma_B}\right)\left(\delta\mu_A+\frac{1}{2}\sigma_A+\frac{1}{2}\sigma_M\right)-(1-\delta)\frac{1}{2}\sigma_A}{(1-\delta)\left(\delta\mu_A+\frac{1}{2}\sigma_A\right)+(1-\beta)\left(\delta\mu_A+\frac{1}{2}\sigma_A+\frac{1}{2}\sigma_M\right)} \tag{6}$$

Between Equation 3 and Equation D1, the cutoff for B is higher for the separating equilibrium relative to the partial-separating equilibrium. This obtains because if B-informed traders were to trade the ETF, they would have to pay the adverse selection costs from A-informed traders. The difference in these bounds is illustrated in Figure 4.

Suppose, for example, that B-informed traders know the true value of security B is 1. They value A at the market maker's prior of δ, and therefore value the ETF at $\phi \cdot \delta + (1-\phi)\cdot 1$. In the partial separating equilibrium, the A-informed traders are mixing between A and the ETF. The market maker, anticipating this adverse selection from A-informed traders, sets the ETF ask at:

$$\phi\delta\frac{\mu_A\psi_1+\frac{1}{2}\sigma_M}{\delta\mu_A\psi_1+\frac{1}{2}\sigma_M}+(1-\phi)\beta$$

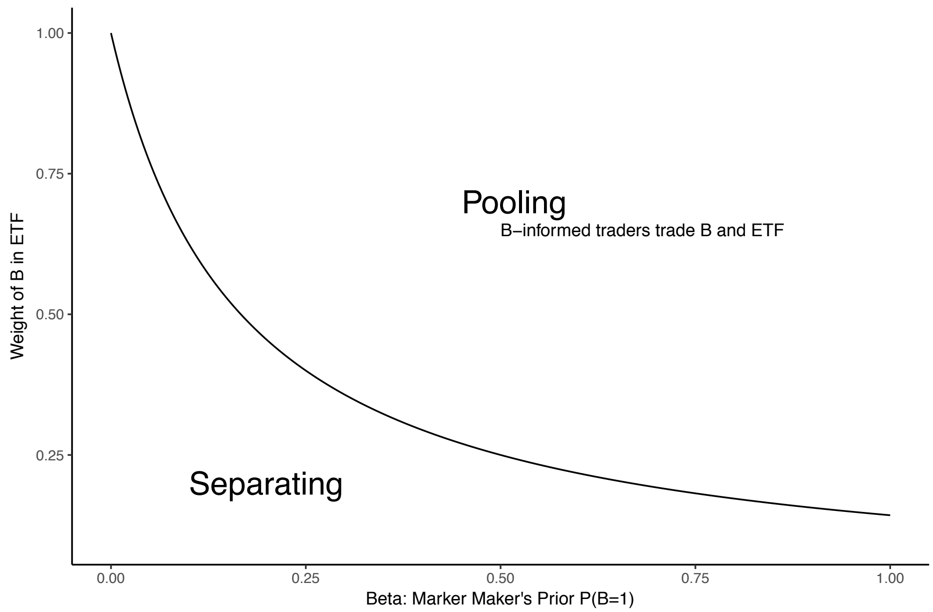
For B-informed investors, the trade-off between trading the ETF and trading stock B becomes:

$$\phi\left(\delta-\delta\frac{\mu_A\psi_1+\frac{1}{2}\sigma_M}{\delta\mu_A\psi_1+\frac{1}{2}\sigma_M}\right)+(1-\phi)(1-\beta)\leq 1-\beta\frac{\mu_B+\frac{1}{2}\sigma_B}{\beta\mu_B+\frac{1}{2}\sigma_B}$$

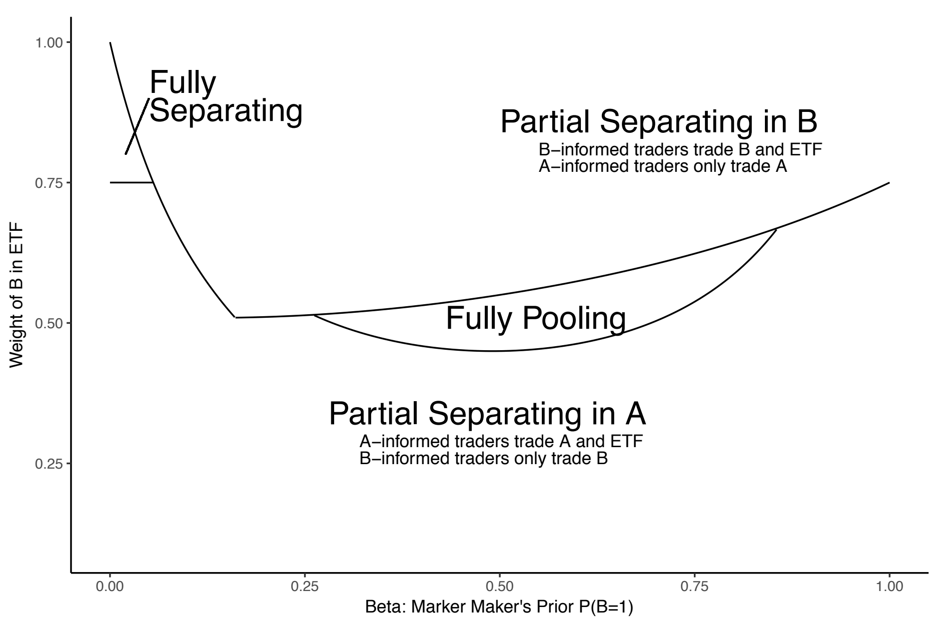
Note that $\phi\left(\delta-\delta\frac{\mu_A\psi_1+\frac{1}{2}\sigma_M}{\delta\mu_A\psi_1+\frac{1}{2}\sigma_M}\right)<0$, and this value represents the adverse selection that B-informed investors would have to pay when they trade the ETF. This adverse selection decreases the prof-

Figure 4. Partial Separating and Pooling Equilibria. This graph depicts which equilibrium prevails for the ask quote as the ETF weight and market maker's prior of stock B change. When there are only informed traders in stock B, there is a large parameter region over which B-informed traders trade both the stock and the ETF. With price discovery in two assets, adverse selection from A-informed traders reduces the region over which the B-informed traders use a mixed strategy of randomizing between the single stock and ETF. Parameters: $\mu_A = .15 = \mu_B, \sigma_A = .05 = \sigma_B, \sigma_M = .6, \delta = .5$.

Panel A: Division of equilibria with Price Discovery in One Assets



Panel B: Division of equilibria with Price Discovery in Two Assets



itability of trading the ETF relative to trading stock B, leading to the higher cutoff values for mixing in Equation D1.

The partial separating equilibrium highlights the importance of the relative size of informational asymmetry. When there are informed traders in just one security, only price impact matters, and the cutoff for mixing responds uniformly to the market maker's prior, β. The closer β is to the true value of B, the higher the market impact of informed traders. When the ETF has no spread, its attractiveness as an alternative is uniformly increasing in price impact. Panel A in Figure 4 depicts this process: the closer β is to the true value of B, the lower the ETF weight needed for B traders to start trading the ETF.

When there are informed traders from more than one security, the size of informational asymmetry can matter as much as price impact. The presence of A-informed traders causes a spread in the ETF. For B-informed traders to be willing to trade the ETF, they must make enough money from the ETF to pay this spread. When β is too close to the true value of B, even though the market impact of trades in B is high, the potential profit to be made in the ETF is also small. Consequently, the B-informed traders no longer trade the ETF when β is close to its true value. Panel B in 4 illustrates the boundaries between fully pooling and partial separating equilbiria, which combines both the price impact and the relative size of the information asymmetry.

COROLLARY 2: *If A-informed investors mix between A and the ETF, investors with information about security B lose money by trading the ETF based on their knowledge of B so long as:*

$$\textit{Bid (B=0 and B traders consider selling the ETF):} \qquad \phi\left(\frac{(1-\delta)\delta\mu_A\psi_2}{(1-\delta)\mu_A\psi_2+\frac{1}{2}\sigma_M}\right) \geq (1-\phi)\beta$$

$$\textit{Ask (B=1 and B traders consider buying the ETF):} \qquad \phi\left(\frac{(1-\delta)\delta\mu_A\psi_1}{\delta\mu_A\psi_1+\frac{1}{2}\sigma_M}\right) \geq (1-\phi)(1-\beta)$$

The adverse selection from A-informed can become so severe that B-informed are completely excluded from the ETF. If the ETF were the only asset B-informed could trade, they would not make any trades. Their exclusion from the ETF occurs because investors in A have information that is more important to the ETF price. This importance of A information can come in two ways. First, A can have a larger ETF-weight than B. Second, the potential change in value in A can be larger than the potential change in B. Together, both the weight and the volatility of A lead to a wide ETF spread on account of the A-informed. When B-informed traders value the ETF at a point between the bid and ask, they are excluded from trading the ETF.

When a trader with stock-specific information considers trading the ETF, they must consider both the availability of noise traders and the presence of traders with orthogonal information. When multiple assets are correlated with their information, they may not trade all assets. In section IV.A, informed traders with A-specific only had to consider whether the additional noise traders justifies trading an asset which is less correlated with their information about stock A. When there are multiple pieces of information, traders must also consider whether the value of their information exceeds the adverse selection from other traders. Even if a signal better predicts an asset return than the information contained in market prices, trading on the signal may not be profitable in the face of adverse selection from traders with other pieces of information.

This resultant exclusion underscores the asymmetric effect of ETFs on the underlying securities. Investors whose information is substantial—i.e. either about a large stock or predictive of a large value change—can profitably trade the ETF. But their presence creates adverse selection; in the ETF, this adverse selection screens out traders with information which is about small stocks or small value changes.

B. Fully Pooling Equilibrium

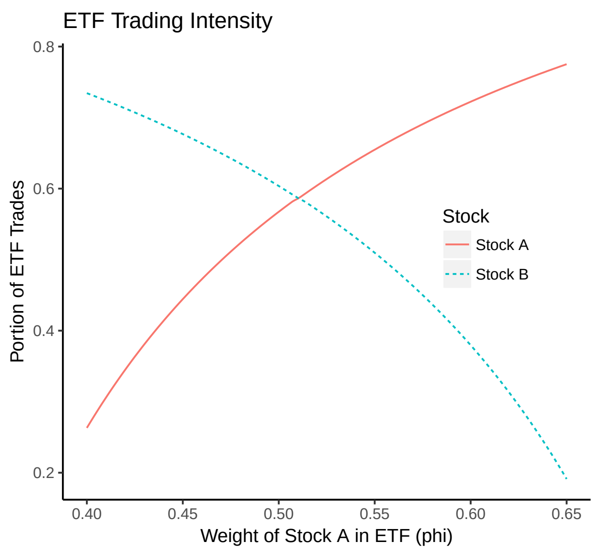
PROPOSITION 4: *If the conditions of Proposition 3 are violated for both securities, then there is a fully pooling equilibrium. Both traders trade the ETF, and following an ETF trade, the market maker has the following Bayesian posteriors:*

$$\delta_{buy} = \delta \frac{\mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M} \qquad \delta_{sell} = \delta \frac{\frac{1}{2}\sigma_M}{(1-\delta)\mu_A \psi_{A,2} + (1-\beta)\mu_B \psi_{B,2} + \frac{1}{2}\sigma_M}$$

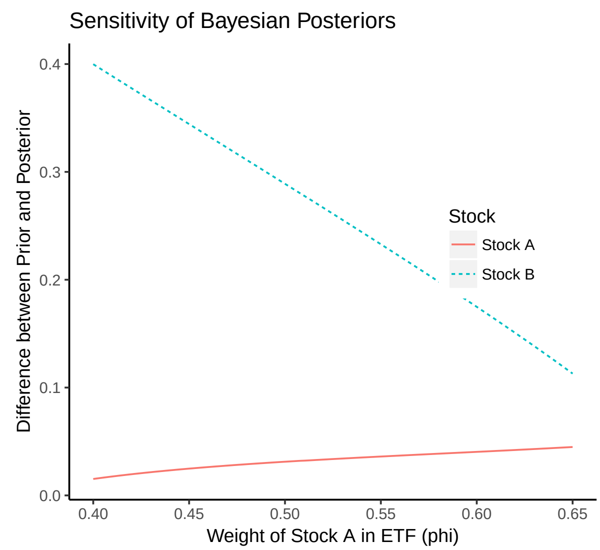
$$\beta_{buy} = \beta \frac{\delta \mu_A \psi_{A,1} + \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M} \qquad \beta_{sell} = \beta \frac{\frac{1}{2}\sigma_M}{(1-\delta)\mu_A \psi_{A,2} + (1-\beta)\mu_B \psi_{B,2} + \frac{1}{2}\sigma_M}$$

In a fully pooling equilibrium, both informed traders use a mixed strategy of trading the ETF and trading the single stock. Since both investors are mixing, an ETF trade could come from either informed trader. Following an ETF trade, the market maker updates beliefs about the value of both A and B.

Figure 5. Pooling Equilibrium With Changes in ETF Weight. I plot how changes in ETF weight of stock A affect the trading behavior and market maker's updating for the pooling equilibrium. I plot trader behavior when $A = 1 = B$, and the updating following a buy order. The securities are symmetric in trader masses: $\mu_A = \mu_B = .15$ and $\sigma_A = \sigma_B = .15$. The priors differ, with the market maker slightly more certain about the value of stock A: $P(A = 1) = .8$ while $P(B = 1) = .75$.



Panel A: As the ETF weight of stock A increases (x-axis), the portion of orders sent to the ETF by A-informed traders increases (solid red line) while the portion of orders sent to the ETF by B-informed traders decreases (dashed blue line). Different pieces of stock-specific information act as substitutes.

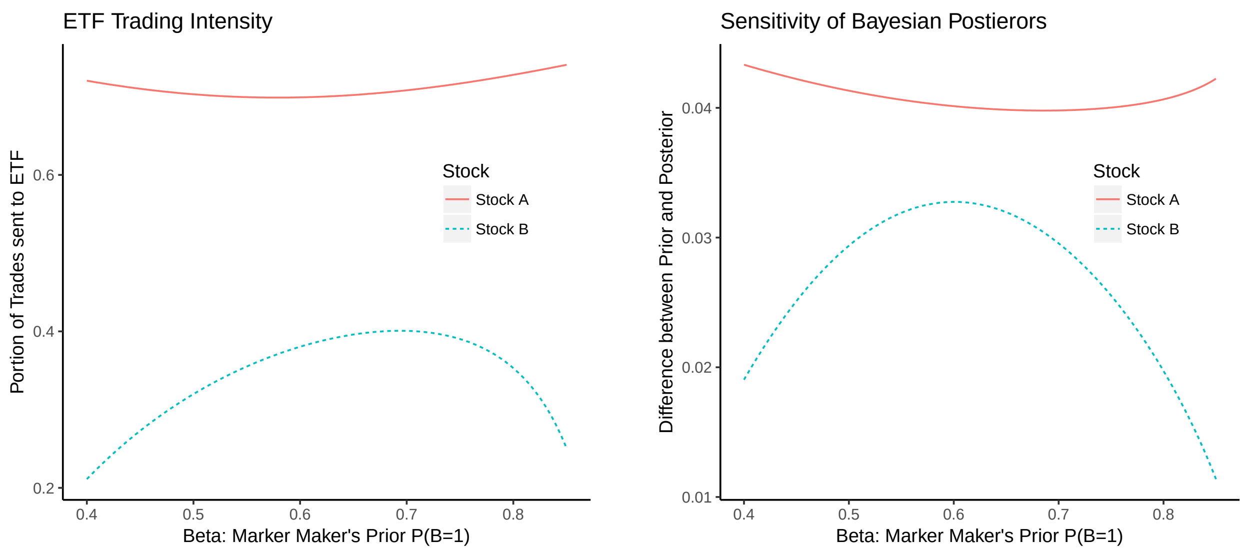


(a) Panel B: The y-axis plots the difference between the market maker's prior and posterior $(\delta - \delta_{buy})$ for stock A, and $(\beta - \beta_{buy})$ for stock B. Increases in the ETF weight of stock A lead to a small increase in updating for stock A, and a large decrease in updating for stock B.

The change in beliefs about each stock depends on more than just the stock weight in the ETF; the informational asymmetry, the portion of informed traders, and the market maker's uncertainty in belief about the stock all shape the updating process. Two stocks with equal weight in the ETF can see dramatically different adjustments in response to an ETF order.

Figure 5 illustrates how trader behavior and the market maker's updates vary with changes in the ETF weights of stocks. As shown in Panel A of Figure 5, according as the stock weight in the ETF increases, investors send a higher portion of their orders to the ETF. Panel B of Figure 5 plots the difference between the market maker's prior and posterior. For stock A, this difference, $|\delta_{buy} - \delta|$, is relatively constant across a range of values of ϕ. By contrast, the difference for stock B, $|\beta_{buy} - \beta|$, changes dramatically with changes in ϕ. The difference between A and B arises from

Figure 6. Differences in ETF Trading and Market Maker's Posterior as a Function of Prior. I plot trader behavior when $A = 1 = B$, and the updating following a buy order. The securities are symmetric in trader masses: $\mu_A = \mu_B = .15$ and $\sigma_A = \sigma_B = .15$. The ETF is 60% A (i.e. $\phi = 0.6$), and the market maker has a prior $\delta = \mathbb{P}(A = 1) = .6$.



Panel A: Increases in the market maker's prior β about the value of stock B have a non-linear affect on trading behavior. At low levels, higher levels of β increase stock-specific spreads, leading B-informed traders to send more orders to the ETF. At high levels of β, the profit B-informed traders can make in the ETF is small relative to the adverse selection they face from A-informed traders, and the portion of trades they send to the ETF decreases in β.

Panel B: The difference between the market maker's prior and posterior belief depends on a combination of the market maker's prior, the ETF weight, and trader behavior. Stock A has a higher weight, so the market maker updates more based on stock A. Quotes in Stock B change most at $\beta \approx .6$, reflecting a mix between the market maker's uncertainty (which peaks at $\beta = .5$) and the ETF-trading by B-informed traders (which peaks at $\beta \approx .7$).

the difference in priors: the market maker is slightly more certain about the value of stock A than the value of stock B.

Changes in the prior beliefs have both a direct and indirect effect on the market maker's updating. For the direct effect, more certainty in the prior reduces the importance of new evidence. For the indirect effect, uncertainty in the stock changes spreads and therefore trading behavior. Informed traders in stocks for which the market maker has an uncertain prior face wider spreads; these wide stock spreads lead traders to trade the ETF with higher probability. Panel A of Figure 6 illustrates these effects. As the market maker's prior β about stock B increases from low levels, the B-informed traders send a higher portion of their trades to the ETF. At very high levels of β, the B-informed traders face small trading profits relative to the adverse selection from A-informed traders, and the portion of orders they send to the ETF falls off sharply. The market maker's update subsequent to an ETF trade, illustrated in Panel B of Figure 6, reflects a balance of the uncertainty in the Bayesian prior, which peaks at $\beta = \frac{1}{2}$, and the trading intensity, which peaks at $\beta \approx 0.7$.

Each stock-specific property—the ETF weight, the population of traders, and the prior estimate of value—contributes to the market maker's updating process. The law of one price dictates that ETF and the sum of the underlying stocks should be equal, but it imposes no rigid rules about co-movement between the ETF and an individual stock. Even in a fully pooling equilibrium, ETF trades contribute to stock-specific price discovery, with some stocks seeing more adjustment than others in response to an ETF trade.

VI. Empirics

A. Data

Under my model, investors with stock-specific information trade ETFs whenever their stock has a sufficiently large ETF weight or has a sufficiently large information asymmetry. To test this, I examine links between stocks and ETFs, and I investigate how these links vary with stock-specific characteristics. My sample of ETFs is SPDR and the ten Sector SPDR ETFs from State Street. The Sector SPDRs divide the stocks of the S&P500 into ten GICS industry groups,[4] and have the advantage of being very liquid, fairly concentrated, and representative of a broad set of securities. Within each ETF, constituents are weighted according to their market cap. As a result, the ETFs have fairly concentrated holdings, as depicted in Figure 8, with the stocks with more than 5% weight comprising between 25% and 50% of each ETF.

The SPDR ETFs are extremely liquid. SPDR itself has the largest daily trading volume of any exchange traded product. All of the Sector SPDRs are in the top 100 most heavily traded ETFs, with 6 in the top 25 most traded ETFs. With $30 billion per day in trading volume, the ETFs in my sample represent over 30% of total ETF trading volume. All the stocks they own are also

[4] The GICS Groups are: Financials, Energy, Health Care, Consumer Discretionary, Consumer Staples, Industrials, Materials, Real Estate, Technology, and Utilities. During my sample period, two reclassifications of groups occurred. In September 2016, the Real Estate Sector SPDR (XLRE) was created from stocks previously categorized as Financials. In October 2018, the Communications Sector SPDR (XLC) was created from stocks previously categorized as Technologies or Consumer Discretionary. Since XLC has only three months of transaction data in my sample, I exclude it from the analysis.

domestically listed and traded on the main US equities exchanges. Trading volume of these ETFs is high even compared to the very liquid underlying stocks. For example, the Energy SPDR (XLE) has an average daily trading volume of around 20 million shares, at a price of $65 per share. As listed in Panel 8b, 17% of the holdings of XLE are Chevron stock. This means that when investors buy or sell these 20 million ETF shares, they are indirectly trading claims to $218 million worth of Chevron stock. The average daily volume for Chevron stock is $800 million, so the amount of Chevron that changes hands within the XLE basket is equal in size to 30% of the daily volume of Chevron stock.

Microsecond TAQ data was collected on all trades of SPDR and the ten Sector SPDR ETFs as well as all trades in the stocks that comprise them. The sample period is from August 1, 2015 to December 31, 2018. These trades were cleaned according to Holden and Jacobsen (2014). ETF holdings were collected directly from State Street as well as from Master Data. Daily return data was obtained from CRSP. Intraday news events were collected from Ravenpack. Summary statistics on each stock are presented in Table II.

B. Simultaneous Trades: Basic Setting

In this section, I test the prediction of the model that investors with stock-specific information also trade ETFs. Under my theory, investors use this mixed strategy when both their single stock informational asymmetry is high and their information has sufficient weight in the ETF. My identification of trade-both behavior relies on examining simultaneous trades. While TAQ data is anonymous, some traders who trade a stock and an ETF submit their orders at precisely the same time. As a result, I can identify their trading behavior. This idea is motivated by the measure of cross market activity proposed by Dobrev and Schaumburg (2017), which seeks to identify cross-market linkages through lead-lag relationships.

Rather than looking for a lead-lag between two markets, I look for simultaneous activity where trades occur too closely in time for one trade to be a response to another. Table III presents the latency between the gateway and limit order book for the major US exchanges. To respond to a trade, even the fastest co-located trading firms must pass through the gateway to the limit order book. All exchanges have a minimum latency of at least 20 microseconds; therefore, if two trades occur within 20 microseconds of each other, one trade cannot possibly be a response to the

Table II: Summary Statistics on Securities

(a) Panel A: Stock Summary Statistics
My sample is comprised of the stocks of the S&P 500 Index. During my sample period from August 1, 2015 to December 31, 2018, there are 860 trading days.

Statistic	Mean	St. Dev.	Min	Max
Daily Simultaneous Trades	102	321	0	13,665
ETF Weight	1%	1.6%	0.1%	25%
Daily ETF Orders	81,052	149,876	480	2,035,648
Daily Stock Orders	20,216	21,161	12	748,384
Daily Return	0.1%	1.7%	−41%	71%

(b) Panel B: Sector SPDR Summary Statistics The ten Sector SPDRs divide the S&P 500 index into portfolios based on their GICS Industry Code. I categorize small stocks as stocks with an ETF-constituent weight of $< 2\%$, medium stocks as stocks with an ETF-constituent weight between 2% and 5%, and large stocks as stocks with an ETF-constituent weight greater than 5%.

ETF	Industry	Small Stocks	Medium Stocks	Large Stocks	Mean ETF Return (%)	Std Dev. (Return %)
XLV	Health Care	46	11	4	0.028	0.71
XLI	Industrial	53	12	4	0.027	0.76
XLY	Consumer Disc.	55	6	3	0.041	0.70
XLK	Technology	54	10	4	0.030	0.83
XLP	Consumer Staples	19	9	4	0.010	0.64
XLU	Utilities	7	16	6	0.042	0.78
XLF	Financials	40	6	3	-0.008	0.85
XLRE	Real Estate	14	13	4	0.031	0.79
XLB	Materials	10	11	4	0.007	0.77
XLE	Energies	15	12	3	-0.008	0.93

other. Using this physical limitation from the exchanges, I define trades as simultaneous if they occur within 20 microseconds of each other, and calculate the total number of such trades for each stock–ETF pairing[5].

To ensure that this raw measure of simultaneous trades is not influenced by increases in overall trading volume, I use the same baseline estimation correction suggested by Dobrev and Schaumburg (2017). This baseline estimate measures how many trades occur in both markets at a point close in time, but not exactly simultaneously. For each stock trade in my sample, I calculate how many

[5]To ensure the trades take place within 20 microseconds of each other, I use the TAQ participant timestamp field and not SIP timestamps. All exchanges are required to timestamp their trades to the microsecond during my sample time period. Alternative trading facilities (ATF)'s, sometimes referred to as dark pools, are under less strict regulations, and only time stamp their trades to the nearest millisecond. As a result, I must exclude these millisecond-stamped trades from my analysis.

ETF trades occur exactly X microseconds before or after the stock trade. I calculate the average number of trades as X ranges from 1000 to 1200 microseconds; this boundary is far enough away to avoid picking up high-frequency trading response trades, but close enough to pick up patterns in trading at the millisecond level. I then scale this average up by 20 and subtract this baseline level of trades from each daily calculation of simultaneous trades. The level of simultaneous trades between stock i and ETF j on day t can be written as:

$$\text{Simultaneous Trades}_{ijt} = \text{Raw Simultaneous}_{ijt} - \frac{20}{200}\text{Baseline}$$

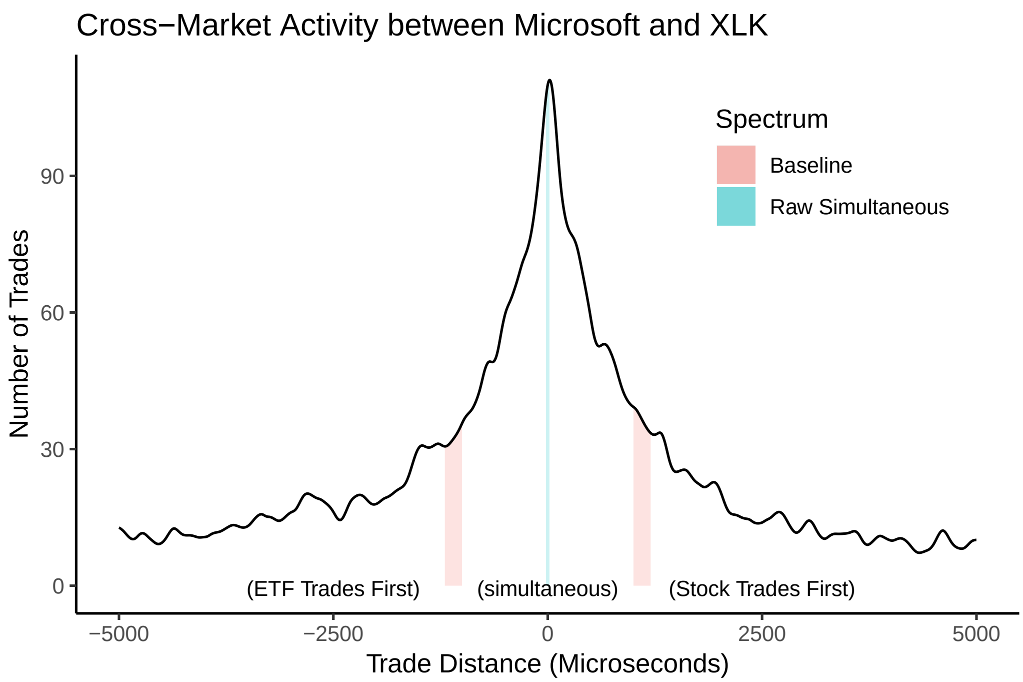
This baseline-corrected measure of simultaneous trades accounts for chance simultaneous trades which varies with changes in daily trading volume. Figure 7 plots a sample observation of cross market activity, along with the raw simultaneous and baseline regions.

Table III: **Gateway to Limit Order Book Latency from Major Exchanges**. This table gives the latencies reported by the major exchanges. All times are in microseconds, and reflect the total round-trip time from the gateway to limit order book of an exchange. All traders, including co-located high-frequency traders, must make this trip. Note that IEX and NYSE American have significantly longer round-trip times due to the inclusion of a 350 microsecond speed-bump.

	Min	Average
CBOE/BATS	31	56
Nasdaq	25	sub-40
NYSE	21	27
NYSE Arca	26	32
NYSE American	724	732
IEX	700+	700+

To test the model, the main regression examines how stock–ETF simultaneous trades change with stock-specific information. I consider two measures of stock-specific information: earnings dates and daily stock-specific return. This leads to two variations of the same regression:

Figure 7. Cross Market Activity in between Microsoft and XLK on October 2, 2018. The cross-market activity plot between Microsoft and the technologies Sector SPDR XLK shows a clear spike in trades which occur at the same time. The x-axis depicts the offset of X microseconds between an XLK trade timestamp and Microsoft trade timestamp. The y-axis depicts the number of trade pairs which occur with that exact offset.
Trades in the thin blue region are the raw measure of simultaneous trades: when a stock and ETF trade less than 20 microseconds apart, physical limits from the exchange mean these trades cannot be responding to each other. To account for daily changes in overall number of trades, I estimate a baseline level of cross-market activity with the region in red, where trades in the ETF occur 1000 to 1200 microseconds before or after trades in the stock.



REGRESSION 1: *For stock i, ETF j, and day t:*

$$\begin{aligned} \textit{Simultaneous Trades}_{ijt} &= \alpha_0 + \alpha_1 \textit{Earnings Date}_{it} + \alpha_2 \textit{Weight}_{ij} \\ &\quad + \alpha_3 \textit{Weight}_{ij} * \textit{Earnings Date}_{it} + \alpha_4 \textit{Controls}_{ijt} + \epsilon_{ijt} \end{aligned} \tag{7}$$

$$\begin{aligned} \textit{Simultaneous Trades}_{ijt} &= \alpha_0 + \alpha_1 \textit{Abs Return}_{it} + \alpha_2 \textit{Weight}_{ij} \\ &\quad + \alpha_3 \textit{Weight}_{ij} * \textit{Abs Return}_{it} + \alpha_4 \textit{Controls}_{itj} + \epsilon_{ijt} \end{aligned} \tag{8}$$

Simultaneous Trades measures the number of simultaneous trades between stock i and ETF j on date t. Earnings Date is an indicator that takes the value of 1 on the trading day after a company releases earnings. Abs Return is the absolute value of the intraday return of a stock. Controls include a fixed effect for each ETF, the ETF return, and an interaction between stock weight and the ETF return.

Theory predicts a positive value for α_3. When a stock has a large weight in the ETF and there is a large amount of stock-specific information, investors should trade both the stock and the ETF. A semi-pooling or fully pooling equilibrium takes place only in the stocks that are sufficiently heavily-weighted or have a sufficiently large informational asymmetry. When pooling does occur, the probability of submitting an order to the ETF is increasing in both the weight and the size of the informational asymmetry (Propositions 3 and 4). Results for Regression 1 are presented in Table IV.

The estimate of α_3, the interaction between weight and the size of the information, is positive for each of the measures of information considered in Regression 1. The increase in simultaneous trades is also sizeable; as an example, consider Exxon-Mobile, which is 20% of the Energies SPDR. Following earnings announcements, Exxon would have an additional 120 trades between Exxon and the ETF. For an extra 1% absolute return, Exxon would see an additional 400 simultaneous trades.

These increases are substantial in magnitude. On a day with return of less than 1%, Exxon averages 800 simultaneous trades with the Energies ETF. Relative to this number, earnings dates see a 15% increase in simultaneous trades while days with a 1% or 2% return see a 50% to 100% increase in simultaneous trades for each percentage point increase in return or volatility. And these results hold after controlling for the ETF return.

C. ETF Weight and Return Size Comparison

To further explore how the stock–ETF relationship changes with the stock weight, I split my sample of Sector SPDR stocks by size. I define small stocks as those with a weight less than 2%, medium stocks with weight between 2% and 5%, and large stocks with a weight greater than 5%. As Figure 8 shows, this produces a reasonably sized group across each of the ten sector SPDRs. I then estimate the following regression:

REGRESSION 2: *For stock i, ETF j, and day t:*

$$Simultaneous\ Trades_{ijt} = \alpha_0 + Size * \alpha_1 Earnings\ Date_{it} + \alpha_2 Controls_{ijt} + \epsilon_{ijt} \tag{9}$$

$$Simultaneous\ Trades_{ijt} = \alpha_0 + Size * \alpha_1 Abs\ Return_{it} + \alpha_2 Controls_{itj} + \epsilon_{ijt} \tag{10}$$

Table IV: **Estimation of Regression 1**
This table reports estimates of Regression 1, which estimates the effect of changes in stock-specific information on simultaneous trades between stocks and ETFs which contain them. I consider two different measures of stock-specific information: earnings dates and absolute value of the return. Earnings Date is an indicator which takes the value 1 for stocks which announce earnings before the day's trading session. Abs Return is the absolute value of the intraday return, measured as a percentage. The sample is SPDR and the ten Sector SPDR ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

	Dependent variable: Simultaneous Trades			
	(1)	(2)	(3)	(4)
Weight	60.867***	54.191**	48.015***	51.383***
	(20.408)	(21.120)	(16.075)	(19.594)
Earnings Date	−12.717***	−8.568***		
	(2.679)	(1.486)		
Abs ETF Return		106.948**		104.848**
		(44.355)		(43.799)
Abs Return			21.432***	3.721**
			(8.247)	(1.645)
Weight∗ Abs Return			14.732***	10.809*
			(5.715)	(6.033)
Weight∗ Earnings Date	6.188***	3.827**		
	(1.659)	(1.761)		
Weight∗ Abs ETF Return		8.652		−0.579
		(9.632)		(11.832)
Observations	873,196	873,196	873,178	873,178
R^2	0.095	0.131	0.110	0.133
Residual Std. Error	410.309	402.051	406.833	401.431
Standard Errors Clustered by ETF.		*p<0.1; **p<0.05; ***p<0.01		

Results are presented in Table V. Small stocks see fewer trades on earnings dates, while large stocks see far more. This is consistent with the idea that investors with information about small stocks face adverse selection in the ETF. During earnings dates, the adverse selection in the ETF would outweigh any benefit from trading the ETF based on their small-stock info. Across returns, however, there is no evidence of exclusion, with larger absolute returns leading to more simultaneous trades for each of the three stock categories.

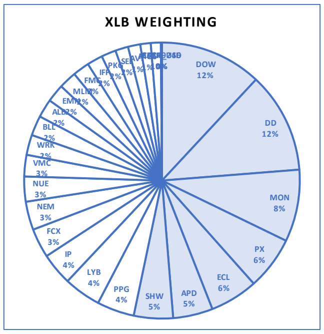
To investigate how simultaneous trading activity varies with the stock-specific return, I further sub-divide my sample based with an indicator on the size of each return:

REGRESSION 3: *For stock i, ETF j, and day t:*

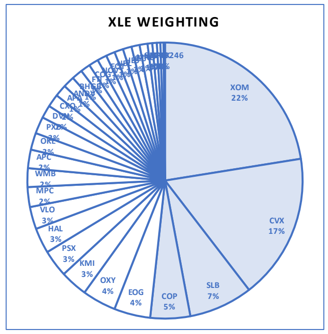
$$Simultaneous\ Trades_{ijt} = \alpha_0 + Size * \alpha_1 Largest\ X\ Abs\ Return_{it} + \alpha_2 Controls_{itj} + \epsilon_{ijt} \tag{11}$$

Largest X Abs Return is an indicator that takes the value of 1 on the dates for which each stock has its $X\%$ most positive and $X\%$ most negative intraday returns. Controls include a fixed effect for each ETF as well as a similarly defined Largest X indicator which takes the value of 1 on the dates for which each ETF has its $X\%$ most positive and $X\%$ most negative intraday returns.

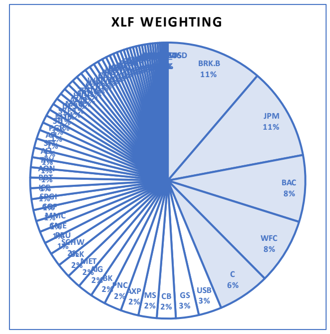
Results are presented in Table VI. Across all three size categorizations of stocks, stocks have more stock–ETF simultaneous trades on dates with large absolute returns. This pattern increases in the level of the return: as the indicator on returns selects more extreme returns, the estimated coefficient increases. Large stocks have the highest level of simultaneous trades, but all three size categories of stocks present the same pattern that more extreme returns lead to more trade-both behavior by investors.



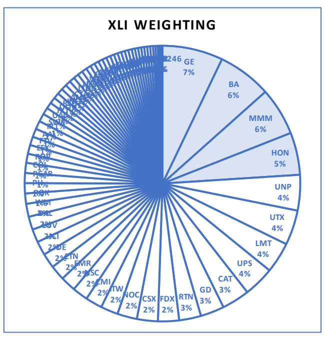
(a) Materials



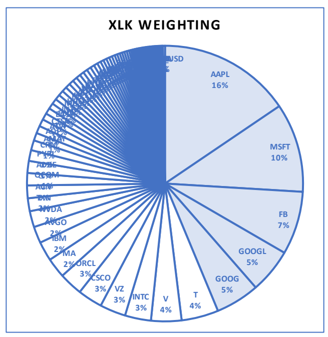
(b) Energy



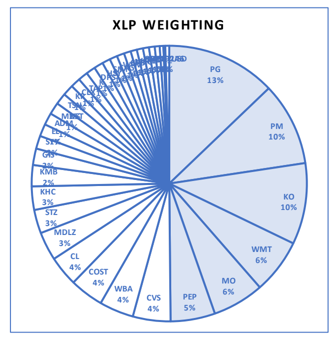
(c) Financials



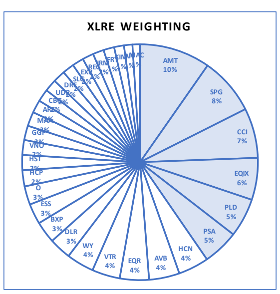
(d) Industrials



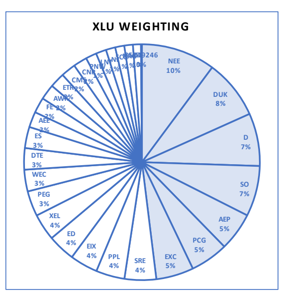
(e) Technology



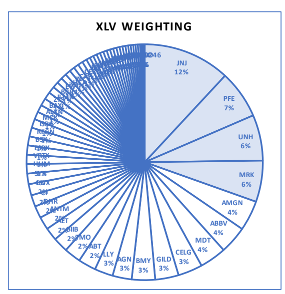
(f) Consumer Staples



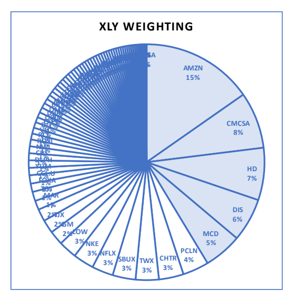
(g) Real Estate



(h) Utilities



(i) Health Care



(j) Consumer Discr.

Figure 8. Holdings of the Sector SPDRs. Stocks which comprise more than 5% of the ETF holdings are highlighted in light blue. The Sector SPDRs are highly concentrated. Exxon Mobile, for example, comprises 22% of the holdings of the Energy ETF, and just four stocks comprise over half the holdings of XLE.

Table V Estimation of Regression 2: Size Comparison
This table reports estimates of Regression 2, which estimates the effect of changes in stock-specific information across different ETF weights. Earnings Date is an indicator which takes the value 1 for stocks which announce earnings before the day's trading session. Abs Return is the absolute value of the intraday return, measured as a percentage. I categorize small stocks as those with a weight less than 2%, medium stocks with weight between 2% and 5%, and large stocks with a weight greater than 5%. The sample is the ten Sector SPDR ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

	Simultaneous Trades	
	(1)	(2)
Medium Stocks	133.403***	106.088***
	(30.442)	(24.025)
Large Stocks	334.801***	233.591***
	(84.419)	(53.749)
Earnings Date∗Small Stock	−2.109	
	(2.876)	
Earnings Date∗Medium Stock	12.477**	
	(5.566)	
Earnings Date∗Large Stock	34.357***	
	(13.075)	
Abs Return∗Small Stock		12.362***
		(3.170)
Abs Return∗Medium Stock		39.851***
		(10.803)
Abs Return∗Large Stock		127.834***
		(37.647)
Observations	443,500	443,490
R^2	0.255	0.284
Residual Std. Error	215.612	211.320
Standard Errors Clustered by ETF:	*p<0.1; **p<0.05; ***p<0.01	

Table VI : Estimation of Regression 3 - Return Comparison

This table reports estimates of Regression 3. For each stock, largest $X\%$ Abs Return is an indicator which takes the value one on days for which the intraday return is among the most positive $X\%$ or most negative $X\%$ of returns for that stock. I include an equivalently defined daily indicator on the ETF return for whether the ETF return is among the most positive $X\%$ or most negative $X\%$. Small stocks are stocks with less than 2% ETF weight, medium stocks are 2% to 5%, and large stocks have greater than 5% weight. The sample is the ten Sector SPDR ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

Panel A: Regression Estimates with Small Stocks

	Simultaneous Trades			
	(1)	(2)	(3)	(4)
Largest 1% Abs Return	32.216***			
	(8.522)			
Largest 5% Abs Return		22.117***		
		(4.611)		
Largest 10% Abs Return			21.275***	
			(3.809)	
Largest 20% Abs Return				17.605***
				(3.000)
Largest X% ETF return	x	x	x	x
Observations	310,127	310,127	310,127	310,127
R^2	0.175	0.196	0.194	0.187
Residual Std. Error (df = 310115)	120.300	118.734	118.858	119.417

Panel B: Regression Estimates with Medium Stocks

	Simultaneous Trades			
	(1)	(2)	(3)	(4)
Largest 1% Abs Return	106.289***			
	(35.573)			
Largest 5% Abs Return		65.571***		
		(18.475)		
Largest 10% Abs Return			56.882***	
			(16.180)	
Largest 20% Abs Return				49.015***
				(14.523)
Largest X% ETF return	x	x	x	x
Observations	96,276	96,276	96,276	96,276
R^2	0.270	0.296	0.293	0.285
Residual Std. Error (df = 96264)	222.686	218.712	219.168	220.378

Table VI: (continued from previous page)

Panel C: Regression Estimates with Large Stocks

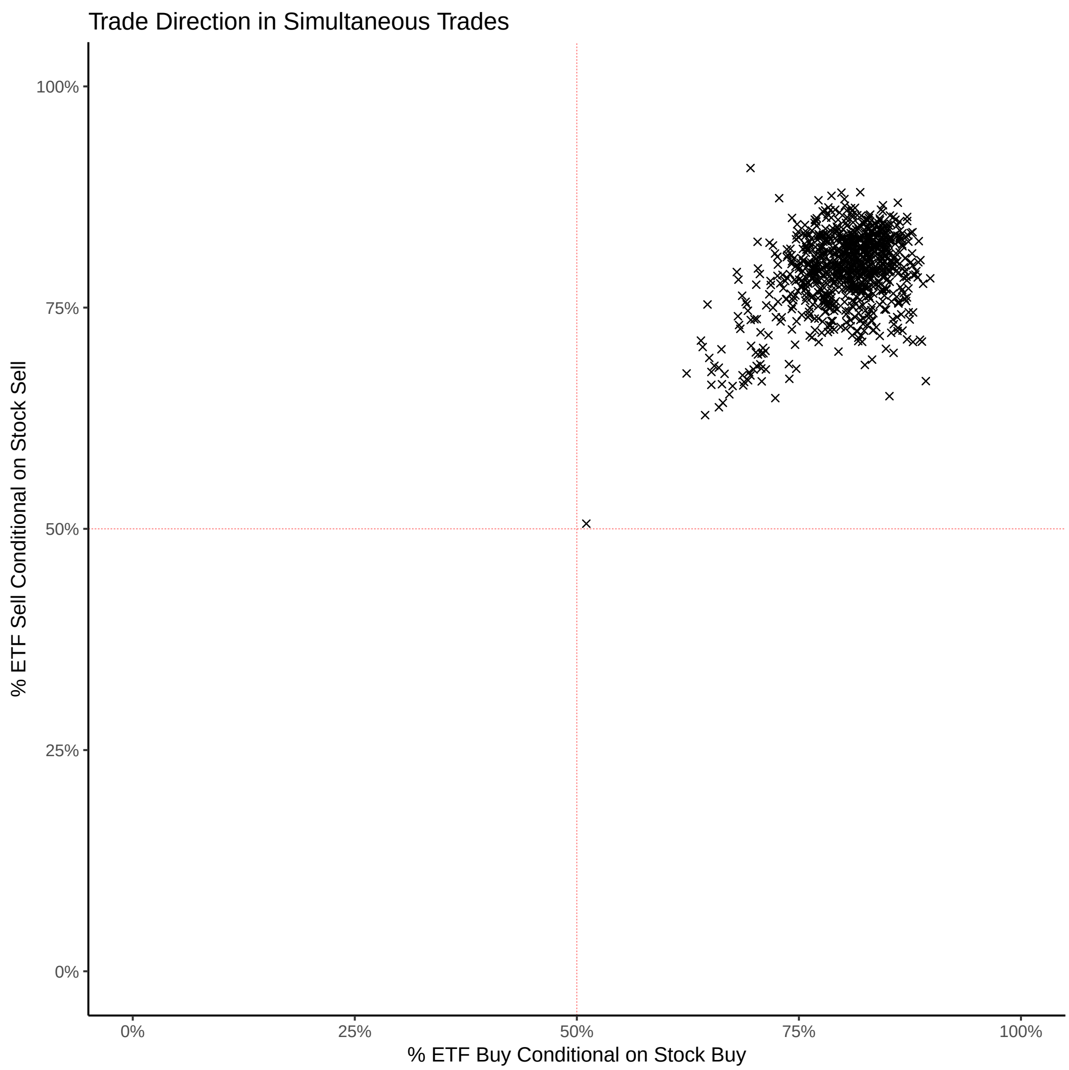
	Simultaneous Trades			
	(1)	(2)	(3)	(4)
Largest 1% Abs Return	261.189***			
	(93.334)			
Largest 5% Abs Return		160.613***		
		(55.250)		
Largest 10% Abs Return			142.541***	
			(44.012)	
Largest 20% Abs Return				116.319***
				(34.302)
Largest X% ETF return	x	x	x	x
Observations	37,097	37,097	37,097	37,097
R^2	0.265	0.291	0.287	0.280
Residual Std. Error (df = 37085)	491.080	482.633	483.990	486.316

D. *Signed Trades*

One alternative explanation for the spike in cross market activity is that it represents hedging or "arbitrage," where an investor takes opposite positions in the two securities. Evidence from signed trades rules out this story. I show that these simultaneous trades are primarily simultaneous buy orders, where an investor buys both the stock and the ETF, or simultaneous sell orders, where an investor sells both the stock and the ETF.

I sign trades following Chakrabarty, Li, Nguyen, and Van Ness (2007), though results with trades signed according to Lee and Ready (1991) are similar. Figure 9 plots the percentage of simultaneous trades which have the same sign (ETF buys with stock buys or ETF sells with stock sells). With respect to both stock buy orders and stock sell orders, ETF trades overwhelmingly have the same sign. Trades in the same direction are inconsistent with arbitrage trades, which would require that investors buy one security while selling another. Attenuation from mis-signed trades would move data toward a 50-50 chance of buying or selling. Since almost all days are clustered around 80% of trades having the same sign, any inaccuracies in trade signing biases the results toward more mixed-sign trades, and fewer same-sign trades.

Figure 9. Trade Direction. Simultaneous trades are overwhelmingly in the same direction. Each point represents one day of an ETF-stock pairing. For the buy orders in the stock, the X-axis shows the percentage of simultaneous ETF trades which are also buy orders. For the sell orders in the stock, the X-axis shows the percentage of simultaneous ETF trades which are also sell orders. Thus the top right of the graph, at $(100, 100)$ would have all simultaneous trades from the day having the same sign, while the bottom left of the graph $(0, 0)$ would have all simultaneous trades having the opposite sign.



To confirm the intuition from Figure 9, I run a regression to analyze the effect of measures of stock-specific information on the change in simultaneous trades with the same direction. As before, substantial stock-specific, either due to the size of the information asymmetry or the ETF weight, should lead to more simultaneous activity. In this specification, however, I use signed trades and check that there are more simultaneous trades of the same sign. For the stock sign $S_i = \{buy, sell\}$

and ETF sign $Y = \{buy, sell\}$, I run four regressions of the form:

REGRESSION 4:

$$\begin{aligned} Simultaneous\ Trades\_S\_Y_{ijt} = \alpha_0 + \alpha_1 Earnings\ DateX_{ijt} + \alpha_2 Weight_{ijt} \\ + \alpha_3 Weight_{ijt} * Earnings\ DateX_{ijt} + \alpha_4 Controls_{ijt} + \epsilon_{ijt} \end{aligned} \tag{12}$$

Results are presented in Table VII. After an earnings announcement, stocks see a large increase in simultaneous trades in the same direction. Investors buy both the stock and the ETF at the same time, or sell both the stock and the ETF at the same time. The greater the weight of the stock in the ETF, the larger this increase in simultaneous trades of the same sign. I also estimate Regression VII for the absolute stock return, and find similar results.

Finally, it is worth noting that these results do not rule out that hedging occurs, but only that the simultaneous trades are not hedging. If an investor is seeking to buy both a stock and an ETF which contains that stock, executing the trades simultaneously is important, as trading in one asset could push up the cost of the other. If investors are using ETFs to hedge industry exposure, as in Huang et al. (2018), there is no need to execute the trades within microseconds of each other. If anything, an investor would want to wait to take the hedging position, as a buy order for a stock may push up the ETF price prior to their selling the ETF (and vice versa).

Table VII : Estimation of Regression 4 - Signed Trades

This table reports estimates of Regression 4, which estimates the effect of stock-specific information on stock–ETF simultaneous trades of a particular trade sign. Column (1) estimates the effect for simultaneous buy orders. Column (2) estimates the effect for simultaneous trades comprised of a buy order in the stock with a sell order in the ETF. Column (3) estimates the effect for a sell order in the stock with a buy order in the ETF. Column (4) estimates simultaneous sell orders. Earnings Date is an indicator which takes the value 1 for stocks which announce earnings before the day's trading session. Abs Return is the absolute value of the intraday return, measured as a percentage. The sample is SPDR and the ten Sector SPDR ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

Panel A: Regression Estimates with Absolute Return

	Dependent variable: Simultaneous Trades			
	(1)	(2)	(3)	(4)
Stock Trade Sign:	BUY	BUY	SELL	SELL
ETF Trade Sign:	BUY	SELL	BUY	SELL
Weight	5.762***	1.710**	1.835**	5.813***
	(1.990)	(0.684)	(0.736)	(2.072)
Abs Return	0.510***	0.164	0.165	0.526***
	(0.182)	(0.105)	(0.105)	(0.203)
Abs ETF Return	11.673***	5.096**	5.534**	14.275***
	(4.206)	(2.091)	(2.356)	(5.269)
Weight∗Abs Return	1.305**	0.523**	0.526**	1.390**
	(0.647)	(0.219)	(0.227)	(0.668)
Weight∗Abs ETF Return	0.439	0.101	−0.013	0.367
	(1.256)	(0.534)	(0.553)	(1.410)
Observations	873,422	873,465	873,417	873,460
R^2	0.178	0.126	0.128	0.172
Residual Std. Error	41.195	17.398	17.812	44.335
Standard Errors Clustered by ETF.				*p<0.1; **p<0.05; ***p<0.01

Table VII: (continued from previous page)

Panel B: Regression Estimates With Earnings Dates

	Dependent variable: Simultaneous Trades			
	(1)	(2)	(3)	(4)
Stock Trade Sign:	BUY	BUY	SELL	SELL
ETF Trade Sign:	BUY	SELL	BUY	SELL
Weight	6.094***	1.844**	1.971**	6.166***
	(2.142)	(0.735)	(0.790)	(2.230)
Earnings Date	−0.374	0.007	−0.114	−0.626**
	(0.276)	(0.231)	(0.182)	(0.307)
Weight∗Earnings Date	0.740***	0.354***	0.344***	0.967***
	(0.263)	(0.120)	(0.128)	(0.214)
Abs ETF Return	11.972***	5.186**	5.625**	14.580***
	(4.282)	(2.155)	(2.419)	(5.361)
Weight∗ Abs ETF Return	1.553	0.546	0.436	1.554
	(1.045)	(0.472)	(0.476)	(1.193)
Observations	873,440	873,483	873,435	873,478
R^2	0.174	0.123	0.125	0.169
Residual Std. Error (df = 873424)	41.286	17.430	17.844	44.430

Standard Errors Clustered by ETF. *p<0.1; **p<0.05; ***p<0.01

E. *Effect of Simultaneous Trades*

The trade characteristics of simultaneous trades are consistent with these trades being informationally-motivated. I consider two measures: price impact and realized spread. Price impact measures the change in price per unit of volume. Realized spread is the difference between the trade price and the price five minutes after the trade. Table X summarizes these trade characteristics. Simultaneous trades have a much larger price impact in both the ETF and the single stock. Realized spreads for simultaneous trades are negative, suggesting the traders who place these orders earn immediate trading profits. For stock trades, the average realized spread is around 1 cent, which would suggest market makers earn an average of 1 cent per share. In simultaneous trades, this is reversed, with a negative 1 cent spread, suggesting market makers loose 1 cent per share to traders who trade stocks and ETFs simultaneously. This is consistent with the idea that these simultaneous trades are placed by informed traders who increase their profits by trading both a stock and the ETF.

The total size of these simultaneous trades is also considerable. Table IX presents volume shares for Sector SPDRs, while Table VIII presents the volume shares for SPY. As much as 1% to 2% of sector ETF volume comes from these simultaneous orders from a single stock. In SPY, simultaneous trades with a stock like Apple or Microsoft can comprise 0.3% to 0.8% of daily ETF volume. All these numbers are obtained by taking the raw simultaneous volume and subtracting off a baseline level of cross-market activity estimated from trades that take place between 1 and 2 microseconds apart.

Table VIII: SPY Volume Shares. This table shows the volume share of simultaneous trading activity in each ETF for stocks which have at least 1.5% weight in SPY. For each stock, I give the 10^{th}, 50^{th} and 90^{th} percentiles of daily observations of this share. For example, on a median day 0.33% of the daily trading volume in SPY occurs in trades that are simultaneous with trades in Apple.

Stock	ETF	10%	50%	90%
AAPL	SPY	0.19	0.33	0.68
MSFT	SPY	0.15	0.25	0.86
XOM	SPY	0.05	0.1	0.15
JNJ	SPY	0.06	0.1	0.18
GE	SPY	0.05	0.08	0.15
FB	SPY	0.11	0.2	0.4
AMZN	SPY	0.05	0.08	0.19
JPM	SPY	0.12	0.26	0.46
GOOG	SPY	0.06	0.1	0.13

Table IX: Sector SPDR Volume Shares. This table shows the volume share of simultaneous trading activity in each ETF for stocks which have at least 10% weight in a Sector SPDR. For each stock, I give the 10^{th}, 50^{th} and 90^{th} percentiles of daily observations of this share. For example, on a median day, 1.15% of the daily trading volume in XLK occurs in trades that are simultaneous with trades in Apple.

Stock	ETF	10%	50%	90%
AAPL	XLK	0.74	1.15	1.92
MSFT	XLK	0.69	1.19	2.49
CVX	XLE	0.30	0.44	0.66
XOM	XLE	0.30	0.48	0.83
GE	XLI	0.30	0.45	0.63
PG	XLP	0.34	0.52	0.75
DD	XLB	0.24	0.33	0.49
DOW	XLB	0.32	0.47	0.67
DWDP	XLB	0.55	0.8	1.08
LIN	XLB	0.16	0.23	0.25
JNJ	XLV	0.29	0.45	0.71
AMZN	XLY	0.38	0.7	0.97
HD	XLY	0.28	0.37	0.48
JPM	XLF	0.55	0.92	1.46
WFC	XLF	0.53	0.53	0.53
PM	XLP	0.38	0.38	0.38
KO	XLP	0.38	0.51	0.73
FB	XLC	1.52	2.12	3.10
GOOG	XLC	0.75	0.95	1.25
NEE	XLU	0.31	0.54	0.77

Table X Summary Of Trade Characteristics. This table reports mean price impacts and mean realized spreads for trades, measured in cents. Simultaneous trades have much higher price impacts and earn negative realized spreads, consistent with market makers viewing these trades as well informed.

	All Trades	Simultaneous Trades
ETF Price Impact	0.189	1.739
Stock Price Impact	2.934	3.284
ETF Realized	0.042	-0.583
Stock Realized	1.011	-1.032

F. Intraday News Events

As an alternative measure of stock-specific news events, I use the Dow Jones Edition and PR Edition data from Ravenpack Analytics. These datasets aggregate news wires and media articles about companies. From August 2015 to December 2018, there are 136,000 unique news articles related to the stocks in my sample. Ravenpack data allows analysis of intra-day trading patterns. For a stock which has a news event, I calculate—over 5 and 30 minute intervals both before and after the news event—simultaneous activity between that stock and the Sector SPDR. I also calculate these measures of stock-Sector SPDR simultaneous trades for each of the other stocks from the Sector SPDR of the stock which had the news event. This allows a comparison between the stock which has the news event against the other stocks in the sector.

I re-estimate Regression 2 for the 5 and 30 minute intervals before and after each news event. Information is now an indicator which takes the value of one for the stock in the sector SPDR which had the news event. I also include a fixed effect for each news event.

Results are presented in Table XI. When small stocks have a news event, there is no increase in simultaneous trading at any time horizon. This is consistent with the idea that traders with small-stock information face exclusion from the ETF due to the adverse selection they face from traders with more substantial information. For medium stocks, there is a modest increase in simultaneous trades around the event, with an extra 1 to 2 simultaneous trades per hour. Large stocks have a substantial increase in simultaneous activity over a wide time horizon. When a large stock has a news story, there are an additional 17 simultaneous trades per hour relative to the other stocks in that sector. Large stocks typically see 30 to 60 simultaneous trades per hour, so this represents a 25 to 50% increase over the normal rate of simultaneous trades.

Table XI: **Estimation of Regression 2 Using Ravenpack News Events**

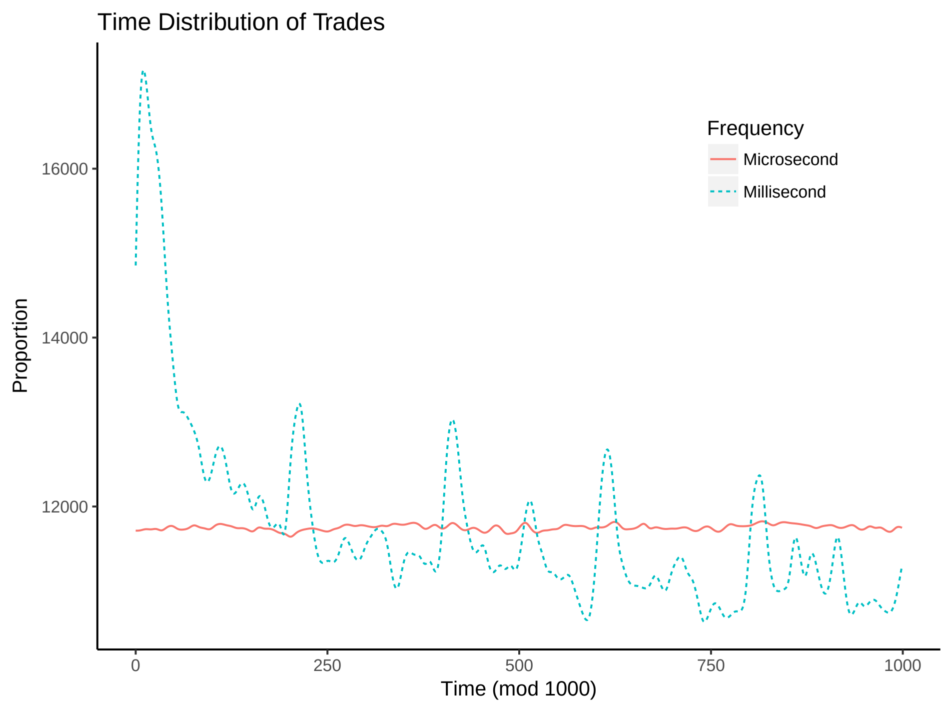
This table reports estimates of Regression 2 around news events. For each company-specific news event, I take all stocks from that company's GICS sector, and measure all the stock-Sector SPDR simultaneous trades over 5 and 30 minute intervals both before and after the event. *Stock News* is an indicator which takes the value of 1 for the company which had the news event. Small stocks are stocks with less than 2% ETF weight in a Sector SPDR. Medium stocks have 2 to 5% ETF weight, and large stocks have an ETF weight greater than 5%. Controls include a fixed effect for each ETF, a fixed effect for each stock category, as well as a fixed effect for each news event. Standard Errors are clustered by ETF.

	Total Trades Per Hour			
	Before		*After*	
	30 Min	5 Min	5 Min	30 Min
Small Stock News	-0.056	0.267	-0.029	-2.615^{***}
	(0.150)	(0.284)	(0.376)	(0.366)
Medium Stock News	0.291^{**}	1.349^{***}	1.462^{***}	1.547^{**}
	(0.131)	(0.505)	(0.442)	(0.612)
Large Stock News	3.350^{**}	9.206	9.062^{*}	17.074^{***}
	(1.649)	(5.707)	(4.737)	(4.679)
Observations	8,825,809	8,825,809	8,825,809	8,825,809
R^2	0.446	0.299	0.304	0.379
Residual Std. Error	8.874	47.356	48.421	11.607
Standard Errors Clustered by ETF:				*p<0.1; **p<0.05; ***p<0.01

G. Trade Timing

In this section, I verify that the results are not due to patterns in the timing of trading activity. Trading activity is not uniform throughout the day. Hasbrouck and Saar (2013), for example, note that there is a large spike in trading activity in the first few milliseconds of each second, suggesting algorithmic trading at a one-second frequency. Higher levels of algorithmic trading would lead to higher levels of trading in the first few microseconds of each second.

Figure 10. Time Distribution of Trades. I plot clock-time periodicities of trades for a subset of the data: XLE and the top 10 underlying stocks for September, 2016. Consider a timestamp in the form HH:MM:SS.mmm$\mu\mu\mu$. The three blue digits are the milliseconds, while the three red digits are the microseconds. There is a clear spike in trades in the first few milliseconds of each second (dashed blue line). Hasbrouck and Saar (2013) argue this could be algorithmic trading activity. The distribution of trades at the microsecond level (solid red line), however, is uniform.



I plot the distribution of trades at the millisecond and microsecond level in Figure 10. At the microsecond level, trade distribution is uniform. To confirm that my results are not driven by some form of periodic algorithmic trading, I re-estimate Regression 1 on a restricted subsample. From the sample of all trades, I eliminate trades occurring in the first 200 milliseconds of each second. This leaves trades occurring only between $(200, 999)$ of each millisecond to avoid any spikes in activity around 0 microseconds. Results for this regression are presented in Table XII and are similar to the previous estimation of Regression 1.

Table XII: **Robustness Check of Regression 1- Time Restricted Sub-Sample**
This table reports estimates of Regression 1 on a time restricted subsample. To control for changes in algorithmic trading, I exclude all trades which occur in the first 200 milliseconds of each second. I measure stock–ETF simultaneous trades on the trades which remain. Earnings Date is an indicator which takes the value 1 for stocks which announce earnings before the day's trading session. Abs Return is the absolute value of the intraday return, measured as a percentage. The sample is SPDR and the ten Sector SPDR ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

	Simultaneous Trades	
	(1)	(2)
Weight	16.064***	15.110***
	(5.882)	(5.468)
Earnings Date	−1.099	
	(0.909)	
Weight∗Earnings Date	2.400***	
	(0.640)	
Abs Return		1.367**
		(0.583)
Weight∗Abs Return		3.738**
		(1.754)
Abs ETF Return	37.335***	36.548***
	(14.203)	(13.908)
Weight∗Abs ETF Return	4.089	0.898
	(3.179)	(3.749)
Observations	873,244	873,226
R^2	0.166	0.169
Adjusted R^2	0.166	0.169
Residual Std. Error	116.811	116.553
Standard Errors Clustered by ETF.	*p<0.1; **p<0.05; ***p<0.01	

H. Equal Weight Sector SPDRs

In this section, I analyze cross market activity between the same stocks of the S&P 500, and a set of equal-weighted ETFs from Investco. For each of the State Street SPDR ETFs, there is an equivalent Investco Equal Weight ETF which holds the same exact stocks. The Investco ETFs, however, give each stock an equal weight in the ETF rather than value weights.

I measure cross market activity between stocks and the equal-weight ETF. When I look at how cross market activity changes across stocks, however, I use the market value weights of each stock. Thus I expect a null result: large-cap stocks should not have any more cross market activity with Investco ETFs than small-cap stocks, given that the Investco ETFs hold all stocks in equal proportion. Table XIII shows the estimation of Regression 1. Coefficient estimates are almost all near zero, and there is no difference between large and small stocks.

One drawback of the Investco Equal Weight ETFs is that they have low daily trading volume. I therefore conduct a second test, this time using the Sector SPDRs with improper pairings. By improper pairings, I match a stock from sector i with the ETF for sector j, using the sector weight of stock i. As before, I expect a null result: if a stock like Exxon announces earnings or has a large return, investors with Exxon-specific information should not simultaneously trade Exxon and an unrelated Sector SPDR, like the Financials or Health Care ETF.

Table XIV presents the results of this comparison. The coefficient estimate for earnings dates is negative and insignificant. The coefficient estimates for the weight-return and weight-volatility interaction terms are positive, but around 5 times smaller than the previous estimates.

Table XIII : Estimation of Regression 1 with Equal Weight ETFs (Placebo)
This table reports estimates of Regression 1 on a placebo sample. stock–ETF simultaneous trading activity is measured with a set of Investco equal-weight ETFs. Sector SPDR Weight is the (value-weighted) ETF weight of each stock in the State Street SPDR. The sample is the ten Investco Sector ETFs and their stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

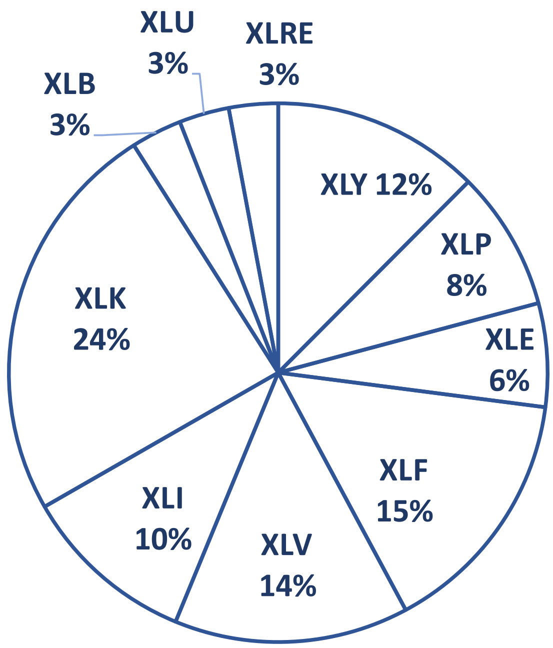
	Simultaenous Trades			
	(1)	(2)	(3)	(4)
Sector SPDR Weight	0.501	0.869	0.558	0.850
	(0.466)	(0.640)	(0.439)	(0.615)
Earnings Date	-0.578^{**}	-0.469^{***}		
	(0.258)	(0.161)		
Abs Return			0.821^{**}	0.176^{*}
			(0.368)	(0.099)
Sector SPDR Weight∗Earnings Date	0.105^{**}	0.096^{***}		
	(0.048)	(0.036)		
Sector SPDR Weight∗ Abs Return			−0.021	0.106
			(0.056)	(0.111)
Abs ETF Return		3.621^{*}		3.506^{*}
		(1.860)		(1.802)
Sector SPDR Weight∗Abs ETF Return		-0.474^{**}		-0.567^{*}
		(0.241)		(0.331)
Observations	969,378	969,378	969,378	969,366
R^2	0.100	0.125	0.100	0.126
Residual Std. Error	13.079	12.890	13.079	12.885
Standard Errors Clustered by ETF.		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table XIV : Estimation of Regression 1 with Improper SPDR Pairings (Placebo)
This table reports estimates of Regression 1 on a placebo sample. stock–ETF simultaneous trading activity is measured between each sector SPDR and any S&P 500 Constituents which are not in that sector. Weight is the value weight of each stock in its industry sector. The sample is the ten Sector SPDR ETFs and the S&P stock constituents from August 1, 2015 to December 31, 2018. The frequency of observations is daily. I include a fixed effect for each ETF and cluster standard errors by ETF.

	Dependent variable: Simultaneous Trades	
	(1)	(2)
Weight	3.239***	3.030***
	(0.644)	(0.631)
Earnings Date	−0.234	
	(0.425)	
Abs Return		0.152
		(0.563)
Weight∗ Earnings Date	−0.442	
	(0.308)	
Weight∗ Abs Return		0.844**
		(0.394)
Abs ETF Return	5.149***	5.188***
	(0.939)	(1.039)
Weight∗ Abs ETF Return	2.312*	1.599
	(1.326)	(1.351)
Observations	4,366,305	4,366,251
R^2	0.172	0.186
Adjusted R^2	0.172	0.186
Residual Std. Error	45.107	44.721
Standard Errors Clustered by ETF.		*p<0.1; **p<0.05; ***p<0.01

I. SPDR and Sector SPDRs

Figure 11. SPDR Sector Weights. The stocks of SPDR are divided into sector SPDR ETFs according to their GICS Industry Classification codes. This chart shows the weight of each sector in the S&P 500.



The stocks of S&P 500 are divided into Sector SPDR ETFs according to their GICS Industry Classification codes. The SPDR ETF could therefore be thought of as a portfolio of the different Sector SPDRs. Figure 11 shows the weight of each sector in the S&P 500.

Just as investors with stock-specific information should trade ETFs, investors with Sector SPDR information should trade SPDR. I re-estimate Regression 1 using the Sector SPDR pairings with SPDR. While there are not earnings dates for sector SPDR, I can use the absolute value of the intraday sector return as a measure of information asymmetry.

Results are in Table XV. Larger absolute sector returns lead to a significant increase in simultaneous trades. This is consistent with the idea that investors with sector-specific information who are looking for additional liquidity in a sector also trade SPDR itself. In the estimation of Equation 8, larger weight sectors also see a significant increase in cross market activity. The weight-return interaction is positive, but not significant after controlling for the index return.

Table XV: Estimation of Regression 1 with Sector ETFs and SPDR

This table reports estimates of Regression 1 using Sector-SPDR pairings with the SPDR index. Abs Sector Return measures the intraday return of a Sector SPDR. I also control for the return on the SPDR index, and control for a weight-return interaction. The sample is SPDR and the ten Sector SPDR ETFs from August 1, 2015 to December 31, 2018. The frequency of observations is daily.

	Dependent variable: Simultaneous Trades	
	S	
	(1)	(2)
Weight	45.652***	55.705***
	(5.717)	(5.221)
Abs Sector Return	735.027***	411.890***
	(114.259)	(127.013)
SPY Return		918.593***
		(114.557)
Weight∗Abs Sector Return	61.662***	7.574
	(8.996)	(12.866)
Weight∗SPY Return		52.398***
		(16.509)
Constant	475.265***	181.741***
	(73.155)	(69.840)
Observations	8,257	8,257
R^2	0.154	0.199
Adjusted R^2	0.154	0.198
Residual Std. Error	2,789.534 (df = 8253)	2,715.770 (df = 8251)
Note:		*p<0.1; **p<0.05; ***p<0.01

VII. Conclusion

My paper is the first to model and empirically demonstrate when investors strategically trade stocks and ETFs in tandem, and how this leads to stock-specific price discovery from ETFs. Trading stocks and ETFs in tandem allows investors with stock-specific information to reduce the market impact of their trades and increase profits. This trade-both behavior attenuates concerns about the impact of ETFs on price discovery. If noise traders do move to ETFs, informed traders follow them. Profitable trading opportunities, as well as the requisite acquisition of private information, are maintained. Rigid co-movement is avoided; following an ETF trade, market makers have flexibility in updating quotes. Stocks with a certain value or a low level of informed trading receive small quote changes, while stocks with an uncertain value or a high level of informed trading receive larger quote changes.

The stock–ETF relationship varies depending upon both the stock weight in the ETF and the level of asymmetric information in the stock. Viability of the trade-both strategy requires both a sufficiently high weight of the stock in the ETF and a large enough information asymmetry. When these conditions are met, investors trade both the stock and the ETF—and they trade both in the same direction. This behavior creates adverse selection in the ETF, whereby different pieces of information in the ETF behave as substitutes. On the other hand, traders with information about small stocks or small information asymmetries can be excluded from the ETF whenever their information's value in pricing the ETF is less than the cost of adverse selection from other traders in the ETF.

With precise timestamp data, I am able to exploit exchange latencies to identify investors who trade both the stock and the ETF simultaneously. These simultaneous trades have the same sign—buys in both markets or sells in both markets—which is inconsistent with an arbitrage story. Simultaneous trades have larger price impacts than average trades, and earn negative realized spreads on both the stock and ETF portion of the trade. Market makers appear to view these simultaneous trades as well informed.

Large stock-specific information—as measured by earnings dates, returns, or news events—leads to large increases in single-stock–ETF simultaneous trades. This increase in simultaneous trades does not show up between a stock and an unrelated ETF, and does not appear to be sensitive to the distribution of trades across time. As the model predicts, effects are stronger both in larger stocks and larger informational events as measured by the realized return. The overall volume of these simultaneous trades is significant, comprising 1% to 2% of sector ETF daily volume and 0.3% to 0.5% of SPDR volume.

The price discovery process takes place across multiple assets and many exchanges. I show that ETFs are an important venue for stock-specific price discovery. Potential harms from ETFs rely on the assumption that ETFs completely screen out stock-specific information. I show that these harms are mainly localized to small stocks and small informational asymmetries. When investors have stock-specific information which is substantial on account of the ETF-weight or the size of the informational asymmetry, investors with this stock-specific information trade both stocks and ETFs. In these settings, I conclude that ETFs can provide provide stock-specific price discovery.

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Appendix A. Analysis of Informed Trader Profits

In this subsection, I consider the effect of the existence of the ETF on the profits of informed traders. In the fully separating equilibria, informed investors do not trade the ETF. The level of noise traders in the ETF is inconsequential to the profits of informed traders. In the absence of the ETF, if any of the market noise traders would trade single stocks, then the existence of the ETF has an unambiguously negative effect on informed trader profits.

With the pooling equilibria, informed traders can make profits from market noise traders in the ETF. If there are ζ_A stock A noise traders in the absence of the ETF, then informed trader profits are:

$$\delta \frac{\frac{1}{2}\varsigma_A}{(1-\delta)\mu_A + \frac{1}{2}\varsigma_A} \qquad \text{(Profit with no ETF)}$$

$$\delta \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A(1-\psi_2) + \frac{1}{2}\sigma_A} \qquad \text{(Profit with ETF)}$$

$$\begin{aligned}
\delta \frac{\frac{1}{2}\varsigma_A}{(1-\delta)\mu_A + \frac{1}{2}\varsigma_A} &\leq \delta \frac{\frac{1}{2}\sigma_A}{(1-\delta)\mu_A(1-\psi_2) + \frac{1}{2}\sigma_A} \\
\varsigma_A\left((1-\delta)\mu_A(1-\psi_2) + \frac{1}{2}\sigma_A\right) &\leq \sigma_A\left((1-\delta)\mu_A + \frac{1}{2}\varsigma_A\right) \\
\varsigma_A(1-\delta)\mu_A(1-\psi_2) + \varsigma_A\frac{1}{2}\sigma_A &\leq \sigma_A(1-\delta)\mu_A + \sigma_A\frac{1}{2}\varsigma_A \\
\varsigma_A(1-\delta)\mu_A(1-\psi_2) &\leq \sigma_A(1-\delta)\mu_A \\
\varsigma_A(1-\psi_2) &\leq \sigma_A \\
\varsigma_A\left(1 - \frac{\phi(1-\delta)\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{\mu_A(1-\delta)[\sigma_A + \phi\sigma_M]}\right) &\leq \sigma_A \\
\varsigma_A \frac{\mu_A(1-\delta)\sigma_A - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{\mu_A(1-\delta)[\sigma_A + \phi\sigma_M]} &\leq \sigma_A \\
\varsigma_A \frac{\mu_A(1-\delta) - \frac{1}{2}(1-\phi)\sigma_M}{\mu_A(1-\delta)[\sigma_A + \phi\sigma_M]} &\leq 1 \\
\varsigma_A &\leq \frac{\mu_A(1-\delta)[\sigma_A + \phi\sigma_M]}{\mu_A(1-\delta) - \frac{1}{2}(1-\phi)\sigma_M}
\end{aligned}$$

Suppose that in the absence of the ETF, the market noise traders would trade each stock in proportion to its ETF weight. Then we have that $\zeta_A = \sigma_A + \phi\sigma_M$. Under this assumption, trading profits for investors with stock-specific information will always be lower with the ETF than without the ETF. If there are cases where $\zeta_A > \sigma_A + \phi\sigma_M$, however, informed profits could be higher rather than lower. This case is a natural one when noise traders adjust their volume with market conditions. Under Admati and Pfleiderer (1988), noise traders seek to trade at times when adverse selection is low. In the absence of the ETF, σ_M traders might trade only stocks with low adverse selection, and avoid stocks with high adverse selection. Once the ETF is added, the market noise traders may trade the ETF at a more constant rate. This means that the market noise traders are always available for the informed traders, and investors with stock-specific information may see improved profits.

The ETF allows a change in trading profits both across stocks and across time. Large stocks can more easily access ETF liquidity than small stocks, especially because different pieces of information act as substitutes in the ETF. But traders informed about a large informational asymmetry (i.e. the information disparity between the informed and uninformed is large) can also more easily access noise traders in the ETF. While the ETF offers some screening from stock-specific information, the ETF is always available to informed traders, and becomes most useful when stocks face extreme illiquidity.

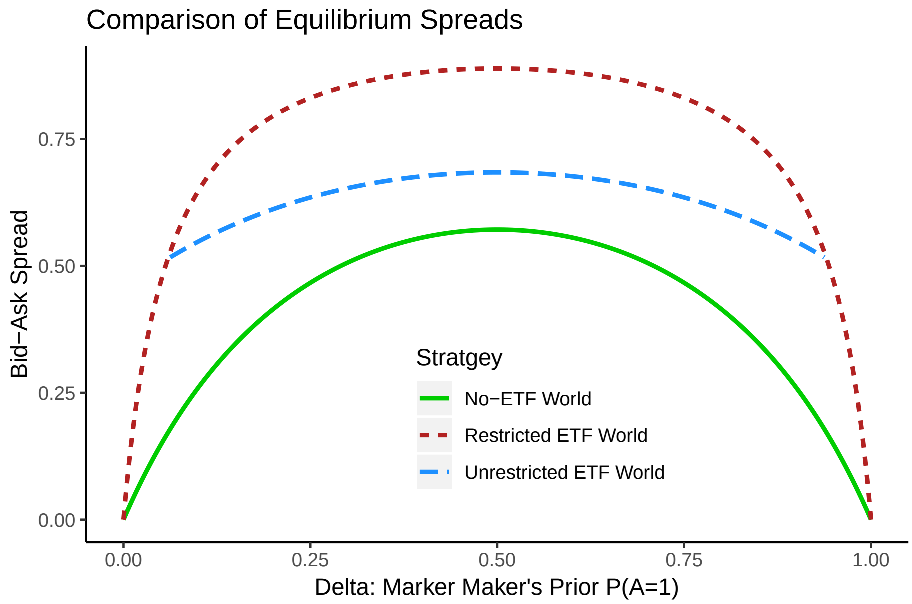
Appendix B. Trading Profits with and without ETF

Without the ETF, I assume that noise traders who receive market shocks must trade the underlying stocks. Rather than having trades in fractional shares, I assume that the σ_M traders trade stock A with Poisson intensity $\phi\sigma_M$ and stock B with intensity $(1-\phi)\sigma_M$. In this no ETF world, stock A therefore has $\zeta_A := \sigma_A + \phi\sigma_M$ noise traders.

More noise traders in Stock A means more profits for A-informed investors. Figure 12 depicts equilibrium spreads as a function of the market maker's prior belief δ that $A = 1$. When an ETF is added, the level of noise trading in stock A drops from ζ_A to σ_A. If the μ_A informed traders are assumed, as in prior literature, to be unable to trade the ETF, then the stock has a high ratio of informed to uninformed traders. As a result, the market maker must charge a wide spread.

When informed investors have the option to trade the ETF, they do so for a wide region of the parameter space. Trading the ETF isn't free; if informed investors trade the ETF with higher

Figure 12. Comparison of Equilibrium Spreads in Stock A. In the absence of the ETF, market noise traders trade individual stocks. This leads to an abundance of noise traders in stock A, and a narrow bid-ask spread (green line). With the introduction of the ETF, market noise traders switch to trading the ETF. If, as in previous literature, ETFs are assumed to totally screen out informed traders, stock A has wide spreads (red line). When informed traders are allowed to trade both stocks and ETFs, they do so. The resulting pooling equlibrium leads to improved spreads (blue line). Parameters: $\phi = .5, \sigma_M = .5, \mu_A = .4, \mu_B = 0, \sigma_A = \sigma_B = .05$.



probability, they must trade the stock with lower probability. But their information is informative about the ETF value, and the abundance of market noise traders means the ETF has a lower spread. In the pooling equilibrium, trading both the stock and the ETF allows informed investors to once again benefit from market noise traders. The benefits from trading the ETF as well as the stock are largest precisely when the stock-specific spreads are widest—at $\delta = \frac{1}{2}$. As Figure 12 depicts, the pooling equilibrium brings equilibrium spreads down, close to their value in the no-ETF world.

Appendix C. Capital Limit

Informed investors in the model are risk neutral but face a capital limit of a single share of any security. This capital limit could be thought of as a position limit on how much investors are allowed to trade, but it can also be justified as risk aversion to an underlying common factor risk. Under this latter framework, the payoffs of assets can be redesigned as idiosyncratic payoff plus common factor risk. While Stock A previously paid a liquidating dividend from $\{0, 1\}$, the dividend d_A with an underlying factor risk can be written as:

$$d_A = \beta_A r_M + x_A$$

where $x_A \in \{0, 1\}$. Similarly for Stock B, the liquidating dividend d_B can be written as

$$d_B = \beta_B r_M + x_A$$

where $x_B \in \{0, 1\}$. Let r_M have $E(r_M) = \mu_M$ and $Var(r_M) = \sigma^2$. Each stock-specific component is idiosyncratic, thus we have that $Cov(r_M, x_i) = 0$ for $i = A, B$.

With the standard assumptions of Ross (2013), the risk premium of idiosyncratic components of risk is zero, while common factors, such as r_M, carry a risk premium.

Under this setup, an investor who trades one share of stock A takes on β_A unites of market risk, while an investor who trades one share of stock B takes on β_B units of market risk. A single share of the ETF carries one unit of market risk. This single share of the ETF contains ϕ shares of A and $(1 - \phi)$ shares of B. If $\beta_A = 1 = \beta_B$, then an investor takes on the same amount of market risk regardless of whether they trade one share of the stock, one share of the ETF, any mixed strategy which randomizes between which asset is traded. Alternatively, if $\beta_A \neq 1$, ϕ can be redefined to ϕ^* where $\phi^* = \beta_A \phi$. In this way, an investor who trades one share of Stock A obtains β_A units of risk, while trading the ETF to take on β_A units of market risk gives $\phi\beta_A$ shares of stock A. Thus the ETF weights can be redefined so that one share of the ETF contains $\phi\beta_A$ units of stock A, and $(1 - \phi)\beta_B$ units of stock B.

Thus the normalization across securities that investors either purchase one share of the stock or one share of the ETF potentially relies on redefining the ETF weight. The ETF weight parameter, ϕ can be thought of as the literal weight of stock A in the event that $\beta_A = 1$. In the case where $\beta_A \neq 1$, ϕ is a more general trade-off between the stock and the ETF. It is a linear transformation of the raw ETF weight of stock A, scaled by the value of β. For higher β stocks, the ETF is a closer substitute, as investors are already taking on considerable factor risk when they trade the individual stock. For low β stocks, however, the ETF is a poor substitute, as they must take on considerable factor risk which they wouldn't take when trading just the stock.

As a numerical example, consider an ETF with $\beta_A = \frac{4}{3}, \beta_B = \frac{3}{4}$. Then the market portfolio has $\phi_A = \frac{3}{7}, \phi_B = \frac{4}{7}$. Suppose an investor is willing to take on \$100 worth of market risk. This investor could invest \$75 in Stock A, or \$100 in the ETF and indirectly obtain \$42.86 worth of Stock A. This ratio satisfies: $\phi_A^* = \frac{42.86}{75} = \phi_A\beta_A$. In this numerical example, $\beta_A > \beta_B$, and therefore $\phi_A^* > \phi_A$ and $\phi_B^* < \phi_B$.

Appendix D. Proofs

Proof of Proposition 2: *In a pooling equilibrium, informed investors mix between A and the ETF and submit orders to the ETF with the following probability:*

$$\text{ETF Buy Probability (A=1): } \psi_1 = \frac{\phi\delta\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{\delta\mu_A[\sigma_A + \phi\sigma_M]}$$

$$\text{ETF Sell Probability (A=0): } \psi_2 = \frac{\phi(1-\delta)\mu_A\sigma_M - \frac{1}{2}(1-\phi)\sigma_A\sigma_M}{(1-\delta)\mu_A[\sigma_A + \phi\sigma_M]}$$

For the informed trader to be willing to mix, he must be indifferent between buying the ETF or buying the individual stock. When $A = 1$, ψ_1 must solve:

$$\begin{aligned}
\phi + (1-\phi)\frac{1}{2} - ask_{(AB)} &= 1 - ask_A \\
\phi(1-\delta)\frac{\mu(1-\psi_1) + (1-\mu)\frac{1}{2}(1-\sigma_A)}{\delta\mu(1-\psi_1) + (1-\mu)\frac{1}{2}(1-\sigma_A)} &= 1 - \delta\frac{\mu\psi_1 + (1-\mu)\frac{1}{2}\sigma_A}{\delta\mu\psi_1 + (1-\mu)\frac{1}{2}\sigma_A} \\
\phi\frac{(1-\sigma_A)}{\delta\mu(1-\psi_1) + (1-\mu)\frac{1}{2}(1-\sigma_A)} &= \frac{\sigma_A}{\delta\mu\psi_A + (1-\mu)\frac{1}{2}\sigma_A} \\
\psi_1 &= \frac{\delta\mu\phi(1-\sigma_A) - \frac{1}{2}(1-\mu)(1-\sigma_A)\sigma_A(1-\phi)}{\mu\delta[\sigma_A + \phi(1-\sigma_A)]}
\end{aligned}$$

When $A = 0$, we have the following indifference condition for mixing:

$$
\begin{aligned}
bid_{(AB)} - (1-\phi)\frac{1}{2} &= bid_A \\
\phi\delta\frac{(1-\mu)\frac{1}{2}(1-\sigma_A)}{(1-\delta)\mu(1-\psi_2) + (1-\mu)\frac{1}{2}(1-\sigma_A)} &= \delta\frac{(1-\mu)\frac{1}{2}\sigma_A}{(1-\delta)\mu\psi_2 + (1-\mu)\frac{1}{2}\sigma_A} \\
(1-\sigma_A)(1-\delta)\mu\psi_2 + (1-\sigma_A)(1-\mu)\frac{1}{2}\sigma_A &= (1-\delta)\mu(1-\psi_2)\sigma_A + (1-\mu)\frac{1}{2}(1-\sigma_A)\sigma_A \\
\psi_2 &= \frac{(1-\delta)\mu\phi(1-\sigma_A) - \frac{1}{2}(1-\mu)(1-\sigma_A)\sigma_A(1-\phi)}{\mu(1-\delta)[\sigma_A + \phi(1-\sigma_A)]}
\end{aligned}
$$

Note that the condition for $\psi > 0$ is the same as the cutoff values for a pooling equilibrium to exist.

Proof of Proposition 3: Derivation of The Partial Separating Bound

Partial Separating Equilibrium. If A traders mix between A and the ETF, B traders stay out of the ETF so long as:

$$
\text{If B} = 0\text{: } \phi \geq \frac{\beta\left(\frac{(1-\beta)\mu_B}{(1-\beta)\mu_B + \frac{1}{2}\sigma_B}\right)\left((1-\delta)\mu_A + \frac{1}{2}\sigma_A + \frac{1}{2}\sigma_M\right) - \frac{1}{2}\delta\sigma_A}{\delta\left((1-\delta)\mu_A + \frac{1}{2}\sigma_A\right) + \beta\left((1-\delta)\mu_A + \frac{1}{2}\sigma_A + \frac{1}{2}\sigma_M\right)} \tag{D1}
$$

$$
\text{If B} = 1\text{: } \phi \geq \frac{(1-\beta)\left(\frac{\beta\mu_B}{\beta\mu_B + \frac{1}{2}\sigma_B}\right)\left(\delta\mu_A + \frac{1}{2}\sigma_A + \frac{1}{2}\sigma_M\right) - (1-\delta)\frac{1}{2}\sigma_A}{(1-\delta)\left(\delta\mu_A + \frac{1}{2}\sigma_A\right) + (1-\beta)\left(\delta\mu_A + \frac{1}{2}\sigma_A + \frac{1}{2}\sigma_M\right)} \tag{D2}
$$

Let $\sigma_M = (1 - \mu_A - \mu_B - \sigma_A - \sigma_B)$. Suppose also that A traders are mixing between the ETF and the stock. For A traders, the mixing probabilities for either the bid or the ask are:

$$
\begin{aligned}
\text{ETF Buy Probability (A=1): } \psi_1 &= \frac{\phi\delta\mu_A\sigma_M - (1-\phi)\frac{1}{2}\sigma_A\sigma_M}{\delta\mu_A(\sigma_A + \phi\sigma_M)} \\
\text{ETF Sell Probability (A=0): } \psi_2 &= \frac{\phi(1-\delta)\mu_A\sigma_M - (1-\phi)\frac{1}{2}\sigma_A\sigma_M}{(1-\delta)\mu_A(\sigma_A + \phi\sigma_M)}
\end{aligned}
$$

The ETF bid and ask prices are:

$$(AB)_{ask} = \phi\delta \frac{\mu_A \psi_1 + \sigma_M \frac{1}{2}}{\delta \mu_A \psi_1 + \sigma_M \frac{1}{2}} + (1-\phi)\beta$$

$$(AB)_{bid} = \phi\delta \frac{\sigma_M \frac{1}{2}}{(1-\delta)\mu_A \psi_2 + \sigma_M \frac{1}{2}} + (1-\phi)\beta$$

Traders in B face the following trade-off between trading the basket at a small spread and trading the individual stock at a wide spread. The B-informed traders know the true value of B, but they share the market maker's prior about A that $P(A=1)=\delta$. Therefore they estimate the value of the ETF at $(1-\phi)B + \phi\delta$. The trade-offs that B-informed face is:

$$\text{Buy (B=1): } \phi\delta + (1-\phi) - (AB)_{ask} \le 1 - B_{ask}$$

$$\text{Sell (B=0): } (AB)_{bid} - \phi\delta \le B_{bid}$$

Solving for ϕ gives the result.

Proof of Proposition 4: Existence of the Pooling Equilibrium

If the conditions of Proposition 3 are violated for both securities, then there is a fully pooling equilibrium. Both traders trade the ETF, and following an ETF trade, the market maker has the following Bayesian posteriors:

$$\delta_{buy} = \delta \frac{\mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M} \qquad \delta_{sell} = \delta \frac{\frac{1}{2}\sigma_M}{(1-\delta)\mu_A \psi_{A,2} + (1-\beta)\mu_B \psi_{B,2} + \frac{1}{2}\sigma_M}$$

$$\beta_{buy} = \beta \frac{\delta \mu_A \psi_{A,1} + \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M} \qquad \beta_{sell} = \beta \frac{\frac{1}{2}\sigma_M}{(1-\delta)\mu_A \psi_{A,2} + (1-\beta)\mu_B \psi_{B,2} + \frac{1}{2}\sigma_M}$$

Consider the case where $A = 1 = B$. Let $\psi_{A,1}$ be the probability that an A-informed investor buys the ETF when $A = 1$. Let $\psi_{B,1}$ be the probability that a B-informed investor buys the ETF when $B = 1$. Then it must be that $\psi_{A,1}$ and $\psi_{B,1}$ solve:

$$\phi(1-\delta_{buy}) + (1-\phi)(\beta - \beta_{buy}) = 1 - \delta \frac{\mu_A(1-\psi_A) + \frac{1}{2}\sigma_A}{\delta \mu_A (1-\psi_A) + \frac{1}{2}\sigma_A} \tag{D3}$$

$$\phi(\delta-\delta_{buy}) + (1-\phi)(1 - \beta_{buy}) = 1 - \beta \frac{\mu_B(1-\psi_B) + \frac{1}{2}\sigma_B}{\beta \mu_B (1-\psi_B) + \frac{1}{2}\sigma_B} \tag{D4}$$

where

$$\delta_{buy} = \delta \frac{\mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}$$
$$\beta_{buy} = \beta \frac{\delta \mu_A \psi_{A,1} + \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}{\delta \mu_A \psi_{A,1} + \beta \mu_B \psi_{B,1} + \frac{1}{2}\sigma_M}$$

The right side of Equation D3 represents the profits to A-informed investors from from trading the ETF. These profits are decreasing in ψ_A. If $\psi_B = 0$, we would have $\psi_A = \psi_1$. Since ETF profits are decreasing in ψ_B, then it must be that $\psi_A < \psi_1 < 1$.

We also know that if $\psi_A = \psi_1$, then the violation of Equation D2 in Propsition 3 would imply that B-informed investors have a profitable trading opportunity, and thus $\psi_B > 0$.

A similar logic applied to Equation D4 gives that $\psi_B < 1$ and $\psi_A > 0$.

Now since the right side of Equation D3 is decreasing in ψ_A and the left side is increasing, we have a unique ψ_A solution. Similarly, Equation D4 gives a unique ψ_B solution.

A similar argument holds for $B = 0 = A$.