Two Essays on the Information Embedded in Flow of Exchange-Traded Funds (ETFs)

Hamed Yousefi

Old Dominion University, hyousefi@odu.edu
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by:

Hamed Yousefi
B.Sc. in Mechanical Engineering, Ferdowsi University, Mashhad, Iran 2011
MBA in Finance, University of Economic Sciences Tehran, Iran 2015
M.A. in Economics, Old Dominion University, USA 2018

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Approved by:
Dr. Mohammad Najand (Chair)
Dr. Licheng Sun (Member)
Dr. David Selover (Member)
ABSTRACT

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Hamed Yousefi
Old Dominion University
Director: Dr. Mohammad Najand

An exchange-traded fund (ETF) is a pooled investment vehicle with shares similar to common equities, and it can be bought or sold on the stock exchanges. As more money flow into an ETF, its assets increase as do the number of shares outstanding. The demand for ETFs, especially after the 2008 crisis, has grown remarkably in the United States. Features such as intraday tradability, tax efficiency, low fees, and transparency have contributed to the ETFs’ appeal to investors. According to Bloomberg terminal data, as of January 2021, there were 2584 U.S.-registered ETFs, with over $5.5 trillion assets under management. Recent studies have stressed the role of passive investing and its importance in the financial markets. Several lines of evidence in recent studies suggest that institutions play a role in nonfundamental demand shocks on their underlying securities (Ben-David et al., 2018; Coval & Stafford, 2007; Etula, Rinne, Suominen, & Vaittinen, 2020; Lachance, 2020; D. Lou, 2012).

Essay 1 examines the flow-performance relation in passive Exchange-Traded Funds (ETFs) and find a robust positive relation. This evidence is inconsistent with the smart-money hypothesis. Our results, however, show a stronger positive relation for the active ETFs. We further develop a measure of flow shocks to individual stocks by aggregating daily changes in ownership of 5600 stocks held by 1200 ETFs. Using an event study at the time of flow shock, we show that the flow-driven return effect (price pressure) can fully account for the positive flow-performance relation in passive ETFs but can only partially explain this relationship in active ETFs.
Essay 2 examines the relations between dollar flows of U.S. listed ETFs with exposure to the U.S., Europe, Asia, and the rest of the world during the COVID-19 crisis utilizing a Markov Switching Model (MSVAR). We find convincing evidence that investors use ETFs to gain exposure to foreign markets. We further extend our study to ETFs listed in Europe and Asia and show investors around the world rebalance their portfolio in response to changes in the number of new COVID-19 cases in every location. While investors in Eastern Asian countries direct their money to domestic funds and reduce their foreign investment following the pandemic, European investors increase foreign investment and reduce home bias. This is consistent with the flight-to-safety effect, when investors shift their asset allocation away from riskier investments and into safer ones during the adverse economic shock.

Overall, this dissertation contributes to the finance and business literature by reconciling some of the gaps left by prior studies based on unexplored thus far key effect of passive investing and exchange-traded funds, which can have a significant effect on broad financial market.
This dissertation is dedicated to my parents, my brothers, and my sisters-in-law who always supported me and endured the bitterness of being far apart from each other for several years.
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Essay 1: How Fund Flows Affect Future Performance? Evidence from Exchange-Traded Funds (ETFs)

Introduction

Studies over the past three decades have established a positive relationship between mutual fund flow and future fund performance, however, there has been little agreement on the reasons for this fact. For instance, studies by Gruber (1996) and Zheng (1999) show that mutual fund investors have the ability to use past information to predict short-term fund performance and direct money accordingly from poor performers toward better-managed funds, a finding that has been dubbed the “smart money” effect. Berk and Green (2004) derive a model of market equilibrium for mutual fund investment that is consistent with empirical findings of the smart money hypothesis. A key assumption of their model is that fund managers are skilled and this skill is heterogeneous across managers. On the other hand, a number of studies have proposed an alternative explanation for the positive relationship between fund flow and future fund performance which is known as the “price pressure” hypothesis. According to the price pressure, flow-driven buying pushes up the stock prices beyond the effect of the previously documented momentum effect. For example, Coval and Stafford (2007) show that in the case of an immediate outflow shock (demand for capital), the fund manager without enough cash reserves has to liquidate the fund’s holdings. This outflow shock puts negative price pressure on the underlying securities of the fund. Conversely, the same phenomena in the opposite direction happen when the fund receives an inflow shock (supply of capital). This flow-induced pressure is persistent and can play a significant role in shaping a firm’s real economic activities (X. Lou & Wang, 2018). Unlike

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1 See, for example, Wermers (2003b), Kamstra et al. (2017), Lou (2012), Frazzini and Lamont (2008)
the smart money hypothesis, which attributes the positive flow-performance\textsuperscript{2} relationship to the ability of investors to spot a skilled fund manager, the price pressure hypothesis suggests that flow-induced shocks deviate stock prices from their information-efficient value. As a result, previous inference about the extent of skill may be overstated if a fund’s outperformance is driven not by the superior investment skill, but by the price pressure induced by a flow shock.

Differentiating non-fundamental demand shocks from fundamental stock price changes is difficult because mutual fund flows are confounded by information about fund manager skill and her portfolio selection ability. For example, a mutual fund manager may take a long position on a fundamentally good stock, but at the same time pushes the price upward when buying en masse. Thus, differentiating skill from price pressure in the flow-performance relationship of open-end funds is difficult, and little is known about the distinct effect of these two competing hypotheses. To cope with this issue, the present study sets out to assess the flow-performance relationship in the laboratory of passive and active exchange-traded funds (ETFs). The intuition is that while passive ETF flows are unlikely to exhibit managerial portfolio selection skills, active ETF flows contain information about the manager’s discretion. The index tracking characteristic of passive ETFs makes the arbitrage trading between ETFs and their underlying assets mechanical and independent of the managerial involvement (Ben-David, Franzoni, & Moussawi, 2018). In line with this, Brown, Davies, and Ringgenberg (2019) derive a model that shows that flows into passive ETFs provide signals of non-fundamental demand shocks. Therefore, unlike mutual fund flows which contain information about the investors’ demand and/or sentiment, passive ETF flows provide a cleaner and more extensive measure of the non-fundamental shock. We exploit this

\textsuperscript{2} Now and hereafter, “Flow-Performance” refers to the relationship between flow at time $t$ and performance in the subsequent period ($t+1$).
feature of the ETFs to disentangle the price pressure effect induced by non-fundamental shocks (observable in passive ETFs) from the embedded information in the flow of active ETFs. Additionally, the availability of daily frequency of flow observation in ETFs compared to the lower frequency estimated flows associated with open-end funds enables us to monitor the flow-performance relationship on a timely basis. The primary goal of the current research is to use the novel laboratory of ETFs to explore the flow-performance relationship, its driver, and its implications for the fund management industry.

Our first objective is to investigate the flow-performance relationship in passive ETFs. Zheng (1999) and Sapp and Tiwari (2004b) test for smart money in a mutual fund by forming a trading strategy based on new money flows and examine the risk-adjusted returns realized by constructed portfolios. We form a trading strategy based on the passive ETFs’ new money flow. Surprisingly, the trading strategies suggest evidence that the risk-adjusted returns for passive ETFs with positive new money flow are significantly higher than those with negative new money flow. For the whole sample of passive ETFs, a trading strategy based on the flow into or out of the fund outperforms the market by more than 2% a year during our study period. From the viewpoint of the smart money hypothesis, this finding is puzzling since smart money is attributed to the ability of the investors to select skilled managers, while managerial skill is not a significant factor for selecting passively managed ETFs by investors. Moreover, similar to the findings of Jiang and Yuksel (2017) in mutual funds, we find that the significant positive flow-performance relation is mainly driven by ETFs with cash outflows. This unbalanced pattern casts further doubt on the smart money hypothesis since according to the smart money effect, investors should have a heterogeneous ability to identify both good and poor performing funds.
The second main contribution of this paper is to test if the price pressure can explain the behavior of active ETFs in response to a flow shock. To measure the flow-performance relationship on active ETFs, we conduct a trading strategy for a sample of almost 200 actively managed ETFs, analogous to the trading strategy on passive funds. The results are similar in spirit but interestingly, more pronounced for the actively managed ETFs. On average, a trading strategy on a sample of actively managed funds produces before-fee alphas that are 2 to 3 times higher than alphas produced by the passive funds. Also, unlike passive ETFs in which the significant relation between flow and subsequent performance was mainly driven by funds with outflow, active ETFs represent a symmetric pattern for the effect of inflow and outflow on performance. This finding is consistent with that of Cai and Lau (2015) who investigate smart money in mutual funds by examining informed trading around earnings announcements and find that only “buy” trades-based measure is useful to measure fund manager skill. We further adopt a multivariate panel regression to provide a deeper insight into the relationship between flow and performance and the moderating role of active management in this setting. Confirming the previous findings of this study, the outcome of the multivariate model manifests a positive and significant relationship between the fund flow and future risk-adjusted returns. The results also show a more pronounced flow-performance relationship for active ETFs, even after controlling for other possible explanatory factors. Despite documenting the significant and robust flow-performance relationship for passive and active ETFs, yet none of the competing hypotheses -i.e. smart money and price pressure- can solely and fully explain this relationship.

In the third contribution of this paper, we carry out a method to disentangle the price pressure from smart money and further investigate the underlying reason for the positive flow-performance relationship. We conduct an event study on the constituent level of the ETFs and
explore the channel linking ETF ownership to flow shock. The objective of an event study is to assess the extent to which one can earn abnormal returns from an event that carries new informational content. To this extent, the testable hypothesis of this section is to investigate whether nonfundamental demand shocks from the ETF market can affect the prices of the underlying stocks. A nonfundamental inflow (outflow) shock can propagate to the underlying holdings of the ETF through the arbitrage channel and fabricate a price jump (drop). If the price pressure can explain the flow-performance relation in ETFs, then the average abnormal return at the time of flow shock should be significantly different from zero. This is due to the fact that nonfundamental demand shocks are irrelevant to the information pertaining to the underlying stocks and affect all the stocks proportional to their weight in the basket of the ETF.

We construct a measure of ETF ownership change (EOC) for more than 5400 stocks held by almost 1000 ETFs from 2012 to 2018. We calculate the daily change of the ETF ownership following a flow shock. We then aggregate the daily changes in ETF ownership for each stock and quantify the abnormal return generated by this shock in an event study framework. The results of the event study provide support for predictable flow-induced price pressure on passively managed ETFs. More specifically, over the −3- to 22-day window (one month), the difference between the cumulative abnormal return (CAR) of a portfolio with the largest positive EOC and a portfolio with the largest negative EOC is 15.4 basis points. This is comparable to the 16 basis points abnormal return earned by a monthly flow weighted trading strategy in the portfolio approach. These results are mainly driven by the price pressure of negative EOC stocks, which can explain the unbalanced pattern of the portfolio approach. We do the same event study on a sample of stocks held by actively managed ETFs. Notwithstanding the more pronounced results for active ETFs, the price pressure cannot fully explain the difference in the abnormal return of the inflow and the
outflow portfolio. Over the −3- to 22-day window, the difference in the CAR for the portfolio of stocks with the largest positive and negative EOC is 26 basis points, which is much lower than the performance of a flow weighted portfolio (45 basis points). Moreover, we find that the effect of non-fundamental shocks induced by passive ETF flows on their holding reverts over the next 40 to 50 days; a finding which is consistent with the 40 days reversal period reported by Ben-David et al. (2018).

What drives the positive flow-performance relationship? We first document this relationship for a sample of passive ETFs where managerial skill does not play a role. Next, we demonstrate that active ETFs’ flow has a different nature and contains information. Exploiting an event study at the time of flow shock, we differentiate the effect of price pressure and smart money. Price pressure can only explain almost half of the positive flow-performance relation in active ETFs. The unexplained portion of the performance can be attributed to the ability of the investors to find skilled fund managers and direct their money toward better performing funds. This empirical evidence indicates that smart money and price pressure are intertwined phenomena for active funds. As a result, part of what is known as stock-picking and portfolio selection ability of the fund manager may simply be the byproduct of a nonfundamental flow shock that has pushed the prices away from their fundamental value. Consequently, the role of skill may be overstated when fund flow is considered as a measure for skill.

The main empirical results are robust to alternative estimation methods. Due to the difference in the number of ETFs in each group, the initial concern is the comparability of the active and passive ETFs. Moreover, recognizing that the selection of stocks by active ETFs may be endogenous, a propensity score matching method is used to ensure that the sample of active ETFs has statistically similar characteristics to the sample of passive ETFs. The propensity score
matching algorithm provides an approach to generate a passive ETFs’ subsample that is comparable with the active ETFs. The results reveal that following a flow shock, the average change in ETF ownership is similar for active and passive ETFs. We also undertake another robustness test that provides additional evidence that our main results are not sensitive to size or type of ETF.

The present research provides several contributions to the advancement of both theory and practice. Our study is among the first studies that use ETFs to better understand the performance of active fund management. We exploit the publicly available information of ETFs and construct a measure of the change in ETF ownership of stocks to isolate the effect of flow-induced trades. The only research we are aware of that touches upon this issue is the recent work by Crane and Crotty (2018), who document that index fund’s skill exists, and is persistent. We extend their research into ETFs and make contributions to the literature by investigating the underlying reason for this finding and differentiating skill from price pressure. Our method and results are consistent with the finding of Ben-David et al. (2018) who find a positive and significant relationship between ETF flow and subsequent stock return. Our findings, on one hand, contribute to the growing body of literature on the price impact of institutional flows and on the other hand, sheds light on the continuous debate in the literature on the skill of fund manager. While Gruber (1996), Zheng (1999), and Keswani and Stolin (2008) interpret the positive flow-performance relation as evidence of “smart” investors; Coval and Stafford (2007), D. Lou (2012), and Jiang and Yuksel (2017) suggest that this pattern is solely driven by flow-induced price pressure. One of the most significant findings to emerge from this study is that we could differentiate the two competing hypotheses of the previous literature as we were able to measure the effect of the price pressure induced by the institutional flow shocks. In particular, we show that while price pressure is
responsible for almost half of the positive (negative) abnormal returns of winner (loser) active funds subsequent to a flow shock, the role of the manager and the skill of investors in finding well managed funds is also significant.

From a practical perspective, this study raises important questions about the nature of passive investing and its importance in the financial markets. Several lines of evidence in recent studies suggest that institutions play a role in nonfundamental demand shocks on their underlying securities (Ben-David et al., 2018; Coval & Stafford, 2007; Etula, Rinne, Suominen, & Vaittinen, 2020; Lachance, 2020; D. Lou, 2012; Vayanos & Woolley, 2013). While event study is usually used to show the market efficiency in information incorporation and to measure price reaction to an event (Binder, 1998), we exploit this method as a market inefficiency metric in a noninformation-based event. Consistent with the previous literature, our findings show that by propagating the nonfundamental flow shocks, institutions indirectly can affect asset prices.

The remainder of this paper is organized as follows. Section 1 discusses the institutional details of ETFs. Section 2 explains the ETF data sample and the methods used to measure the performance of new-money portfolios. Section 3 provides evidence on the performance of the new-money portfolios by using two different approaches: portfolio and multivariate regression. Section 4 investigates the etiology of the flow-performance relationship. Section 5 employs the propensity score matching to conduct a robustness check for the previous results, and section 6 is the conclusion of the study.

Institutional Details

An exchange-traded fund (ETF) is a pooled investment vehicle with shares similar to common equities, and it can be bought or sold on the stock exchanges. As more money flow into an ETF, its assets increase as do the number of shares outstanding. ETF shares can only be created
or redeemed at the end of the day. This creation/redemption plays the role of the primary market for the ETF. As in other funds, the net asset value (NAV) of an ETF is calculated by the weighted average of the underlying assets. However, the ETF price on the stock exchange follows the supply and demand rule where the price is determined by the market.

Theoretically, the ETF’s market price should be equal to its NAV and they should also equal the (latent) fundamental value. However, due to market inefficiencies, such as illiquidity, the lack of transparency, and the inability of authorized participants (AP), this price equality does not necessarily hold\(^3\). Even if relative pricing efficiency is restored, it does not necessarily imply absolute pricing efficiency (i.e., ETF/NAV price may not equal fundamental value). APs are a group of institutional investors designated by the ETF issuer and have the exclusive right to control the supply of ETFs in the market and maintain their liquidities. When there is a shortage of ETFs in the stock exchange (secondary market), the AP buys the underlying assets matching their weights in the corresponding ETF and delivers this basket of securities to the ETF issuer. In return, the issuer gives the AP a block of ETF shares called a “creation unit”, which the AP will sell in the market. Conversely, the AP redeems some of the existing ETF units and sells the underlying assets when there is an oversupply in the market. In reality, however, these events do not follow the normal sequence. For example, when ETF is trading at a premium relative to the NAV, the AP long the undervalued constituents of the ETF and simultaneously short the relative overvalued ETF shares. By submitting a creation order at the end of the trading day (4 PM EST), the AP essentially locks in her profit. Even though there is no legal obligation for APs to enter the market, the arbitrage mechanism encourages them to provide liquidity when there is an imbalance in the buy and sell side. According to the 2015 Investment Company Institute (ICI) report, on average,

\(^3\) For more details about the arbitrage frictions refer to Petajisto (2017)
each ETF has 34 AP agreements, and this number increases as the ETF increases the number of assets under its management. Having said this, APs are not the only liquidity providers in the trading of ETF shares in the secondary market. Market makers (MMs), lead market makers (LMMs), designated liquidity providers (DLPs) and competitive liquidity providers (CLPs) are some other ETF ecosystem players who try to provide liquidity for ETFs⁴. Relying on the liquidity provided by these entities, the ETFs are able to have a dual existence in both primary and secondary markets.

The demand for ETFs, especially after the 2008 crisis, has grown remarkably in the United States. Features such as intraday tradability, tax efficiency, low fees, and transparency have contributed to the ETFs’ appeal to investors. According to Bloomberg terminal data, as of January 2019, there were 2271 U.S.-registered ETFs, with over $3.7 trillion assets under management. Among these, 1582 ($2.93 trillion) ETFs are focused on equity, and the remainder are covering other asset classes such as fixed income assets, commodities, and real estate. ETFs are similar to mutual funds, as they offer investors a proportionate share in a pool of securities. Additionally, ETFs are required to report their portfolio NAVs at the end of each trading day and to execute the creation/redemption procedure at the end of each day. In contrast to these similarities, ETFs shares can be traded in the secondary market, while mutual fund shares are not listed on the stock exchanges. Pricing is also different between mutual funds and ETFs, as all orders placed during the day for mutual funds will receive the same price equal to the calculated NAV at the end of the day. This mutual fund’s pricing mechanism, which is known as “forward pricing”, is different from the ETF pricing mechanism in which the market determines the share price during the day⁵.


⁵ Investment Company Fact Book 2018.
Notwithstanding these similarities and differences, with over $18 trillion in total net assets, the US mutual fund industry remained the largest in the world at the end of 2018. However, this giant industry has started to shrink since 2015, losing market share to ETFs. Figure 1.1 shows the cumulative new money flows into U.S. mutual funds and ETFs since 2007. U.S. mutual funds have had a net outflow since 2015, while ETFs have gained a substantial inflow. Figure 1.1 shows an ongoing shift by investors from mutual funds to ETFs.

Figure 1.1

Data and Methodology

ETF Flow

Data used for this study is collected from three databases: Bloomberg, ETF Global and the Center for Research in Security Prices (CRSP), which ETFG and CRSP are available through the Wharton Research Data Service (WRDS). Founded in 2012, ETF Global (ETFG) is an independent data provider that records all the ETFs’ characteristics, holdings and new money flows. The ETFG data is sourced on a daily basis directly from the ETF issuers and their custodians. Covering 2315 ETFs with $3.6 trillion assets under management by the end of December 2018, ETFG can be considered a comprehensive database for ETF researchers. On a daily frequency, ETFG provides fund flow data and ETF characteristics for almost all the ETFs listed in the U.S. stock exchanges. Daily data on fund flows and the net asset value of ETFs has been available since 2006, while other ETF characteristics and ETF constituents’ data has only been available since 2012. The daily flow data must be approached with some caution because of the different accounting standards used by ETFs. While some funds use T+1 accounting, whereby share creation/redemption is

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6 Bloomberg database covers 2237 ETFs with $3.4 trillion assets under management in the same time period.
reported one day after the execution, some others use T accounting standard (Staer, 2017). Our cross-check analysis between the two databases that report flow (i.e. Bloomberg and ETFG) shows that reporting standards may even change through the time for a single ETF. To cope with this issue, in case of a discrepancy between the two databases, we take the first date that flow is reported in either database as the flow date. Data for the price, return, volume, number of shares outstanding and the bid-ask spread has been obtained from the CRSP and the ETFG database. These observations consist of surviving and nonsurviving funds that appear in both the ETFG and the CRSP databases.

The sample period spans from January 1, 2006, through December 31, 2018. Nonequity funds and international equity funds have been excluded from the sample because these funds may be affected by asset pricing factors and regulations other than those that have been controlled in this study. According to Cheng and Madhaven (2009), leveraged ETFs are, on average, held for a duration of 1 day (-3X or +3X) to 14 days (+2X). In the context of our study, it is not clear whether one can hold (or short) these assets at the time of portfolio rebalancing. Moreover, leveraged ETFs do not use the “in-kind” mechanism in share creation/redemption and like mutual funds, are settled in cash. As a result, leveraged ETFs which generally are viewed as trading vehicles are also removed from the sample. Funds with missing information on returns, total assets under management (AUM) or fund flows have been excluded from the sample. To compute the monthly alpha, we further require a fund to have observations on monthly returns for at least 200 trading days. The final sample contains 1136 fund-entities, comprising more than 1,300,000 fund-day observations. Based on the management style, ETFs are further classified into passive (948 funds) and active (188 funds). Actively managed ETFs were introduced to the market in 2008. ETFG distinguishes the actively managed funds with a Boolean variable (is_active), which takes the
value of 1 for funds that are considered active based on the SEC definition and equals zero otherwise. This variable, however, is only available after the year 2012. Therefore, for the years prior to 2012, specifically in the period of 2008 to 2012, the active variable is being extrapolated by using the values of 2012. This procedure is similar to substituting missing “active” variables with the nearest available data.

Table 1 presents the annual descriptive statistics for both passive and active ETFs from 2006 to 2018. The total assets under management for equity ETFs have risen more than 8-fold, from $275 billion in 2006 to $2.2 trillion in 2018. Despite the dramatic growth of the active ETFs, especially in 2018, this group of funds only controls 7.5% of the total assets under management in our sample, while at the same time, the group constitutes more than 22% of the total number of equity ETFs. An average passive ETF is 3 times larger than an average active ETF in the sample. However, the size of the assets under management of ETFs is skewed toward the large ETFs. In fact, by the end of 2018, the first four largest ETFs in the U.S. market, namely, SPY, IVV, VTI, and VOO, controlled more than 20% of the whole ETF market, leaving hundreds of other ETFs trying to scrape up the leftovers. The gap between the average size of these two groups shrinks when we compare the median size of a passive ETF ($100 M) with the median active ETF ($40 M). Unlike the previous mutual fund and ETF literature in which the difference in total net assets were used to estimate the funds flow during a period (Ben-David et al., 2018; Gruber, 1996; Sapp & Tiwari, 2004a; Sirri & Tufano, 1998; Zheng, 1999), we use the data for the daily flow of ETFs. This daily flow data significantly increases the accuracy of the study, since the price change of the underlying assets and the funds’ mergers and acquisitions can no longer contaminate the flow values. The fourth column of Table 1.1 shows the total net flow to the ETFs for each year. Despite the significant difference between the flow of active and passive funds, the total net flow has
almost always been positive for both groups. It is important to bear in mind that the flow column reflects the total net flow to ETFs in each year and does reflect newly listed/delisted funds. The average expense ratio for passive and active ETFs is 0.46% and 0.74%, respectively. The asset-weighted average expense ratio at the end of 2018, however, was equal to 0.20% for passively managed funds and 0.33% for actively managed funds. While passive managers in recent years have dramatically lowered the cost of ETF investing down to close to zero, active managers have restructured the fee-charging policy where the expense ratio depends on the fund performance.

Table 1.1

Measurement of the Performance

To test the smart money hypothesis and the fund selection ability of the investors, one must follow the new money flow by the time period. For this purpose, all the ETFs are sorted by the net flow at the beginning of each period and then grouped into ten deciles based on the net flow. We show the flow of ETFs that experienced outflow (inflow) with negative (positive) sign. Figure 1.2 shows the distribution of funds with outflow, no flow, and inflow across deciles during the period of this study. As it is depicted in Figure 1.2, the first decile is always filled with the information of ETFs with outflow, and the last decile is loaded with ETFs with inflow. Previous studies in the mutual fund literature estimated the net cash flow by differencing the total net assets of the fund at the end of each period from its value at the beginning of the period (e.g., Zheng (1999) and Sapp and Tiwari (2004a)). This estimation affects the accuracy of the flow variable since it implicitly assumes that investors reinvest their dividends and that the new money is invested at the end of each time period. Moreover, the total net asset’s value can change due to the changes in the net asset value of the ETF, which itself is dependent on the value of the underlying assets. Utilizing available daily fund flow, the present study uses the daily flow for each ETF to calculate the fund flow.
Figure 1.2

Weekly, monthly, and quarterly return is calculated by compounding the daily returns of ETF. For each decile portfolio, returns have been calculated with three different weighting criteria. The base model is an equally weighted return for each cash flow portfolio. A size-weighted return and a normalized-flow-weighted return are also calculated. The former employs AUM of the fund as the weighting criteria, while the latter normalizes each new cash flow by the lag of AUM.

The performance of each portfolio is evaluated using four different models as follows:

I. CAPM model (CAPM):

\[ r_{p,t} = \alpha_p + \beta_{1,p}RMRF + \varepsilon_{p,t} \]  

(1)

II. Fama-French three-factor model (Fama, French (1993)) (FF3):

\[ r_{p,t} = \alpha_p + \beta_{1,p}RMRF + \beta_{2,p}SMB + \beta_{3,p}HML + \varepsilon_{p,t} \]  

(2)

III. Fama-French five-factor model (Fama, French (2015)) (FF5):

\[ r_{p,t} = \alpha_p + \beta_{1,p}RMRF + \beta_{2,p}SMB + \beta_{3,p}HML + \beta_{4,p}RMW + \beta_{5,p}CMA + \varepsilon_{p,t} \]  

(3)

IV. Carhart four-factor model (Carhart (1997)) (FFC):

\[ r_{p,t} = \alpha_p + \beta_{1,p}RMRF + \beta_{2,p}SMB + \beta_{3,p}HML + \beta_{4,p}UMD + \varepsilon_{p,t} \]  

(4)

where \( t \) is the time period of the analysis (week, month, or quarter), \( r_{p,t} \) is the return of the ETF in excess of the risk-free return in the same period of \( t \). RMRF is the excess return on the market (value-weighted return of all CRSP firms listed on the U.S. stock exchanges), and SMB (Small minus Big) is the average return of the nine small stock portfolios minus the average return on the nine big stock portfolios. HML (High minus Low) is the average return on the two value portfolios minus the average return on the two growth portfolios, and RMW (Robust minus Weak) is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. CMA (Conservative minus Aggressive) is the average...
return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, and UMD (Up minus Down) is the average return on the two high prior return portfolios that went up minus the average return on the two low prior return portfolios that lost value. The historical data for the aforementioned factors has been collected from the Kenneth French website. The models represented by equation 1 to 4 will be used as the performance attribution models, and $\alpha_p$ calculated by each model is the risk-adjusted performance factor of each portfolio.

**New Money and Performance**

*Performance of the New Money Portfolio: Passive ETFs*

This part of the study investigates the investor’s fund selection ability by comparing the performance of inflows and outflows for passive portfolios. Employing quarterly flow data, prior research in mutual funds shows investors can earn superior returns by spotting the skilled managers (Gruber, 1996; Zheng, 1999). The evidence presented in Keswani and Stolin (2008) suggests that this finding is stronger at a higher (monthly) frequency. Using the same methodology, we test the smart money effect in three different frequencies (quarterly, monthly and weekly) in the context of ETFs. The idea is that investors at time T can long a portfolio with the highest inflow during period T-1 to T and short the opposite portfolio with the highest outflow in the same period. Table 1.2 presents results for the equally weighted, size-weighted and normalized-flow-weighted new money portfolios for a sample of 948 passive ETFs during the time period 2006 to 2018. The first two columns of each weighting criteria show the returns for the inflow and outflow portfolios, and the third column denotes the long-short portfolios’ return, which is the difference between the inflow and outflow portfolios. The risk-adjusted return has been calculated by using four different models. Newey and West (1987) heteroscedasticity and the autocorrelation-consistent t-statistics are reported in parentheses.
Table 1.2

Panel A of Table 1.2 presents the results of the inflow and outflow fund portfolios for all funds and the difference in the alphas between inflows and outflows for weekly portfolios. The first three columns report the results for equally weighted portfolios, while columns 4 through 6 show the size-weighted portfolio results, and columns 7 to 9 represent the normalized-flow-weighted portfolio results.

The results in Panel A of Table 1.2 show that for the entire sample of passive ETFs, the difference in the FF5 alphas of the positive and negative flow portfolios is 0.04%, 0.01%, and 0.04% per week for the equal-, size-, and normalized-flow-weighted portfolios, respectively. The results for the CAPM and the Fama-French three-factor (FF3) models are also similar in sign and slightly different in values. This finding is consistent with Gruber (1996) and Zheng (1999). Sapp and Tiwari (2004a) argued that the smart money effect is, in fact, a byproduct of the previously documented momentum effect, which can fade away after controlling for the momentum factor. They suggest that investors simply chase the recent winner funds and that these funds happen to have a higher density of recent winner stocks. These funds are also more likely to enjoy the benefits of stock return momentum than are other funds. Subsequently, funds with a higher concentration of recent winners attract more new money flow. This phenomenon can lead to the positive relationship between flow and performance, while investor ability in selecting the skilled manager has nothing to do with this positive relationship (Jiang & Yuksel, 2017). The results for the alpha in the FFC model show that after controlling for the momentum factor, the significance of the new money inflow is reduced. Nevertheless, the difference between the inflow and outflow portfolios remains unchanged across different performance benchmark models. A similar pattern is observable as well across different weighting criteria. While the alpha for the inflow portfolio is
always significant, it loses its significance in the normalized-flow-weighted portfolio. For outflow portfolios, however, the situation is consistent across different models. The outflow portfolios in all models have negative and significant alphas, ranging between 2 to 4 basis points, depending on the performance benchmark and the weighting criteria. The difference between inflows and outflows shows a trading strategy that longs the inflow portfolio and shorts the outflow portfolio. What is interesting about the difference column is that unlike mutual funds, which do not allow short selling of their shares, ETFs are allowed to be sold short since they are treated as a stock on the exchange market. Moreover, ETFs do not even have the uptick rules’ limitations, and investors can short the ETF shares in a downturn market. The excess return shown on the long-short strategy might be an indicator of the investor’s ability to move away from poor performing funds toward stronger performers. Comparing the different weighting measures, the inflow portfolio has the most significant and pronounced results for the Equally-weighted portfolios. This result can be attributed to the inflows for large funds, as regardless of their performance, large funds tend to have larger flows. By moving toward the normalized-flow-weighting columns, the role of smaller funds magnifies: while the inflow portfolio loses its significance, the difference portfolio becomes more pronounced.

Panels B and C of Table 1.2 examine the same alpha models and weighting criteria except for the frequency of observation and rebalancing, which are different from that in panel A. Panel B shows the monthly return for inflow and outflow portfolios, and panel C displays quarterly return portfolios. A comparison of the three panels reveals a robust significant negative return for the outflow portfolios across different models and frequencies. On the other hand, the alpha for the inflow portfolio loses its significance as the observation frequency increases from weekly to quarterly. However, the difference between inflow and outflow alphas remains significant in all
models. This outcome is consistent with the findings of Keswani and Stolin (2008) and Jiang and Yuksel (2017), who found flow-performance relation is stronger and more robust at a higher frequency.

Judging from the differences between the inflow and outflow alphas across different models, there are similarities between the flow-performance relationship in passive ETFs and other studies in the area of actively managed mutual funds. Note that in almost all models, the difference column results remain intact, even after controlling for the momentum factor. In fact, Table 1.2 shows that the flow-performance relationship in ETFs is more sensitive to the frequency of the observation and size of the fund. Furthermore, this is rather interesting that compared to the performance of the inflow portfolio, which becomes insignificant in lower frequencies, the performance of the outflow portfolio is always significant and negative. A similar pattern is reported in previous studies on mutual funds (Sapp & Tiwari, 2004a; Zheng, 1999). Collectively, these shreds of evidence are inconsistent with the smart money hypothesis. According to Berk and Green’s (2004) rational model of active portfolio management, investors are smart enough to learn about the ability of fund managers based on the past performance and allocate capital to the funds with highest expected return. In other words, smart money follows the skilled managers. In the absence of managerial skill, flow should lose its predictor power because investors on average receive the market return. Moreover, the unbalanced absolute return between inflow and outflow portfolio is also contrary to expectations of the smart money. An investor should be able to direct the capital from the less skilled to the more skilled managers (Jiang & Yuksel, 2017). This asymmetric behavior of inflow and outflow portfolios might also be attributed to high expense ratios and loading fees (Sapp & Tiwari, 2004a), which investors consider as poor performance signs. Finding of some studies suggest that responses to positive and negative information are
asymmetric and that negative information has a much more significant impact on the investors’ attitudes than does positive information (Soroka, 2006). Finally, the liquidity shock exerted on the ETF’s underlying assets after flowing a large amount of cash out of the fund might be an alternative explanation for the underperformance of the ETFs subsequent to a cash outflow. As mentioned earlier, the creation and redemption processes of ETF units are mainly mechanical; i.e., ETFs expand their existing holdings with capital inflows and liquidate their assets in response to the outflow, and during this process, the only performance criteria is to minimize the tracking error (Ben-David et al., 2018; D. Lou, 2012). Wermers (2003) found that a fund’s buying induced by flow can push the prices above the level that is explainable by the stock return momentum. D. Lou (2012) also corroborated this finding and attributed the smart money effect to the price pressure. A more detailed account of this hypothesis is provided in section 4.

The results show that based on new money flows of passively managed U.S. equity ETFs over recent sample period from 2006 to 2018, there is a significantly positive flow-performance relation. The results hold for all the equal-, size-, and flow-weighted portfolios. If the flow-performance relation is drive by the price pressure, then one can expect to see a less pronounced relationship between flow and performance in actively managed funds. As presented in Table 1.1, active funds are on average smaller with lower inflow/outflow, compared to passive funds. As a result, the flow shocks, which are responsible for the price pressure, are less significant for active ETFs. To examine this, we form a trading strategy for active ETFs, analogous to the passive funds.

**Performance of the New Money Portfolio: Active ETFs**

As previously stated, actively managed funds constitute almost 20% of the initial sample for this study. For the sake of comparability with the mutual funds’ research, Table 1.3 shows the performance of the new money for actively managed ETFs. The approach used for constructing
Table 1.3 is similar to that used in Table 1.2. Table 1.3 shows the new money portfolio returns for 188 active ETFs, during time period 2009 to 2018.

Table 1.3

What stands out in Table 1.3 is that the pattern of outflows and differences in these portfolios is similar to that in the portfolios in Table 1.2, while unlike passive ETFs, inflow portfolios show a statistically significant predictor power in active ETFs. A closer inspection of Table 1.3 shows that compared to the flow portfolios in the passive ETFs, the flow portfolios in the actively managed funds have a surprisingly more pronounced return. Regardless of the model used for calculating the alpha, the difference portfolio, which is generated by taking a long position for ETFs with inflows and a short position for ETFs with cash outflows, has risen almost 3-fold for actively managed ETFs. Panel C of Table 1.2 shows that for a quarterly portfolio, the average return of the $\text{Alpha}_{FFC}$ for passive portfolios is 0.43, 0.14 and 0.42 across different weightings, while the same return for actively managed ETFs are 1.54, 1.04 and 1.8. Judging from this, the return for active ETFs seems to be more sensitive to the size of the fund and the flow. This is consistent with the mutual fund findings that revealed that performance erodes by the increase in the fund size (J. Chen, Hong, Huang, & Kubik, 2004; Indro, Jiang, Hu, & Lee, 1999). Comparing the return of passive and active ETFs, we can conclude that the difference between the two groups might be attributable to the skill of the fund manager, as the only difference between the two groups is their management style. Interestingly, as it can be inferred from Tables 2 and 3, when measured by the average alpha of all models, the actively managed funds outperform the passively managed funds by around 30 basis points per month. This significant superiority cannot be explained by the management fee and the ETF expenses. On average, the asset-weighted average
expense ratio for actively managed funds in the sample of study is 33 basis points and for passive funds is 20 basis points.

Taken together, the results of the portfolio analysis indicate that both competing theories - smart money and price pressure - failed to explain the positive flow-performance relationship in the context of active and passive ETFs. While smart money cannot explain the significant relation in passive ETFs, price pressure fails to explain the more pronounced result of active ETFs. Turning now to the regression analysis, we verify the flow-performance relation in the presence of other possible explanatory variables.

**Panel Data Analysis of New Money Flow**
To test the smart money effect, previous studies of mutual funds have generally based their methodology on new money portfolios. This section extends the analysis to examine the flow-performance relation in a Panel analysis. The primary advantage of panel data regressions is that we control for the effects of several independent variables at the same time. For this purpose, a panel with more than 1200 ETFs listed on the U.S. stock exchanges during the period of 2012 to 2018 was selected. This sample is smaller than the previous section due to the limitation in data availability for control variables. The flow and other control variables are extracted from the Bloomberg combined with the ETF Global database and matched with the ticker of the CRSP Monthly Stock Database to retrieve the data on volume, spreads, and prices. The return values are adjusted for survivorship bias by using the delisting return reported by CRSP. Funds with missing data for AUM, monthly price or expense ratios were omitted from the sample. similar to the previous sample, all the nonequity funds, non-U.S. funds, and leveraged ETFs were also dropped from the sample due to the possible unique characteristics of these funds. Finally, the alphas were calculated by using a rolling regression based on Equations 1 to 4. To calculate the alpha, an ETF needs to have at least 200 days of observations for use in the asset pricing model. Along with the
limitations mentioned above, this restriction left 996 ETFs with 49,888 ETF-month observations in the final sample. A summary statistic on the ETF sample at the fund-month level is presented in Table 1.4.

Table 1.4

The average net monthly flow is $22.3 million, while the median is equal to zero. Consistent with Figure 1.1, the difference between the mean and the median of the flow shows the average new money flow into or out of ETFs is skewed by inflows. Approximately 11% of the sample comprises active funds, for which there are 2600 observation for almost 100 actively managed ETFs. Share turnover and bid-ask spread control for the liquidity in the model. The price ratio, which is calculated by dividing the market price of the ETF by the net asset value (NAV), is on average equal to one. This measure shows the low arbitrage opportunity and the efficiency of the authorized participants in keeping the price close to the NAV. The average ETF size measured by log (AUM) is 5.38 and the relatively close median (5.32) is a sign that the sample is normally distributed. The size variable has been converted into a natural logarithm to alleviate the effect of skewness. ETFs in the present sample are between 1 to 26 years of age, with an average life of 7 years. Options are on average available on more than 41% of the ETFs. Even though an average ETF has an expense ratio equal to 51 basis points, as mentioned earlier, the AUM weighted expense ratio for the passive (active) ETFs is approximately 20 (33) basis points. All the ETFs in the present sample are under the umbrella of 157 fund families. However, despite the growing and competitive ETF market, a large portion of assets under management is dominated by three firms: Blackrock, State Street, and Vanguard. Each of these 157 families offers a range of ETF types, which have similarities in construction within their family. Finally, each ETF of the study sample holds on average 315 constituents.
Equation 5 has been used to estimate the marginal effect of new money cash flow on returns:

$$\alpha_{i,t} = \alpha + \beta_1 \text{Net Flow}_{i,t-1} + \beta_2 \text{Active} \times \text{Net Flow}_{i,t-1} + \beta_3 \text{Active}_t + \beta_4 \text{Share Turnover}_{i,t-1} + \beta_5 \text{Spread}_{i,t-1} + \beta_6 \text{Price Ratio}_{i,t-1} + \beta_7 \text{Size}_{i,t-1} + \beta_8 \text{Age}_{i,t-1} + \beta_9 \text{Option Available}_{i,t-1} + \beta_{10} \text{Expense Ratio}_{i,t-1} + \beta_{11} \text{Family Size}_{i,t-1} + \beta_{12} \text{Constituents}_{i,t-1} + \text{Family FE} + \text{Time FE} + \epsilon_t \quad (5)$$

where $\alpha_{i,t}$ is the risk-adjusted return calculated by four different models (CAPM, FF3, FF5 and FFC) and is based on daily returns across the past 12 months. $\text{Net Flow}_{i,t-1}$ denotes the lag of flow into or out of the fund in millions of dollars scaled by market capitalization. Following the mutual fund literature, some other control variables, which work for ETFs in almost a similar way as they do for mutual funds, have been added to the model (Bergstresser, Chalmers, & Tufano, 2008; J. Chen et al., 2004; Clifford, Fulkerson, & Jordan, 2014; Friesen & Sapp, 2007; Huang, Sialm, & Zhang, 2011; Jiang & Yuksel, 2017; Keswani & Stolin, 2008). For actively managed ETFs, the results of the previous section (Table 3) show an economically and statistically significant evidence of the smart money effect, which is almost 3 times greater in active funds than in the passive ETFs. To test for the validity of this result in the presence of other factors, the interaction of Active*Flow has been added to the equation 5. Active is a dummy variable that takes the value of one when the ETF is actively managed and equals zero otherwise. Two variables, Spread (bid-ask spread) and Share Turnover (volume scaled by avg. shares outstanding), have been added to the model to control for the liquidity (Brennan & Subrahmanymam, 1996; Chordia, Subrahmanymam, & Anshuman, 2001). The price ratio can also be considered as a liquidity factor, as any deviation from 1 indicates an arbitrage opportunity for authorized participants. As the number of APs covering an ETF increases, the arbitrage opportunity shrinks, and the price ratio
converges to 1. Option Available is also a dummy variable that take the value of 1 when the ETF has option derivatives available. Age, Size, and Expense Ratio are also common controls in mutual fund literature (see, e.g., Chevalier and Ellison (1997), Sirri and Tufano (1998), Jain and Wu (2000)). Family size also shows the overall assets under management of an ETF family. Finally, Constituents is a variable that controls for the number of ETF holdings. It can be assumed that ETFs with a larger number of holdings have more difficulties in tracking an index and experience less effect from flows on their underlying securities. The panel model includes family and time fixed effect to control for the unobservable variations at these levels. The standard errors are clustered by both time and fund.

To lessen the correlation between interaction terms and the simplification of the interpretation, all the continuous dependent variables have been standardized and mean centered on zero (converted to Z-score). For the sake of simplicity, the discussion for the variables will be only based on the FFC model. However, to a large extent, the results are comparable to the other models. Spread has an inherent opposite direction to the Share Turnover, as a larger spread between bid and ask forewarns the illiquidity risk, while higher share turnover indicates higher volume. Spread is a statistically and economically important characteristic. One standard deviation change in spread decrease the alpha by 11%. Share turnover is statistically insignificant. Liquidation is costlier when liquidity is lower; therefore, a rational investor demands a higher return for holding a less liquid asset (Amihud, 2002; Pástor & Stambaugh, 2003). Correspondingly, a one standard deviation increase in the price ratio increases the alpha by 20 basis points. ETF-specific characteristics can also affect the fund’s return. Of the factors that have a negative relationship with fund performance, Option availability is one of the most significant. Option availability reduces the return variance, shrinks the bid-ask spread and provides significant welfare
benefits to investors with greater risk assessment (Damodaran & Lim, 1991). Interestingly, similar to the documented results for mutual funds, older ETFs are less successful in generating a positive alpha. A one standard deviation increase in Age decrease the alpha by 5%. Even though statistically insignificant, Expense Ratio has a negative relationship with fund performance. This finding is compatible with Gruber's (1996) study, which argued that expenses are not higher for top performing funds. Finally, funds in families with larger size and funds with more underlying securities tend to have higher adjusted returns.

Finally, the results tabulated in Table 1.5 suggest that flow has a positive and significant effect on the next month’s return in all models. The earlier findings of this study showed that the positive relation between fund flows and future performance is particularly pronounced for actively managed funds. If this is the case, then in the presence of other control variables, we should expect a stronger relation for active funds than for passive funds. The interaction of Flow with the Active dummy indicates the fact that Flow indeed has a stronger effect on the return of actively managed funds. These results confirm the present study’s previous findings, which were based on the trading strategy.

Table 1.5

The Etiology of Flow-Performance Relationship

The relationship between mutual fund performance and the skill of the manager has been extensively studied in the literature of the mutual funds (e.g., Daniel, Grinblatt, Titman, and Wermers (1997); Brands, Brown, and Gallagher (2005); Amihud and Goyenko (2013); Kacperczyk, Sialm, and Zheng (2005); Berk and van Binsbergen (2015)). Gruber (1996) argued

\footnote{In all models, the result for expense ratio, family size and constituents need to be interpreted with caution. The reason is that these variables have very little or no variation across the family or the time. Thus, with family and time fixed effect, we identify the coefficient only for ETFs that have a variation across these fixed effects.}
that if managers have heterogeneous skills and if some investors can measure that, then capital must move away from the less-skilled manager and become attracted to the skilled ones. This effect is expected to be reinforced over time and as the market becomes more efficient and more information becomes available to the investors. Follow-up studies found a positive relationship between fund flow and fund performance in the subsequent period and recognize it as supportive evidence for the hypothesis that is known as the smart money effect (Zheng, 1999). The results of the present study showed that similar to mutual funds, exchange-traded funds exhibit a positive flow-performance relationship. These results reflect those of Crane and Crotty (2018) who also found that index fund skill exists. They show that benchmark performance heterogeneity, which is argued by Cremers, Petajisto, and Zitzewitz (2010), may not fully explain the positive flow-performance relationship. Instead, Crane and Crotty (2018) attribute their findings to the differences in operational skill (e.g., trading execution, management of securities lending programs, etc.). Most ETFs attempt to track the performance of an index, which is usually concentrated in a specific industry or asset class. If some investors have informational advantages in some indices, then we can expect to see a positive relationship between fund flow and the subsequent performance of the ETF. In the context of actively managed mutual funds, it has already been established that managers who concentrate their holdings in the industries where they have informational advantage outperform other mutual fund managers (Kacperczyk et al., 2005). Even though investor’s operational skill may be a viable conjecture for the positive flow-performance relation, it fails to offer an adequate explanation for the unbalance pattern of inflow and outflow portfolios.

D. Lou (2012) offered an alternative explanation for the relationship between fund flow and the subsequent performance of the mutual funds. Based on this hypothesis, mutual funds that
receive capital inflow tend to invest the new money into their existing holdings. Such flow-induced purchases then drive up the price of the underlying securities, thereby consequently driving up the fund performance. In contrast, and following an outflow, fund managers need to redeem their fund units and sell their existing holdings; this subsequently drives down the price of the underlying securities and fund’s performance. This phenomenon, which is identical to the price pressure documented by Coval and Stafford (2007) and Frazzini and Lamont (2008), is rooted in liquidity constraint. Non-fundamental demand shock induced by new money flow causes the asset prices to deviate from their fundamental values. Brown et al. (2019) argue that unlike mutual fund flow which is confounded by information about managerial skill, ETFs provide a clean measure of non-fundamental shock. We build on this and discuss our findings from the perspective that flow reflect non-fundamental demand.

In this section, the analysis of previous sections is extended from the aggregate institutional flow level to the individual stock level. The goal is to determine whether the results yielded in the portfolio analysis are mechanically derived from a non-fundamental shock propagated to the underlying securities of an ETF, or if the smart money hypothesis indeed explains the abnormal return of ETFs with large flows. The main testable hypothesis of this section is that nonfundamental supply (demand) originated from the ETF units’ redemption (creation) can cause the underlying securities to deviate from their equilibrium price. Following a new money flow into an ETF, the ETF manager creates new units commensurate with the size of the flow. This nonfundamental flow shock, that is, the flow that is unrelated to the information about the future cash flow of the stocks, propagates a price pressure to the underlying securities. This price pressure is proportionate to the security weight in the ETF basket. Eventually, the nonfundamental demand shock puts upward pressure on the securities held by the ETF. A similar mechanism, but in the
opposite direction, is expected following a money outflow from an ETF. The excess supply following a unit redemption by an ETF pushes the price of the underlying securities downward and causes a negative abnormal return for the underlying securities. This phenomenon is compatible with the study by Ben-David et al. (2018) on the ETF effect on market volatility and with Malamud’s (2016) dynamic model of the ETF market. Moreover, and in an intraday study, Lachance (2020) shows that growth of ETF market is associated with highly positive order imbalance which ultimately translates to predictable return.

To examine the impact of price pressure induced by an ETF flow on its underlying securities, a sample of 1,212 equity ETFs and their holdings from 2012 to 2018 were examined. The ETFG-Constituents database was used as a source of the ETF holdings data. This sample was then merged with Bloomberg and ETFG-Flow database to add the daily ETF flow to the dataset. The initial sample comprises approximately 800 million security-day observations. Since the goal of this section is to investigate the flow shock effect on the underlying stocks, the days in which the ETF does not experience flow are removed from the dataset. Next, missing weights, missing CUSIP numbers, and securities that are not traded in major U.S. exchanges are removed to decrease the number of observations to 343 million stock-days. This sample is then matched with the CRSP daily stock price to remove non-equity securities and include price, number of shares outstanding and returns for every stock. We control for the accounting differences and the possible delay in reporting the flow, as it is described in the data and methodology section. The final sample comprises 35,843,288 observations made by 5,600 stocks held by 1,212 ETFs during the period of study. Each observation shows a security that is affected by a flow shock of one ETF during the time period of the study.
To measure the effect of the ETF flow on the underlying securities, the daily ETF ownership change (EOC) is calculated for each stock across all the ETFs that hold the security and then is aggregated as follows:

\[
ETF \text{ ownership change}_i,t = \frac{\sum_{j=1}^{J} w_{i,j,t} \cdot Net \text{ Flow}_{j,t}}{Mkt \text{ Cap}_{t,i}}
\]  

(6)

where \( w_{i,j,t} \) is the daily weight of stock \( i \) in ETF \( j \) at day \( t \) and is based on data extracted from the ETFG-constituents database. \( Net \text{ Flow}_{j,t} \) is the net flow into or out of ETF \( j \) at day \( t \) and is based on data from the Bloomberg combined with ETFG-Flow database. \( Mkt \text{ Cap}_{t,i} \) is also the market capitalization of stock \( i \) at day \( t \). Equation (6) reflects the sum of the percentage changes in the total ownership of ETFs in stock \( i \) at each day. One stock might be affected by multiple flow shocks from both active and passive ETFs in a single day\(^8\). To differentiate, we consider an EOC observation is induced by active (passive) ETFs if at least 50% of the ownership change is induced by active (passive) ETFs. Aggregating the effect of flows for each security across all the ETFs holding the security reduces the sample of the study to 5,096,063 unique stock-day observations.

Following the construction of the EOC, the next step is to investigate if this change in ownership affects the price of the security. To examine the price shock, the cumulative abnormal returns (CARs) for three different windows were calculated. The narrow window of -2 to +2 days is tested to determine if, at the time of the flow shock, the liquidity limitation can generate an abnormal return for the security. Wider windows (-3 to +22 days and -3 to +66 days) are also examined to determine the mean CAR within a month (22 trading days) or a quarter following a flow shock. The abnormal return is calculated based on the Carhart (1997) four-factor model (FFC). For the sake of the comparability of the results in this section with the portfolio results of

\(^8\) As Table 1.7 shows, less than 1% of the flow shocks are directly induced by active ETFs.
Table 1.2, the events at each month are grouped into ten deciles based on the EOC. The first decile is always filled with the largest negative EOC, and the last decile is loaded with the largest positive EOC. The positive EOC represents the change in stock’s ETF ownership following an inflow shock to the holder ETFs, and a negative EOC shows the changes in the security’s ETF ownership following an outflow shock. Moreover, four-factor alpha (FFC) is calculated using the past year’s daily return of the stock.

Panel A of Table 1.6 presents the mean CAR following a flow shock, for passive ETFs. Columns one and two show the mean CAR following an inflow and outflow shock, respectively, and the third column shows the difference between the inflow-induced CAR and the outflow-induced CAR. Mean CARs are reported over 3 event windows: (-2, +2), (-3, +22), and (-3, +66). Panel B of Table 1.6 compares the CARs of active ETFs. We see that CARs of inflow shocks in the passive ETFs’ sample are 4 BPS over the -2- to +2-day window and exceed the return of outflow shock sample by 18 BPS. Results are similar and statistically significant over the -3- to 22-day and -3- to 66-day windows. In panel B, we see that the return of inflow and outflow shocks in the active ETFs’ sample follows the same pattern, but is not statistically significant. Hence, although the difference between inflow and outflow sample for active ETFs is statistically significant, neither of the two flow shocks can reject the null hypothesis that the nonfundamental supply (demand) originated from the ETF units’ redemption (creation) can significantly deviate the underlying securities from their equilibrium price.

| Table 1.6 |

Figure 3 plots the CAR for inflow and outflow shocks in the two styles of ETF management within a 5-day window and from 3 days before the flow shock until 22/66 days after the shock. The figures show that in the days following a flow shock, the CARs of stocks in the inflow-induced
sample lie well above the CARs of the stocks in the outflow-induced sample. The graph suggests that stocks that are held by ETFs with new money inflow deliver higher abnormal returns than do stocks that are held by ETFs that experience money outflow. Panel A of Figure 1.3 shows that for both active and passive ETFs, following a positive flow shock as reflected in increases in ETF ownership, the underlying stocks will gain abnormal returns above those of the market. A similar pattern but in the opposite direction is observable when a holding fund experiences a redemption of units following an outflow. What stands out in Panel B of Figure 1.3 is the unbalanced pattern of abnormal return for passive ETFs which is consistent with our previous finding in trading strategy analysis. While outflow induced abnormal return is more pronounce and persists over the month, inflow induced CAR decreases over the one-month period. Panel C of Figure 1.3 shows that a complete reversal is observable somewhere between 40 to 50 days for passive ETFs. This is consistent with the findings of Ben-David et al. (2018) who document a reversal of the underlying stocks’ prices held by the passive ETFs in 40 days. It is important to bear in mind that the underlying assumption of this test is that the flow shocks induced by the ETFs are non-fundamental and irrelevant to the fund manager skill. While this assumption might be true for passive funds, it doesn’t hold for actives. The EOC variable weighs the magnitude of a flow shock and measures the potential of a flow shock in generating a non-fundamental abnormal return. As a result, it is not surprising to see a CAR pattern different from the trading strategy analysis for active ETFs. In fact, the result of event study for active ETFs shows that the persistent positive flow-performance relation documented for active ETFs in Table 1.3 is not induced solely by the price pressure, and nonfundamental flow shock can ultimately explain half of this relationship.

Figure 1.3
Comparing the results of monthly returns for passive ETFs in Table 1.6 with monthly returns of an equally weighted portfolio in Table 1.2, the price pressure induced by the ETF flow shock can fully explain the positive flow-performance relation in passive ETFs. More specifically, the monthly difference between inflows and outflows for a flow weighted portfolio (FFC) is 16 basis points, which is almost equal to the 15.5 basis points monthly CAR difference between inflows and outflows in passive ETFs. The monthly CAR difference between inflows and outflows for stocks held by active funds, however, is not comparable to the return difference in the portfolio approach. Panel B of Table 1.6 shows that the monthly CAR difference induced by inflows and outflows for stocks held by actively managed ETFs is 26 basis points. This is almost half of the 45 basis points return yielded from the difference between inflows and outflows of the equally weighted portfolio in panel B of Table 1.3.

The findings of this section of the study suggest non-fundamentally motivated ETF flows can lead the underlying stock price to deviate from the information-efficient price. The difference between the results of the active and passive ETFs provided an opportunity to disentangle the smart money hypothesis from the price pressure hypothesis. Even though the price pressure of the ETF flow shock propagated to its underlying securities can explain the positive flow-performance relationship for the passive ETFs, it cannot account for the whole abnormal return generated by active funds. Moreover, the findings of this section also accord with our earlier observations of the unbalanced effect of inflow and outflow on the return of the next period, which the smart money hypothesis failed to explain.
Robustness Tests

A general concern in the main results of the study is that due to predictable and observable reasons, active funds may be different from passive funds. As a result, the presence of a stock in the basket of an active fund may be endogenous. Moreover, assets under management in the ETF industry are not distributed normally within passive funds or between active and passive funds. While the first five largest ETFs are all passive and have between $100 to $270 billion assets under management, EMLP, which is the largest U.S. equity active ETF, has only $2.2 billion in AUM by end of 2018. To alleviate this concern and help resolve selection bias, this section primarily employs a propensity score matching whereby the flow-induced creation/redemption procedure of active ETFs are matched with the same activities of a sample of passive ETFs in each month. There are no significant differences between the subsample of passive funds and the active funds in terms of the size of the ETF, liquidity, and the previous ownership of the underlying security. The main purpose of this test is to examine whether the stocks’ ETF ownership change (EOC) following a flow shock to the ETF for an active ETF is different from that for passive ETFs. We find no evidence of a significant difference in ETF ownership change induced by active and passive funds. Furthermore, we investigate whether the results differ across different fund sizes. Our earlier findings show that the positive relation between fund flow and performance is particularly pronounced for active ETFs. If the relatively smaller size of the active funds is the main cause for this difference, then we expect to see similar result for a subsample of passive ETFs, which are comparable to active ETFs in term of size. We find that there is a significant difference between active and passive ETFs holdings, even after controlling for the extremely large passive ETFs.

EOC Induced by Active ETFs VS. Passive ETFs

If active funds focus their attention on a specific group of stocks (such as small-cap stocks), then the presence of a stock in the basket of the ETF is endogenous. This selection bias, in turn,
can systematically alter the EOC induced by active funds from the EOC induced by passive funds. Previous studies, however, have established that active stock pickers take large but diversified positions away from the index funds (Petajisto, 2013) and have a distinct preference for large stocks (H.-L. Chen, Jegadeesh, & Wermers, 2000).

To test this hypothesis, the final sample of section 4 is used. The sample consists of 35,843,288 observations (ETF-security-days) belonging to 5600 unique securities held by 1212 unique ETFs. Table 1.7 shows the difference between the securities held by active and passive ETFs and the effect of the ETF flow shock on these securities. Out of almost 36 million flow shocks exerted to the securities of this sample, less than 1% is induced by active ETFs. It can be seen from the data in Table 1.7 that passive ETFs report a significantly larger flow, AUM, and previous ownership than do their active peers. Interestingly, securities held by active funds are larger in term of average size and more liquid (lower spread) than those held by the passive ETFs. While the average change in the ETF ownership (EOC) is the same for both active and passive ETFs, it is close to zero because it reflects the average of both positive and negative changes in ownership. Each security in our sample is hit by almost 7 flow shocks induced by passive ETFs in each day, while incurring almost one flow shock induced by active ETFs. Finally, the variable Inflow shows that almost 60-70% of the flow shocks for both fund groups are inflows; considering the growing size of the ETF industry, this comes as no surprise. One can take the results of Table 1.7 as a primary indicator that the pronounced results for active ETFs in Table 1.3 are not solely induced by the price pressure. Taken together, these results suggest that active ETFs hold larger and more liquid securities than do passive funds.

Table 1.7
As discussed earlier, to address selection bias concern, this section of our study primarily employs a propensity score matching research design to find the score-matched pairs from active and passive funds. Matched sampling is a method for selecting observations from a large pool of potential controls (passive ETFs) to produce a control group of modest size that is similar to a treated group (active ETFs) with respect to the distribution of observed covariates (Rosenbaum & Rubin, 1985). The propensity score matching (PSM) method proceeds in two steps. The first step is to estimate the parameters that indirectly affect ETF ownership, by estimating a probit model of the binary outcome that equals one if the ETF is active, with observable firm and fund characteristics as control variables. Table 1.8 shows the result of the probit model for almost 35 million security-ETF-month observations during the time period 2012 to 2018. To differentiate the effect of positive (inflow) and negative (outflow) shocks, the sample is divided into two groups based on the sign of the EOC. The results in Table 1.8 for both inflow and outflow columns show that compared to passive ETFs, active ETFs are more likely to be smaller and to have lower ownership in the stock market. Moreover, the inflow and outflow columns jointly show that active funds are more likely to hold larger securities. In the second step, exploiting the probit estimates to generate the propensity score, the funds are matched by using the nearest neighbor algorithm with caliper 0.001, with no replacement. Table 1.9 presents the average treatment effect of an active management style on the ETF ownership change for both inflow and outflow samples. After matching based on the control characteristics, for inflow (outflow)-induced shock, the difference of the mean EOC between the treated group and the control group decreased from -0.03 (0.07) to zero, indicating that the ETF ownership change following a flow shock is not endogenous to the security selection of the ETFs.

Table 1.8
Table 1.9

In addition to the propensity score matching, in the next section, we measure the performance of the new money portfolio for a passive ETF subsample that is comparable to active ETFs in term of fund size and other characteristics used in propensity score matching.

Performance of the New Money Portfolio; Subsample of Passive ETFs

Two alternative approaches are considered to alleviate the concern of comparability of the passive and active ETFs and to confirm the robustness of the results in section 3. First, since the largest active ETF in our sample has $2.2 billion in AUM, we restrict the size of the passive ETFs sample to the same cap. More specifically, we exclude from the sample all passive ETFs with more than $2.2 billion in AUM in the last available observation. Starting with the sample of section 3 and after excluding large ETFs, the new sample shrinks from 1917 passive ETFs to 1687 ETFs during the time period 2006 to 2018. The mean (median) size of the new sample is $237 M ($69 M). The second approach for creating a subsample of comparable passive ETFs is to use the results of propensity score matching. For this purpose, we select a sample of passive ETFs that have at least 15 matched observations (ETF-security-days) with the active funds. The logic behind this sample selection is to find passive funds in which an effect on the underlying security’s EOC is similar to that in active funds. Combining the results of PSM in the previous section with the sample of passive ETFs in section 3, we ended up with 480 passive ETFs with the highest similarity to active ETFs in terms of affecting the EOC. The mean (median) size of the PSM sample is $1.5 B ($264 M). Table 1.10 shows the monthly return for both subsamples created in this section. In each panel of Table 1.10, four alphas are presented: the CAPM alpha (CAPM), the Fama-French three-factor alpha (FF3), the Fama-French five-factor alpha (FF5), and the Carhart four-factor alpha (FFC). Moreover, each panel represents three different weighting criteria: equally weighted, flow-weighted, and normalized-flow-weighted.
Table 1.10

Panel A of Table 1.10 shows the monthly return for passive ETFs with AUM less than $2.2 Billion. Comparing the difference column of these results with that of the results of panel B in Table 1.2, the alpha calculated for small passive ETFs is in general more pronounced than that for the full sample. This finding confirms the Yan (2008) and J. Chen et al. (2004) findings that small funds significantly outperform large funds. However, comparing these results with the results of panel B in Table 1.3, there is still a significant difference between the alphas calculated from small passive ETFs and the alphas of active ETFs. More specifically, while the alpha’s difference between inflow and outflow portfolios changes from 19 to 24 basis points for different weighting criteria of the small passive ETFs, the same alpha difference changes from 34 to 45 basis points for a size-comparable sample of active ETFs.

The difference between the active ETF sample and the comparable passive ETF subsample is even more pronounced for the PSM passive sample. Panel B of Table 1.10 shows the monthly return for the propensity score matched (PSM) passive ETFs. As the difference column for different weighting criteria shows, the results for this subsample is either insignificant or changes between 8 to 12 basis points, which is lower than the difference for both the active and passive full sample.

In summary, the results suggest that the unexplained difference between the results of active and passive funds is not explainable by the difference in the average size or the endogenous stock selection of active funds. This finding corroborates the study’s previous results that attribute this difference between active and passive funds to the ability of investors to direct money toward better managers.
Conclusion

With over $3.7 trillion assets under management, ETFs have turned into one of the most popular investment vehicles during the recent years. Compared to mutual funds, ETFs have prevailed to attract more new money for four consecutive years after 2014. Part of this success is due to the inherent characteristics of ETFs, such as the novel source of diversification, the lower expense ratio, and seemingly higher liquidity. This significant growth in ETF popularity and assets under management has made ETFs a viable part of the investor’s strategy and a comparable alternative to mutual funds. We exploit this growth to use ETFs as a financial laboratory, where the key differences between ETFs and mutual funds can be studied.

The literature of mutual funds shows a strong relationship between fund flow and future fund performance. The present study tests this relationship in a sample of ETFs to first investigate if this relationship holds among ETFs, and then analyze the role of skill by comparing the response of passive and active funds to the flow. We find that even in a sample of passive ETFs— that is unlikely to exhibit managerial portfolio selection skill—a positive and statistically significant flow-performance relation is observable. We further show in an event study that flow-induced price pressure can explain the superior performance of passive ETFs with past inflow over their peers with past outflow. These findings raise intriguing questions regarding the consistency of the smart money hypothesis which takes flow as a proxy for skill and has been viewed as evidence of heterogeneous managerial ability. To account for skill, we conduct the same study on a sample of active ETFs. The results are stronger for active ETFs and price pressure fails to explain the difference. We attribute this unexplained portion of the performance to the smart money effect.

This finding lends support to the conjecture that nonfundamental demand shocks induced by institutional investors can alter the financial market. The results suggest that smart money
exists; however, despite the results of previous literature in mutual funds, management skill is only responsible for a small portion of that. Moreover, our finding shows that price pressure can explain the unbalanced effect of positive and negative flows on the return of the next period of the funds. Finally, in accordance with the liquidity trading hypothesis and findings of Ben-David et al. (2018), we show that the price impact of non-fundamental shocks induced by passive ETFs can persist for 40 to 50 days.

This work contributes to the existing knowledge of fund management. We isolate the flow-induced trading, which has little to do with managerial skill, from total trading and shed light on the intertwined effect of price pressure and smart money. The present study lays the groundwork for future research into the long-term effect of nonfundamental flow shocks on firms' risk-taking activities, payout policies, and managerial decision making and market timing.
References


Tables and Figures

Table 1.1 Descriptive Statistics for Exchange-Traded Fund Sample
This Table represents the distribution of annual money flows for a sample of 7,915 ETF-Year observations obtained from the ETF Global database combined with the CRSP monthly database and Bloomberg. The sample includes all the ETFs listed in U.S. stock exchanges at any time during January 2006 to December 2018 and for which monthly flow and assets under management values are available. Non-equity ETFs, leveraged ETFs, and International Equity funds have been excluded. Number of Funds shows the number of ETFs with more than 9 months of activity in each year. Average Fund Size is the average of total assets under management for every ETF. Total AUM is the total assets under management of active/passive ETFs. Net flow shows the new money into or out of the fund. Return is the percentage change in the market value of an ETF over the period of a year. Net Expense Ratio is the expense ratio of the active/passive ETFs.

<table>
<thead>
<tr>
<th>Year</th>
<th>Number of Funds</th>
<th>Average Fund Size ($M)</th>
<th>Total AUM ($B)</th>
<th>Net Flow ($B)</th>
<th>Average Return (%)</th>
<th>Net Expense Ratio</th>
</tr>
</thead>
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<td></td>
<td>Passive Active</td>
<td>Passive Active</td>
<td>Passive Active</td>
<td>Passive Active</td>
<td>Passive Active</td>
<td>Passive Active</td>
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<td>2006</td>
<td>187 1471</td>
<td>275 33</td>
<td>12.6 0.38</td>
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<td></td>
</tr>
<tr>
<td>2007</td>
<td>245 1531</td>
<td>375 86</td>
<td>7.2 0.42</td>
<td></td>
<td></td>
<td></td>
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<td>2008</td>
<td>287 9 1119 530</td>
<td>321 5 105 2</td>
<td>-36.5 -33.3</td>
<td>0.44 0.54</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2009</td>
<td>309 10 1225 758</td>
<td>378 8 -5 2</td>
<td>34.0 43.5</td>
<td>0.43 0.55</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2010</td>
<td>350 10 1341 1164</td>
<td>469 12 37 3</td>
<td>16.8 22.7</td>
<td>0.43 0.55</td>
<td></td>
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<tr>
<td>2011</td>
<td>418 15 1269 899</td>
<td>530 13 52 3</td>
<td>-2.1 3.0</td>
<td>0.45 0.70</td>
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<td></td>
</tr>
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<td>611 52 1274 429</td>
<td>779 22 70 5</td>
<td>9.8 5.7</td>
<td>0.47 0.92</td>
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<td></td>
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<td>2013</td>
<td>601 58 1723 520</td>
<td>1035 30 154 5</td>
<td>20.4 14.6</td>
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<td>5.5 3.7</td>
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<td>1595 70 172 13</td>
<td>11.8 7.1</td>
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<td>2017</td>
<td>886 169 2506 683</td>
<td>2143 113 220 31</td>
<td>14.1 12.2</td>
<td>0.48 0.79</td>
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<td>2018</td>
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<td>2208 159 170 32</td>
<td>-6.0 -5.5</td>
<td>0.47 0.70</td>
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Table 1.2 Performance of New Money Portfolio for Passively Managed ETFs
This table describes portfolios of U.S. passive equity ETFs formed on the basis of the fund’s money flow in the preceding period. ETF flow data are for 2009 to 2018. Alpha, as a measure for risk-adjusted return, is calculated with 4 different models: the CAPM, the Fama-French 3-factor model (FF3), the Fama-French 5-factor model (FF5), and the Fama-French-Carhart (FFC). Panel A represents the results for weekly portfolios, while panel B and C represent the results for monthly and quarterly portfolios. Flows are classified by a weighting criterion used in the portfolios’ creation, as the first 3 columns show the results for the equally weighted portfolios, column 4 to 6 show the size-weighted portfolios and columns 7 through 9 show the normalized-flow-weighted portfolio. Flows are also classified by the following directions: as inflow (first column of each weighting criteria), outflow (second column of each weighting criteria), and the difference between inflow and outflow (third column of each weighting criteria). The statistical significance of alpha estimates are based on Newey–West standard errors and the parentheses contain the t-statistics. *, **, and *** respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th>Model</th>
<th>Equally Weighted Portfolio</th>
<th>Size-Weighted Portfolio</th>
<th>Normalized-Flow-Weighted Portfolio</th>
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<tr>
<td></td>
<td>Outflow</td>
<td>Inflow</td>
<td>Difference</td>
</tr>
<tr>
<td><strong>Panel A: Weekly Return</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alpha CAPM</td>
<td>-0.04*** (-8.15)</td>
<td>0.02*** (4.27)</td>
<td>0.05*** (11.98)</td>
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<tr>
<td>Alpha FF3</td>
<td>-0.03*** (-6)</td>
<td>0.01*** (4.07)</td>
<td>0.04*** (9.96)</td>
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<td>Alpha FF5</td>
<td>-0.02*** (-6.33)</td>
<td>0.01*** (3.81)</td>
<td>0.04*** (9.39)</td>
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<td>Alpha FFC</td>
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<td>0.01*** (2.06)</td>
<td>0.04*** (8.25)</td>
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<tr>
<td><strong>Panel B: Monthly Return</strong></td>
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<td></td>
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<tr>
<td>Alpha CAPM</td>
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<td>0.06** (2.38)</td>
<td>0.21*** (8.71)</td>
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<tr>
<td>Alpha FF3</td>
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<td>0.06** (2.06)</td>
<td>0.16*** (6.89)</td>
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<td>0.04** (1.9)</td>
<td>0.14*** (6.22)</td>
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<td>0.03 (1.12)</td>
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<td><strong>Panel C: Quarterly Return</strong></td>
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<td>Alpha CAPM</td>
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<td>0.68*** (4.96)</td>
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<td>Alpha FF3</td>
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<td>0.12 (0.91)</td>
<td>0.52*** (4.99)</td>
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<tr>
<td>Alpha FF5</td>
<td>-0.34*** (-3.01)</td>
<td>0.1 (0.98)</td>
<td>0.45*** (4.36)</td>
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<tr>
<td>Alpha FFC</td>
<td>-0.39*** (-3.36)</td>
<td>0.01 (0.13)</td>
<td>0.43*** (3.89)</td>
</tr>
</tbody>
</table>
Table 1.3 Performance of the New Money Portfolio for Actively Managed ETFs
This table describes portfolios of U.S. active equity ETFs formed on the basis of the fund’s money flow in the preceding period. ETF flow data are for 2009 to 2018. Alpha, as a measure for risk-adjusted return, is calculated with 4 different models: the CAPM, the Fama-French 3-factor model (FF3), the Fama-French 5-factor model (FF5), and the Fama-French-Carhart (FFC). Panel A represents the results for weekly portfolios, while panel B and C represent the results for monthly and quarterly portfolios. Flows are classified by a weighting criterion used in the portfolios’ creation, as the first 3 columns show the results for the equally weighted portfolios, column 4 to 6 show the size-weighted portfolios and columns 7 through 9 show the normalized-flow-weighted portfolio. Flows are also classified by the following directions: as inflow (first column of each weighting criteria), outflow (second column of each weighting criteria), and the difference between inflow and outflow (third column of each weighting criteria). The statistical significance of alpha estimates are based on Newey–West standard errors and the parentheses contain the t-statistics. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

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<th>Size-Weighted Portfolio</th>
<th>Normalized-Flow-Weighted Portfolio</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Outflow</td>
<td>Inflow</td>
<td>Difference</td>
</tr>
<tr>
<td>Alpha CAPM</td>
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<td>0.06*** (5.53)</td>
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</table>

Panel A: Weekly Return

| Model   | Outflow | Inflow | Difference | Outflow | Inflow | Difference | Outflow | Inflow | Difference |
|---------|-----------------------------|-------------------------|-----------------------------------|
| Alpha CAPM | -0.32*** (-4.76) | 0.26*** (4.47) | 0.55*** (6.57) | -0.26*** (-3.76) | 0.17** (2.58) | 0.41*** (4.23) | -0.33*** (-4.23) | 0.28*** (4.05) | 0.59*** (5.97) |
| Alpha FF3 | -0.28*** (-3.72) | 0.21*** (3.62) | 0.47*** (4.9) | -0.23*** (-2.88) | 0.15** (2.35) | 0.36*** (3.35) | -0.29** (-3.45) | 0.23*** (3.27) | 0.5*** (4.67) |
| Alpha FF5 | -0.2** (-2.33) | 0.28*** (4.72) | 0.45*** (4.6) | -0.17* (-1.84) | 0.21*** (3.03) | 0.35** (3.15) | -0.22** (-2.28) | 0.31** (4.32) | 0.5** (4.82) |
| Alpha FFC | -0.25*** (-3.36) | 0.2** (3.36) | 0.43*** (4.5) | -0.2** (-2.63) | 0.15** (2.32) | 0.34** (3.16) | -0.26** (-3.1) | 0.21** (2.93) | 0.45** (4.23) |

Panel B: Monthly Return

| Model   | Outflow | Inflow | Difference | Outflow | Inflow | Difference | Outflow | Inflow | Difference |
|---------|-----------------------------|-------------------------|-----------------------------------|
| Alpha CAPM | -1.04*** (-6.48) | 0.78*** (3.3) | 1.82*** (5.94) | -0.73** (-2.95) | 0.4 (1.22) | 1.12** (2.48) | -1.21*** (-6.1) | 1.01*** (3.75) | 2.22*** (7.68) |
| Alpha FF3 | -0.92*** (-4.88) | 0.68** (2.43) | 1.6*** (4.15) | -0.66** (-2.57) | 0.4 (1.22) | 1.06** (2.15) | -1.03*** (-4.01) | 0.86*** (3.05) | 1.9*** (5.24) |
| Alpha FF5 | -0.74*** (-3.15) | 0.79*** (3.16) | 1.52*** (4.3) | -0.51* (-1.87) | 0.49 (1.53) | 1** (2.08) | -0.8** (-2.51) | 0.98** (3.52) | 1.78** (5.7) |
| Alpha FFC | -0.92*** (-4.38) | 0.62** (2.15) | 1.54*** (3.63) | -0.66** (-2.41) | 0.39 (1.18) | 1.04* (1.98) | -1.04*** (-3.76) | 0.78** (2.64) | 1.81*** (4.6) |
Table 1.4 Panel Analysis Descriptive Statistics

The table provides the summary statistics for the sample of 996 equity ETFs listed on U.S. exchanges from 2012 to 2018. All the variables are calculated based on the monthly data (49888 ETF-Month). Return is the change in the market value of an ETF over the period of a month per dollar of initial investment. Net flow shows the new money into or out of the fund in $M. Active is a dummy variable that takes the value of 1 when the ETF is managed actively and zero otherwise. Share Turnover represents the volume of trade over the number of shares outstanding. Bid-Ask Spread is the difference between the closing bid and ask quotes divided by the bid-ask midpoint. Price Ratio is equal to the price over the net asset value. Size is the logarithm of total assets under management. Age is the difference between the data date and the inception date in years. Has Option is a dummy variable that takes the value of 1 if an option is available for the ETF. Expense Ratio shows the amount an investor pays after accounting for the impact of reimbursements and contractual waivers. Family Size proxies the total assets under management for all the members of a family. A family is all the funds for which the first 6 digits of the CUSIP number are similar. Constituents shows the number of securities an ETF holds in its basket.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Std Dev</th>
<th>Lower Quartile</th>
<th>Upper Quartile</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return</td>
<td>0.60</td>
<td>0.86</td>
<td>4.41</td>
<td>-1.47</td>
<td>2.95</td>
</tr>
<tr>
<td>Net Flow</td>
<td>22.31</td>
<td>0.00</td>
<td>389.19</td>
<td>-1.43</td>
<td>12.20</td>
</tr>
<tr>
<td>Active</td>
<td>0.11</td>
<td>0.00</td>
<td>0.32</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Share Turnover</td>
<td>33.49</td>
<td>13.20</td>
<td>101.22</td>
<td>7.87</td>
<td>24.73</td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>1.00</td>
<td>0.85</td>
<td>0.67</td>
<td>0.60</td>
<td>1.21</td>
</tr>
<tr>
<td>Price Ratio</td>
<td>0.998</td>
<td>1.000</td>
<td>0.045</td>
<td>1.000</td>
<td>1.001</td>
</tr>
<tr>
<td>Size</td>
<td>5.38</td>
<td>5.32</td>
<td>2.20</td>
<td>3.86</td>
<td>6.80</td>
</tr>
<tr>
<td>Age</td>
<td>7.24</td>
<td>6.74</td>
<td>4.47</td>
<td>3.38</td>
<td>10.27</td>
</tr>
<tr>
<td>Has Option</td>
<td>0.41</td>
<td>0.00</td>
<td>0.49</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>8.67</td>
<td>9.11</td>
<td>2.41</td>
<td>7.13</td>
<td>10.15</td>
</tr>
<tr>
<td>Family Size</td>
<td>315.83</td>
<td>101.00</td>
<td>632.74</td>
<td>43.00</td>
<td>336.00</td>
</tr>
<tr>
<td>Constituents N</td>
<td>0.60</td>
<td>0.86</td>
<td>4.41</td>
<td>-1.47</td>
<td>2.95</td>
</tr>
</tbody>
</table>
Table 1.5 Panel Analysis for ETF New Money
This Table represents the coefficients from a panel of 49,884 ETF-Month observations. The dependent variable is the ETF risk adjusted return (alpha), which is calculated by using Equation (5) in the study. The dependent variable’s method of calculation is given at the top of each column. All the continuous variables are converted to a z-score for the sake of convenience to compare their economic significance. Return is the change in the market value of an ETF over the period of a month per dollar of initial investment. Net flow shows the new money into or out of the fund in $M, scaled by the fund size. Active is a dummy variable that takes the value of 1 when the ETF is managed actively and zero otherwise. Share Turnover represents the volume of trade over the number of shares outstanding. Bid-Ask Spread is the difference between the closing bid and ask quotes divided by the bid-ask midpoint. Price Ratio is equal to the price over the net asset value. Size is the logarithm of total assets under management. Age is the difference between the data date and the inception date in years. Option Available is a dummy variable which takes the value of 1 if an option is available for the ETF. Expense Ratio shows the amount an investor pays after accounting for the impact of reimbursements and contractual waivers. Family Size proxies the total assets under management for all the members of a family. A family denotes all the funds for which the first 6 digits of the CUSIP number are similar. Constituents shows the number of securities an ETF holds in its basket. The parentheses contain the t-statistics. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th></th>
<th>CAPM</th>
<th>FF3</th>
<th>FF5</th>
<th>FFC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Net Flow</td>
<td>0.042** (1.99)</td>
<td>0.031* (1.84)</td>
<td>0.029** (2)</td>
<td>0.028* (1.86)</td>
</tr>
<tr>
<td>Net Flow*Active</td>
<td>0.072*** (2.86)</td>
<td>0.063*** (2.86)</td>
<td>0.063*** (2.83)</td>
<td>0.059*** (2.76)</td>
</tr>
<tr>
<td>Active</td>
<td>0.026 (0.36)</td>
<td>0.016 (0.22)</td>
<td>0.004 (0.07)</td>
<td>0.024 (0.36)</td>
</tr>
<tr>
<td>Share Turnover</td>
<td>0.004 (0.17)</td>
<td>0.004 (0.19)</td>
<td>0.001 (0.05)</td>
<td>0.004 (0.19)</td>
</tr>
<tr>
<td>Bid-Ask Spread</td>
<td>-0.182*** (-4.39)</td>
<td>-0.134*** (-3.76)</td>
<td>-0.094*** (-2.91)</td>
<td>-0.112*** (-3.44)</td>
</tr>
<tr>
<td>Price Ratio</td>
<td>0.003*** (10.77)</td>
<td>0.002*** (14.63)</td>
<td>0.002*** (9.54)</td>
<td>0.002*** (13.23)</td>
</tr>
<tr>
<td>Size</td>
<td>0.151*** (4.38)</td>
<td>0.117*** (3.75)</td>
<td>0.083*** (2.82)</td>
<td>0.098*** (3.25)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.065* (-1.84)</td>
<td>-0.043 (-1.26)</td>
<td>-0.032 (-1.04)</td>
<td>-0.054* (-1.71)</td>
</tr>
<tr>
<td>Option Available</td>
<td>-0.081** (-2.97)</td>
<td>-0.079** (-2.99)</td>
<td>-0.054** (-2.39)</td>
<td>-0.073** (-2.9)</td>
</tr>
<tr>
<td>Expense Ratio</td>
<td>-0.019 (-0.82)</td>
<td>-0.022 (-0.79)</td>
<td>-0.022 (-0.93)</td>
<td>-0.026 (-0.92)</td>
</tr>
<tr>
<td>Family Size</td>
<td>0.004 (0.05)</td>
<td>-0.002 (-0.03)</td>
<td>0.004 (0.06)</td>
<td>0.011 (0.14)</td>
</tr>
<tr>
<td>Constituents</td>
<td>-0.009 (-0.73)</td>
<td>0.006 (0.58)</td>
<td>0.004 (0.37)</td>
<td>0.006 (0.61)</td>
</tr>
<tr>
<td>Intercept</td>
<td>-0.195*** (-8.19)</td>
<td>-0.155** (-7.29)</td>
<td>-0.102*** (-5.26)</td>
<td>-0.13*** (-6.85)</td>
</tr>
</tbody>
</table>

Time FE | Yes | Yes | Yes | Yes
Family FE | Yes | Yes | Yes | Yes
Clusters Standard Error: Time and Fund | Yes | Yes | Yes | Yes
Number of Obs. | 49,884 | 49,884 | 49,884 | 49,884
Adjusted R-Squared | 0.099 | 0.0897 | 0.0654 | 0.0793
Table 1.6 Univariate Analysis of CARs

Panel A of Table 1.6 compares the mean cumulative abnormal return (CAR) of stocks that experience the highest ETF ownership change (EOC) following an inflow to the passive ETFs against the mean cumulative abnormal return (CAR) of the stocks that experience the highest EOC following an outflow of the passive ETFs. Panel B compares the mean CAR of stocks that experience the highest EOC following an inflow to the active ETFs against the mean CAR of the stocks that experience the highest EOC following an outflow of the active ETFs. The CARs are presented for the (-1, +5), (-3, +22), and (-3, +67) windows surrounding the date that flow shock occurs to the ETF. Abnormal returns are calculated as the stock’s return minus the CRSP value-weighted market index using FFC model. The parentheses contain the Patell Z-statistics or the t-statistics, as indicated.

<table>
<thead>
<tr>
<th></th>
<th>Panel A. Passively Managed ETFs</th>
<th>Panel B. Actively Managed ETFs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean CAR Following Inflow Shock (Patell Z)</td>
<td>Mean CAR Following Outflow Shock (Patell Z)</td>
</tr>
<tr>
<td>CAR (-2, +2)</td>
<td>0.04*** (7.9)</td>
<td>-0.14*** (-30.9)</td>
</tr>
<tr>
<td>CAR (-3, +22)</td>
<td>-0.04*** (-11.3)</td>
<td>-0.20*** (-19.7)</td>
</tr>
<tr>
<td>CAR (-3, +66)</td>
<td>-0.14*** (-15.9)</td>
<td>-0.2*** (-10)</td>
</tr>
<tr>
<td>CAR (-2, +2)</td>
<td>0.21 (0.2)</td>
<td>0.05 (0.6)</td>
</tr>
<tr>
<td>CAR (-3, +22)</td>
<td>0.02 (-0.8)</td>
<td>-0.25*** (-4)</td>
</tr>
<tr>
<td>CAR (-3, +66)</td>
<td>-0.11*** (-2.3)</td>
<td>-0.43** (-1.7)</td>
</tr>
</tbody>
</table>
Table 1.7 Univariate Analysis of Demand Shocks Exerted to the Securities by Active and Passive ETFs

This Table presents a univariate model for the determinants of a flow shock for active and passive ETFs. Flow is the average value of the ETF shock (flow) in $M. Log(AUM) denotes the natural logarithm of assets under management by the ETF in $M. Sec Mkt Size is the market size ($B) of the stock hit by the flow shock. Spread is the difference between the closing bid and ask quotes divided by the bid-ask midpoint. Previous Holding is the average ETF ownership prior to the shock. EOC is the average ETF ownership change following a flow shock. Shock Frequency is the average number of flow shocks induced by the ETF and exerted on the stock during a month. Inflow is a dummy variable that takes the value of one if the flow shock is positive (inflow) and zero otherwise. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th></th>
<th>Passive</th>
<th>Active</th>
<th>Difference</th>
<th>t Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Flow ($M)</td>
<td>11.7</td>
<td>3</td>
<td>8.7***</td>
<td>19</td>
</tr>
<tr>
<td>Log (AUM) ($M)</td>
<td>8.6</td>
<td>5.1</td>
<td>3.5***</td>
<td>347</td>
</tr>
<tr>
<td>Sec Mkt Size ($B)</td>
<td>15</td>
<td>38</td>
<td>-23***</td>
<td>-320</td>
</tr>
<tr>
<td>Spread</td>
<td>0.028</td>
<td>0.023</td>
<td>0.0046***</td>
<td>139</td>
</tr>
<tr>
<td>Previous Holding (%)</td>
<td>0.61</td>
<td>0.044</td>
<td>0.48***</td>
<td>467</td>
</tr>
<tr>
<td>EOC (%)</td>
<td>0.022</td>
<td>0.022</td>
<td>0**</td>
<td>-2.19</td>
</tr>
<tr>
<td>Shock Frequency</td>
<td>7.3</td>
<td>1.2</td>
<td>6.1***</td>
<td>384</td>
</tr>
<tr>
<td>Inflow Dummy</td>
<td>0.60</td>
<td>0.69</td>
<td>-0.09***</td>
<td>-16</td>
</tr>
<tr>
<td>Obs. Number</td>
<td>3547236</td>
<td>274234</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1.8 Stock Selection Propensity by Funds
This table presents the probit estimates of the determinants of the change in ETF ownership following an inflow shock (first column) and an outflow shock (second column) from 2012 to 2018. The dependent variable is Active, which is a dummy variable that takes the value of 1 if the ETF is actively managed and zero otherwise. Log (AUM) denotes the natural logarithm of the average assets under management by the ETF in $M. Sec Mkt Size is the market size ($M) of the stock held by the ETF. Spread is the difference between the closing bid and ask quotes divided by the bid-ask midpoint. Previous Holding is the average ETF ownership prior to the shock. The parentheses contain the t-statistics. *, **, and *** respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th></th>
<th>Inflow Shock</th>
<th>Outflow Shock</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(AUM) ($M)</td>
<td>-0.543*** (-629)</td>
<td>-0.545*** (-379)</td>
</tr>
<tr>
<td>Sec Mkt Size ($M)</td>
<td>0.309*** (332)</td>
<td>0.345*** (242)</td>
</tr>
<tr>
<td>Spread</td>
<td>0.01*** (8.88)</td>
<td>-0.003* (-1.8)</td>
</tr>
<tr>
<td>Previous Holding</td>
<td>-0.172*** (-64)</td>
<td>-0.261*** (-48.11)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.003*** (-863)</td>
<td>-2.604*** (-530)</td>
</tr>
<tr>
<td>Observations</td>
<td>24,997,582</td>
<td>10,761,303</td>
</tr>
<tr>
<td>Pseudo R squared</td>
<td>0.2680</td>
<td>0.2875</td>
</tr>
<tr>
<td>Year Dummy</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Month Dummy</td>
<td>YES</td>
<td>YES</td>
</tr>
</tbody>
</table>
Table 1.9 Absolute ETF Ownership Change (EOC) of Active ETFs vs. Passive ETFs
This table presents the difference in EOC for active ETFs and passive ETFs, based on the propensity score estimates of active/passive ETFs. Number of Observations for Treated shows the number of active ETF observations and Number of Observations for Controls shows the number of the passive ETF observations. The average treatment effect on the treated (ATT) measures the difference between the two groups.

<table>
<thead>
<tr>
<th>Sample</th>
<th>Treated (Active)</th>
<th>Controls (Passive)</th>
<th>Difference</th>
<th>S.E.</th>
<th>T-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>0.01</td>
<td>0.04</td>
<td>-0.03</td>
<td>0.001</td>
<td>-28.47</td>
</tr>
<tr>
<td>ATT</td>
<td>0.01</td>
<td>0.01</td>
<td>0.00</td>
<td>0.0006</td>
<td>15.04</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>190,336</td>
<td>24,807,246</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel B. Outflow-Induced EOC of Active ETFs vs Passive ETFs

<table>
<thead>
<tr>
<th>Sample</th>
<th>Treated (Active)</th>
<th>Controls (Passive)</th>
<th>Difference</th>
<th>S.E.</th>
<th>T-Stat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unmatched</td>
<td>-0.02</td>
<td>-0.10</td>
<td>0.07</td>
<td>0.004</td>
<td>17.6</td>
</tr>
<tr>
<td>ATT</td>
<td>-0.02</td>
<td>-0.02</td>
<td>0.00</td>
<td>0.001</td>
<td>-2.4</td>
</tr>
<tr>
<td>Number of Obs.</td>
<td>83,704</td>
<td>10,677,599</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Table 1.10 Performance of New Money Portfolio for Subsamples of Passively Managed ETFs

This table describes portfolios of U.S. passive equity ETFs formed on the basis of the fund’s money flow in the preceding month. ETF flow data are for 2006 to 2018. Alpha, as a measure for the risk-adjusted return, is calculated with 4 different models: the CAPM, the Fama-French 3-factor model (FF3), the Fama-French 5-factor model (FF5), and the Fama-French-Carhart (FFC). Panel A represents the results for monthly portfolios of passively managed ETFs with less than $2.2 billion in AUM. Panel B represent the results for monthly portfolios of passively managed ETFs that have at least 15 matched observations (ETF-security-days) with the active funds using the results of propensity score matching. The flows are classified by a weighting criteria used in the portfolios’ creation, as the first 3 columns show the results of the equally weighted portfolios, column 4 to 6 show the size-weighted portfolios, and columns 7 through 9 show normalized-flow-weighted portfolio. Flows are also classified by the following directions: inflow (first column of each weighting criteria), outflow (second column of each weighting criteria), and the difference between inflow and outflow (third column of each weighting criteria). The statistical significance of alpha estimates are based on Newey–West standard errors and the parentheses contain the t-statistics. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th>Model</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha CAPM</td>
<td>-0.2*** (-4.11)</td>
<td>0.13*** (3.64)</td>
<td>0.33*** (10.66)</td>
<td>-0.18*** (-3.35)</td>
<td>0.1*** (2.37)</td>
<td>0.28*** (7.75)</td>
<td>-0.22*** (-3.62)</td>
<td>0.1* (1.65)</td>
<td>0.32*** (5.58)</td>
</tr>
<tr>
<td>Alpha FF3</td>
<td>-0.15*** (-3.4)</td>
<td>0.13*** (3.75)</td>
<td>0.28*** (9.1)</td>
<td>-0.14*** (-2.95)</td>
<td>0.08** (2.39)</td>
<td>0.22*** (6.86)</td>
<td>-0.16*** (-3.16)</td>
<td>0.11** (2.13)</td>
<td>0.28** (5.2)</td>
</tr>
<tr>
<td>Alpha FF5</td>
<td>-0.12*** (-3.7)</td>
<td>0.12*** (3.89)</td>
<td>0.23*** (8.41)</td>
<td>-0.12*** (-3.5)</td>
<td>0.07** (2.48)</td>
<td>0.19*** (6.92)</td>
<td>-0.14*** (-2.98)</td>
<td>0.11** (2.09)</td>
<td>0.25*** (4.64)</td>
</tr>
<tr>
<td>Alpha FFC</td>
<td>-0.16*** (-4.9)</td>
<td>0.08** (2.23)</td>
<td>0.24*** (6.39)</td>
<td>-0.15*** (-4.17)</td>
<td>0.04 (1.17)</td>
<td>0.19*** (5.07)</td>
<td>-0.17*** (-3.81)</td>
<td>0.07 (1.12)</td>
<td>0.23*** (4.05)</td>
</tr>
</tbody>
</table>

Panel A: Monthly Return for Passive ETFs with AUM < $ 2.2 B

<table>
<thead>
<tr>
<th>Model</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
<th>Outflow</th>
<th>Inflow</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alpha CAPM</td>
<td>0.1*** (4)</td>
<td>-0.16*** (-4.06)</td>
<td>0.27*** (7.58)</td>
<td>0.05* (1.75)</td>
<td>-0.12*** (-3.01)</td>
<td>0.17*** (4.38)</td>
<td>-0.01 (-0.15)</td>
<td>-0.31*** (-3.67)</td>
<td>0.3*** (3.88)</td>
</tr>
<tr>
<td>Alpha FF3</td>
<td>0.09*** (4)</td>
<td>-0.09** (-2.31)</td>
<td>0.17*** (5.05)</td>
<td>0.05* (1.87)</td>
<td>-0.05 (-1.53)</td>
<td>0.1*** (2.94)</td>
<td>-0.04 (-0.45)</td>
<td>-0.19*** (-2.71)</td>
<td>0.16* (1.82)</td>
</tr>
<tr>
<td>Alpha FF5</td>
<td>0.06** (2)</td>
<td>-0.09** (-2.38)</td>
<td>0.15*** (4.53)</td>
<td>0.04 (1.29)</td>
<td>-0.05 (-1.46)</td>
<td>0.1*** (2.91)</td>
<td>-0.06 (-0.63)</td>
<td>-0.2** (-2.52)</td>
<td>0.14 (1.44)</td>
</tr>
<tr>
<td>Alpha FFC</td>
<td>0.04 (1.2)</td>
<td>-0.08** (-2.16)</td>
<td>0.12*** (3.32)</td>
<td>0.01 (0.22)</td>
<td>-0.07 (-1.84)</td>
<td>0.08*** (2.34)</td>
<td>-0.06 (-0.49)</td>
<td>-0.18*** (-2.59)</td>
<td>0.13 (1.2)</td>
</tr>
</tbody>
</table>

Panel B: Monthly Return for PSM Sample of Passive ETFs
Figure 1.1 Cumulative New-Money Flow: ETFs VS. Mutual Funds

This figure demonstrates the cumulative new money flow in $B for ETFs and Mutual Funds since 2007 to the end of 2018.
Figure 1.2 Flow Distribution Across Deciles
Panel A: Cumulative Abnormal Return in (-2,+2) Window

Panel B: Cumulative Abnormal Return in (-3,+22) Window
This figure shows the cumulative abnormal returns (CARs) active and passive ETFs from 2 (3) days prior to the flow shock until 2 (22 or 66) days after the flow shock. The black spectrum lines show CARs for passive ETFs and the blue spectrum lines show CARs for active ETFs. Abnormal returns are calculated as the stock return (Fama-French Plus Momentum model) minus CRSP market index.

Introduction

Since the beginning of 2020, the COVID-19 pandemic has turned into the most challenging and urgent task for almost all governments and communities across the world. The severity and high level of contagiousness of this disease have disrupted the supply chain and workforce of the world and resulted in an unprecedented impact on financial markets (Sharif, Aloui, & Yarovaya, 2020). While the adverse effect of the COVID-19 crisis has not been homogeneous across the countries, it has influenced the variance of the US and Europe’s stock markets more than the 2008 financial crisis (Ali, Alam, & Rizvi, 2020; Shehzad, Xiaoxing, & Kazouz, 2020). Governments try to hamper the adverse economic effect of social distancing and lockdowns by income support packages, quantitative easing, and lowering interest rate (Ashraf, 2020; Zhang, Hu, & Ji, 2020). Moreover, recent pandemic plummeted foreign investment by almost 50% across the globe for the first half of 2020, the largest decline on record, according to the Wall Street Journal.\(^9\)

While the benefits of international portfolio diversification have been established in the literature (Grubel, 1968; Hodrick & Zhang, 2014; Lessard, 1973), the way investors can gain exposure to the other countries’ capital market has not progressed at the same rate. Investors can either directly invest in the local market or indirectly through depository receipts (ADRs), closed-end country funds, or international mutual funds. As direct investing requires investors to obtain information about a foreign market, which is time-consuming, indirect investing is an easier option (Huang & Lin, 2011). A relatively new and very popular investment vehicle that can provide international exposure is the Exchange-Traded Fund (ETF). ETFs popularity among investors has grown

remarkably in the United States since 2008 financial crisis to the extent that as of January 2020, ETFs hold more than $4.4 trillion assets under management. Features like intraday tradability, tax efficiency, low fees, and transparency have contributed to the ETFs’ growth. While Pennathur, Delcoure, and Anderson (2002) and Zhong and Yang (2005) challenge the international diversification benefits of iShares closed-end funds, Tsai and Swanson (2009) find that ETFs provide U.S. investors greater diversification benefits than country funds. Huang and Lin (2011) also show that ETFs are an effective instrument for investors to create an internationally diversified portfolio.

In this study, we employ a novel approach to investigate investors’ reactions to the pandemic by examining new money flows into U.S. ETFs with exposure to the U.S., Europe, and Asia. In other words, we employ follow the money approach to examine whether U.S. investors adjust the distribution of assets in their portfolio in response to COVID-19 outbreak in a given geographic location. To this end, we set to find out the joint distribution and linkage between assets with different geographic exposure. A good understanding of the linkage between assets with different geographic exposure is a key element in portfolio management. This joint distribution, however, may not remain constant over time. As a result, investors would require information about the conditional joint distribution of assets to maintain dynamic portfolio rebalancing strategies (Chan, Treepongkaruna, Brooks, & Gray, 2011). For example, Le, Do, Nguyen, and Sensoy (2020) find evidence on the frequency-based dependency networks of various financial assets in the tails of return distributions during the Covid-19 pandemic. Similarly, Corbet, Larkin, and Lucey (2020) report evidence of changes in the distribution of assets and “flight to safety” following the COVID-19 pandemic. These studies illustrate the change in the linkage between assets during the recent
COVID-19 pandemic and highlight the importance of this study for portfolio managers and policymakers.

Unlike previous studies which use asset’s return as a proxy for asset allocation decisions (Guidolin & Timmermann, 2007), we directly use the money flow to measure the asset allocation. We argue that studies that use return to identify the joint distribution of assets have an implicit assumption that flow drives the return by affecting the supply and demand equilibrium. Correspondingly, return, which is easier to track, can proxy the investors’ money flow. Studies like Lou (2012) and Yousefi, Najand, and Sun (2020) have documented the positive relationship between flow and subsequent return of funds. Using flow instead of return results in a cleaner measure of asset allocation and alleviates the endogeneity concerns regarding the reverse effect of return on flow (Clifford, Fulkerson, & Jordan, 2014).

To examine the money flow of different geographic regions, we classified all passively managed ETFs in the U.S. stock exchanges into four groups based on their geographic exposure: U.S., Europe, Asia, and others (Africa, Australia, Middle East, Canada, and unclassified). We seek to model the joint distribution of flows with exposure to these geographic regions, conditional on the level of COVID-19 spread in these areas. For this purpose, we use a Markov Regime Switching model to characterize the conditional joint distribution of these four series. Our model uses the lag of percentage change in the number of new COVID-19 cases in each area as an exogenous macro factor that identifies regimes.

To characterize the marginal flow distribution of each geographic location, we first carry out a univariate Markov switching model. This model allows us to monitor the dynamic of money flow for each geographic location during the period of the pandemic. We then extend our univariate
procedure to the multivariate dynamic factor model. Using a Markov switching vector autoregressive (MSVAR) model, we measure the dynamic linkages between money flow into different geographic locations in response to the prevalence of COVID-19 around the world. Following Guidolin and Timmermann (2006), we adopt multivariate Markov switching intercept autoregressive heteroskedasticity (MSIAH) alongside simpler multivariate Markov switching intercept heteroskedasticity (MSIH) specification in our model selection process.

The results of our univariate analysis indicate that there exist two regimes for each of the U.S., Europe, and Asia flow time series. We label the first regime as “Normal” which is characterized by low volatility and new money inflow into funds with exposure to Asian and European countries. The second regime which we label as “Panic”, denotes periods of high volatility and money outflow from ETFs with foreign countries exposure.

Moreover, our univariate model reveals that investors make swift adjustments to their portfolios in response to rising COVID-19 risk around the world by moving their funds away from high-risk regions to seemingly low risk regions. For example, the panic regime and money outflow from Asian ETFs started in the last week of January 2020, when the number of infected people in China reached from 200 to over 1300 in just a week. This is while the World Health Organization (WHO), declared the novel coronavirus (COVID-19) outbreak a global pandemic on March 11, 2020. As more information become available about the pandemic and the severity of COVID-19 disease, the learning period gets shorter, and investors show a faster response to the outbreak in a geographic area.

Consistent with the univariate results, our multivariate model also reveals a 2-state pattern. Specifically, our MSVAR model, which covers the money flow of all ETFs in the U.S. stock
exchange under the umbrella of four geographic regions, clearly identifies the normal and panic regimes. In our defined normal regime, all four geographic regions experience money inflows characterized by low volatility across all regions. During the panic regime, however, ETFs with non-US exposure exhibit money outflows whereas U.S.-exposed ETFs show significant money inflow.

Our MSVAR model provides a convincing evidence of contagion within the U.S. ETFs and flight-to-safety\textsuperscript{10} effect. In the normal regime which is characterized by low volatility and positive money flow, ETFs with different geographic exposure enjoy new money inflow. By contrast, during the panic regime, which is characterized by higher volatility, ETFs with geographic exposure other than the U.S., experience a negative flow while U.S.-exposed ETFs gain new money flow. Our results are also close to Giannetti and Laeven (2012) who find home bias in capital allocation tends to increase when adverse economic shocks reduce the wealth of international investors.

We further extend our study to a multinational level by investigating the ETF flow of eastern Asian and western Europe countries. We define a variable, Flow Share, which measures the daily distribution of fund flows in each geographic location with respect to the other locations. Using an OLS model, we show that the spread of COVID-19 pandemic in each location affects the level of foreign investment. Investors of countries that were more successful in controlling the pandemic (east Asia) show signs of home bias and reduction in foreign investment during the pandemic. On the other hand, investors of European countries, which were hit harder by the COVID-19, seek to reduce their exposure to domestic funds by increase in foreign investment. This finding is

\textsuperscript{10} Flight to safety is also known as flight to quality in the literature.
consistent with the flight to safety when investors shift their asset allocation away from riskier investments and into safer ones during the adverse economic shock.

The remainder of the paper is organized as follows. Section 2 presents the conditional univariate and multivariate Markov switching models that form the basis of our analysis. Section 3 describes the data description. Section 4 reports the empirical results and discusses their implications for portfolio managers and policymakers. Section 5 concludes the paper.

**Markov Switching models of the conditional joint distribution of flows**

Following Guidolin and Timmermann (2006), and Chan et al. (2011), we employ Markov Switching Intercept Autoregressive Heteroscedasticity (MSIAH) to estimate a general autoregressive Markov switching model as follows:

\[ y_t = \mu_{S_t} + \beta_{S_t} y_{t-1} + \epsilon_t \quad (1) \]

where \( y_t \) refers to a matrix of flows for four ETF groups we examine their interconnection, \( \mu_{S_t} = (\mu_{1S_t}, \mu_{2S_t}, \mu_{3S_t}, \mu_{4S_t}) \) is a vector of mean flows in the state \( S_t \) and \( \beta_{S_t} \) is a 4×4 matrix of autoregressive coefficients in state \( S_t \). \( S_t = 1, 2, \ldots, k \) and \( \epsilon_t \) follows a Normal distribution with zero mean and \( \sigma^2_t \) variance.

\[ \epsilon_t \sim (0, \sigma^2_t) \quad (2) \]

For a k-state Markov process, the transition of states is stochastic and assumed to follow an irreducible ergodic K-state Markov process with transition matrix

\[ P = \begin{bmatrix} p_{11} & \cdots & p_{1k} \\ \vdots & \ddots & \vdots \\ p_{k1} & \cdots & p_{kk} \end{bmatrix} \quad (3) \]
Where \( p_{ij} = PR[S_t = j | S_{t-1} = i]; \quad i, j = 1, 2, \ldots, k \).

While the transition probabilities in Eq. (3) are usually assumed constant, we use the time-varying transition probabilities (TVTP) introduced by (Ding, 2020), for each probability cell. As a result, for a k-state model, we have (k-1) k independent time-varying component as follows:

\[
Q_t = \begin{bmatrix}
q_{11,t} & q_{12,t} & \ldots & q_{1k,t} \\
q_{21,t} & q_{22,t} & \ldots & q_{2k,t} \\
\vdots & \vdots & \ddots & \vdots \\
q_{k-1,1,t} & q_{k-1,2,t} & \ldots & q_{k-1,k,t} \\
1 & 1 & \ldots & 1
\end{bmatrix}
\]  

(4)

For each probability cell of (4), we specify a probability generating function as follows:

\[
q_{ij,t} = \Phi(X_{ij,t}b_{ij})
\]  

(5)

Where \( \Phi \) is the cumulative normal density function, \( X_{ij,t} \) is the state variable vector for cell (i, j), and \( b_{ij} \) is the parameter to be estimated. In our model, we use lag of regional change in the number of new COVID-19 cases in the past one day as an exogenous variable that identifies the regimes.

Next, using \( Q_t \), we generate an auxiliary matrix \( R_t \):

\[
R_t = \begin{bmatrix}
1 & 1 & \ldots & 1 \\
1 - q_{11,t} & 1 - q_{12,t} & \ldots & 1 - q_{1k,t} \\
\vdots & \vdots & \ddots & \vdots \\
\prod_{i=1}^{k-2}(1 - q_{i1,t}) & \prod_{i=1}^{k-2}(1 - q_{i2,t}) & \ldots & \prod_{i=1}^{k-2}(1 - q_{ik,t}) \\
\prod_{i=1}^{k-1}(1 - q_{i1,t}) & \prod_{i=1}^{k-1}(1 - q_{i2,t}) & \ldots & \prod_{i=1}^{k-1}(1 - q_{ik,t}) \\
\end{bmatrix}
\]  

(6)

Finally, the time-varying transition probability matrix can be generated as follows:

\[
P_t = Q_t \cdot R_t = \begin{bmatrix}
p_{11,t} & p_{12,t} & \ldots & p_{1k,t} \\
p_{21,t} & p_{22,t} & \ldots & p_{2k,t} \\
\vdots & \vdots & \ddots & \vdots \\
p_{k1,t} & p_{k2,t} & \ldots & p_{kk,t} \\
1 & 1 & \ldots & 1
\end{bmatrix}
\]  

(7)

Where \( \cdot \) is a sign for elementwise matrix production.
Consequently, the distribution of $y_t$ conditional on state $S_t$ and on a set of parameters $\Psi$ is

$$f(y_t|S_t = j, \Psi) = \frac{1}{(2\pi)^{N/2}|\Sigma_{st}|^{1/2}} \exp\left[-\frac{1}{2} \varepsilon_t^r \Sigma_{st}^{-1} \varepsilon_t\right]$$  \hspace{1cm} (8)$$

Where $N$ is the number of vectors (4 ETF flow groups in our model) whose joint distribution is desired. Considering the $k$ possible regimes, the full log-likelihood function of the model is:

$$\ln L = \sum_{t=1}^{T} \ln \sum_{j=1}^{k} (f(y_t|S_t = j, \Psi) \Pr(S_t = j))$$  \hspace{1cm} (9)$$

Where $T$ is the number of observations. Eq. (9) is in fact, a weighted average of the likelihood function in each state. However, since the probabilities are not observable, Hamilton’s filter is used to make inferences on the probabilities based on the available information (Hamilton, 1989). See Perlin (2015) for further details on this topic.

Eq. (1) represents a general form of the Markov switching model which can turn into simpler models by imposing some restrictions. For example, when $y_t$ is restricted to a vector of aggregated ETF flows of one geographic area over period $t$, then Eq. (1) denotes a univariate MSIAH model. We also investigate the Markov Switching Intercept Heteroscedasticity (MSIH) model by restricting the autoregressive part of the model to zero ($\beta_{S_t} = 0$). Furthermore, we examine the 2-, 3-, and 4-state regimes to ensure the best model is fitted for each univariate case. To evaluate the trade-off between MSIH and MSIAH data fit and to determine the optimum number of states, we rely on the Akaike information criterion (AIC) and Bayesian information criterion (BIC) model fit statistics. We define the “best” Markov switching model as a model with the lowest average AIC and BIC value.
Data description

Our initial sample data consist of daily data of 2417 ETFs listed in US stock exchanges from January 2020 to the end of October 2020. We use two databases to collect the ETF data for this study: Bloomberg and ETF Global (ETFG). The ETFG data is sourced daily directly from the ETF issuers and their custodians and provide information like region and geographical exposure, active or passive status, and leverage level of the ETFs. Even though ETFG provides information about the daily flow of the ETFs, we choose to use Bloomberg as the first source of flow data. The main reason for taking this approach is the reporting agility of the data provider. Our cross-check analysis between the two databases (i.e. Bloomberg and ETFG) shows that Bloomberg is timelier in reporting the flow (generally with a 1-day lag) than ETFG. We also drop the leveraged and active ETFs from our sample. Leveraged ETFs do not use the “in-kind” mechanism in ETF share creation/redemption and similar to mutual funds, are settled in cash. Active ETFs are also removed from the sample because they may frequently change their geographic exposure during the period of the study. The final sample contains 1720 ETFs, comprising more than 336,600 fund-day observations. Needless to say, we keep ETFs from all asset classes (Equity, Fixed income, Currency, Commodities, and Real Estate) that exist in our sample since the focus of our study is on geographic exposure rather than asset type.

Next, ETFs are classified into four groups based on their region’s exposure: Asia, Europe, U.S., and Others. Every region’s exposure in the dataset is presented as a percentage of non-cash assets held by the fund. Exploiting a text analysis on the “geographical_exposure” variable, we could differentiate ETF exposure based on the country. We set 60% as a hurdle for geographic exposure. As a result, a fund is flagged as “Asia”, if at least 60% of its holdings are exposed to Asian countries. For example, “IGOV” is the iShares International Treasury Bond ETF which provides
exposure to bonds issued by the governments of countries around the world (excluding the U.S.). We classify IGOV as an ETF with exposure to Europe because our analysis shows more than 60% of its holdings have exposure to European countries. This is while IGOV holds treasury bills of countries like Japan, Canada, Singapore, and Israel in its portfolio as well. ETFs with exposure to the Middle East, Africa, and Global are also grouped as “Other”. Variable “flow” is then aggregated based on geographical location and day. Finally, the aggregated flow data is merged with daily data on new and total confirmed COVID-19 cases in Asia, Europe, US., and the world. We use the European CDC published daily statistics on the COVID-19 pandemic as the source of our data\(^{11}\). ECDC reports harmonized daily data of COVID-19, not just for Europe, but for the entire world.

Fig. 1 plots the daily time-series of cumulative flows since Jan 2020 for each of the four geographic groups that we examine. Consistent with the “home bias” phenomenon, foreign assets on average account for 35% of the total value of assets owned by U.S. investors at the beginning of the pandemic. This number shrinks to 32% during the period of this study. The U.S. Flow generally exhibits an upward trend with a temporary drop on February 22, 2020, concurrent with the first spike in the number of confirmed cases. The Asian ETFs on the other hand started experiencing outflow beginning January 24, 2020 -- when China confirmed that COVID-19 cases reached 1000 in less than a week. This negative trend continued until the end of May when China records no new coronavirus cases for the first time since the pandemic began. What is interesting in Fig. 2.1 is the gain of the U.S. Flow index following the outflows from Asian ETFs. Similar to Asian ETFs, European funds also experienced outflows by the first signs of the outbreak in Spain and Italy.

\(^{11}\) https://ourworldindata.org/coronavirus-source-data
Table 1 reports the descriptive statistics (Panel A) and a correlation matrix (Panel B) for the daily flow of the four geographic groups. The average flow is the lowest for Asia with $34 million daily outflows; and the highest for the U.S. with over $1 billion daily inflow. Daily changes of all the variables are demeaned and standardized prior to the analysis.

Table 2.1

What is interesting about the data in Table 2.1 is that despite the financial crisis driven by COVID-19 pandemic, ETF market on average grow larger during the first nine months of 2020 and attracted more than $270 billion new money. This is while, mutual funds net new cash flow is -$420 billion for the same time period, according to the investment company institute (ICI) estimated long-term mutual fund flows.

**Empirical Results**

*Univariate Markov Switching model of each geographical group*

We begin by fitting a range of two and three-state MSIH and MSIAH models to each flow series. The goal of this step is to estimate the performance of different models in order to choose the best model for each individual series. We then use the AIC and BIC values to determine the most appropriate multi-regime model specification for each series of flows. Table 2.2 reports the AIC and BIC values for various models fit to the daily flow data of our sample. Judging from the AIC/BIC values, the two-state model is superior to the three-state, as evidenced by lower values. We further test a four-state model which its results are not reported because the model could not converge in some cases due to the large dimensionality level. It is worthwhile to mention that the
lag of daily percentage change in the number of new COVID-19 cases in each geographic group has been used as a macro factor determining the state.

Table 2.2

Our results for fitting a 2-state model for flow are comparable to prior literature which exploit a 2-state model in fitting asset return distribution (Alizadeh, Nomikos, & Pouliasis, 2008; Chan et al., 2011; Guidolin & Timmermann, 2006). Furthermore, the core of this study is to investigate the existence of a hidden regime at the time of crisis which makes this study closer to Wan and Kao (2015) who document a different relationship between oil and financial markets under “stressed” and “normal” regimes. Similarly, Al-Anaswah and Wilfling (2011) use a 2-state model in their study of the stock market to identify bubbles in stock price data.

Table 3 presents the estimates for the univariate 2-state Markov switching model. We, again, utilize AIC and BIC criteria to choose between MSIH and MSIAH models, based on the lowest average of AIC and BIC reported in Table 2.2. Focusing on ETFs with exposure to the Asian market, we find that the mean flows are positive in the normal regime and negative in the panic regime. Consistent with our expectation, the normal regime is recognized by lower volatility compared with the panic regime. Table 2.3 also reports the expected durations for each regime. The duration numbers indicate that the normal regime tends to last longer than the panic regime. Despite the simpler MSIH model fit to Europe flow series, the same conclusion can be inferred for the European ETFs. Negative flow along with higher volatility during the panic regime exhibits signs of flight to quality among ETFs with non-U.S. exposure.

Table 2.3
Analysis of U.S. ETF flows also capture periods of normal regime with low volatility and panic regime with high volatility. However, the direction of U.S. ETF flows is opposite to the Asian and European ETF flows. That is, U.S. ETFs exhibit counter-cyclical characteristics and have a negative flow during the normal regime and a positive flow during the panic regime. This is consistent with the “flight home effect” in which, following a shock, investors tend to rebalance their portfolio away from the international market to their domestic market where they have less information asymmetry. We further investigate this issue in the multivariate section.

To further investigate the effect of COVID-19 pandemic on regime change across ETFs with different geographic exposure, we plot the smoothed probability (Eq. (8)) of panic regime fitted to the individual flow series. We also overlap the graph of daily total COVID-19 cases in each geographic area as an indicator for when a regime switch has occurred. Panels A, B, and C in Fig. 2.2 illustrate the probability of panic regime during the study time, given total COVID-19 cases for the Asia, Europe, and U.S. flows series. For the sake of comparison, the first time that the number of infected people surpasses 100 individual is annotated with an arrow for each geographic area.

Figure 2.2

From the data in Fig. 2.2, it is apparent that the number of new COVID-19 cases in each geographic location affects the regime-switching process. What is interesting about the data in this figure is the quick response of the market to the imminent risk of the pandemic. For example, Asian ETFs are among the first which exhibited signs of regime change and money outflows at the end of January 2020. This is while human-to-human transmission of COVID-19 was confirmed by the WHO and Chinese authorities on January 20, 2020; and on the same day, China reported the first
outbreak by nearly 140 new cases in one day. We also reach a similar conclusion for the Europe flow series. Shortly following the regime change in the flow of Asian ETFs, the probability of panic regime for ETFs with Europe exposure reached to 100% on February 18. This coincides with the surge of new cases and the beginning of the lockdown policy in Europe. In the case of the U.S., however, the situation is different and episodes of panic regime depend on the other locations. The first signs of panic regime emerge in early February and following the outflow of money from Asian ETFs. Similarly, the second wave of panic regime started on February 24, soon after the regime change in Europe flow series. This episode then followed by the prevalence of the pandemic in the U.S. and the stock market crash. As the number of new cases decreased in the U.S., the panic regime gives its place to the normal episode. This normal situation, however, is tentative and turns to panic episodes with every raise in the number of new cases in the U.S.

Thus far, the univariate models broadly identify the relationship between COVID-19 cases and the flow of ETFs. There is also evidence of commonality between the flow of U.S. ETFs with Europe and Asia. For example, the U.S. flow series exhibit episodes of panic regime around the time of the COVID-19 outbreak in China and Europe. One can attribute this trend to the flight to quality, in which capital migrates from where it perceives risky to where it finds as a safe heaven. However, this cannot fully explain the flow shift from international funds to U.S. ETFs, as the U.S. was hit equally hard or even harder by the pandemic than other parts of the globe. We further investigate this in a Markov switching vector autoregressive (MSVAR) model where interaction between flow series can be monitored.

These findings, while preliminary, have important implications for policymakers and portfolio managers. First, our results clearly indicates that investors use ETFs as a tool to geographically diversify their portfolio in order to gain exposure to foreign markets. Exchange-tradability and
high liquidity of ETFs enable investors to show a timely reaction to geographic threats. This outflow (inflow) of money can impose a negative (positive) price pressure on the underlying securities of ETFs and deviate their values from their market efficient price (Lou, 2012; Yousefi et al., 2020). We identify two states for each flow series during a global crisis where any asset allocation decision must follow a 2-state model. Moreover, we find that the panic regime corresponds with higher volatility and lower return across all series; a finding which challenges the efficiency of geographic diversification during a worldwide catastrophe. It is worthwhile to bear in mind that the regime process $S_t$ in our univariate model is constrained by the changes in the number of new infected cases in each geographic area. The fact that the surge in the number of COVID-19 cases in each area is not common across series and thus, regime switches maybe predictable up to an extent, suggests that asset allocation strategies may need to involve switching between geographic locations.

**Markov Switching VAR model for the joint distribution of flows**

To model the joint distribution of flow series in our sample, we need to consider the flow of all ETFs in the U.S. market. It means that flow of ETFs with exposure to other geographic locations other than Asia, Europe, and the U.S., also needs to be considered. To do this, we aggregate the flow of funds with exposure to the Africa, Australia, Middle East and the rest of unclassified ETFs, and labeled them as “Others”. We also use the changes in the number of COVID-19 cases worldwide as a macro factor which can affect regime-switching process. Next, we use AIC and BIC criteria to determine the appropriate model and number of regimes for our multivariate model, as we did in the univariate case. Eventually, a 2-state multivariate MSIAH model is selected to show the linkage between flow series across ETFs. Table 2.4 reports the parameter estimates for this model.
Table 2.4

Table 4 exhibits a homogenous pattern in the conditional flow estimates across four series. Judging from estimated values for duration and $\sigma$ (volatility) in each regime, it can be noted that regime 1 is considerably more persistent and generally less volatile than regime 2. As a result, we label regime 1 as “normal” and regime 2 as “panic” states. Consistent with the growth of index investing, all ETFs aside from their geographic exposure exhibit positive mean flow in the normal regime. During the panic regime, however, ETFs with non-U.S. exposure experience a negative flow, while new money flows into U.S. funds experience upswings.

During the panic period and episodes of economic decline, investors generally prefer safe-haven assets. A safe-haven by definition is an asset with low volatility and high liquidity that investors are drawn to in uncertain times (Flavin, Morley, & Panopoulou, 2014; Kaul & Sapp, 2006). Baur and Lucey (2010) also add another condition where an asset needs to have a zero or negative correlation with the risky portfolio during a market crash to be considered a safe-haven. In our sample, the coefficient of variation (Std. Dev. /Mean) for the U.S. flows is lower than both Europe and Asia. It is also evident from the results in Table 2.4 that the correlation between the flow of U.S. ETFs and other geographic locations turn to negative during the panic regime. Given this, one can conclude that the results of Table 2.4 show that U.S. ETFs represent the main characteristics of a safe asset during the panic regime. Specifically, the significance of $\mu_{2,\text{Asia}}$ and $\mu_{2,\text{others}}$ coefficients show that U.S. investors retract their funds from emerging and developing markets which are perceived to be riskier and direct their investments toward U.S. ETFs, in the presence of a crisis such as the COVID-19 pandemic. This shift in the new money flow away from international ETFs and toward domestic funds during the panic regime is comparable to findings
of Giannetti and Laeven (2012) where they find that home bias in the international allocation of syndicate loans increases in the event of worldwide adverse economic shocks.

Another finding of this study is the autoregressive pattern of flow series in each regime. For normal regime, there is a significant and positive relationship between the current and lagged flow of all four series. This sticky behavior of flow is consistent with the persistent flow hypothesis in mutual funds and ETFs (Jiang & Yuksel, 2017; Sialm, Starks, & Zhang, 2015). During the panic period, however, the persistent flow condition disrupts -- which considering the short duration of the panic period should come at no surprise. We do not provide an explanation for the effect that lagged flow on one geographic location has on the present flow of the other location, because this would be conditional on remaining in the same regime. While the coefficient of $\mu_{s,f}$ represents the average flow for one regime during the period of the study, the value of $\beta_{s,f}$ depends on the state of the regime in consecutive days.

Fig. 3 plots the smoothed probability of being in the panic regime. As can be seen from this figure, the market spends considerably more time in normal regime. More specifically, the normal regime is interrupted by short periods of the panic regime which coincides with the beginning of the pandemic in Asia, Europe, and the U.S. up until April 2020. After that, there are only some periods of panic represented by spikes in Fig. 2.3 which are mainly contemporaneous with the second wave of the pandemic in the U.S. and Europe. In fact, panic regime constitutes only 20% of the total duration of the study which itself is distributed throughout multiple shorter periods. This means that one observation from normal regime is highly likely to be followed by another observation from the same regime, whereas this is not the case for panic regime. Once again, the
heterogeneous distribution and short lifespan of panic regime makes the interpretation of $\beta_{s,f}$ coefficients questionable.

**Figure 2.3**

**Flight Home Vs. Flight to Safety**

In this section, we study whether investors in each geographic location (Eastern Asia, Western Europe, and U.S.), when hit by COVID-19 shock, have a tendency to rebalance their portfolio away from international funds to their domestic funds. Since the beginning of the COVID-19 pandemic, financial markets around the world experience negative shocks following a raise in the number of infected people in each country. Our goal is to explore how negative shocks induced by spread of the virus affect flow of the ETFs and in particular, whether a worldwide exogenous shock like COVID-19 affects flow to foreign and domestic ETFs. We build on the model of Giannetti and Laeven (2012), analyzing how negative shocks differentially affect bank loans to foreign and domestic borrowers. In particular, we focus on flow of ETFs listed in Eastern Asia, Western Europe, and U.S. and classified them based on the geographical exposure of their holdings. We model the flow share of ETFs in location $i$ to location $j$ at day $t$ as follows:

$$\text{Flow Share}_{ijt} = \alpha_1 \text{Foreign Flow}_{ij} + \alpha_2 \text{Foreign Flow}_{ij} \times \text{COVID19 Home Country}_{it}$$

$$+ \alpha_3 \text{Foreign Flow}_{ij} \times \text{COVID19 Host Country}_{it} + \beta \Psi_{ijt} + \epsilon_{ijt}$$

Where $\text{Foreign Flow}_{ij}$ is a dummy variable that takes the value of one if the geographical location that ETF $i$ is listed is different from its geographical exposure, and zero otherwise. $\text{COVID19 Home Country}_{it}$ measures the change in number of new COVID-19 cases in the
geographic location where ETF is listed; \( COVID19 \text{ Host Country}_{it} \) measures the change in number of new COVID-19 cases in the geographic location where ETF has exposure to; \( \Psi_{ijt} \) is a vector of control variables; and \( \alpha_{jt} \) is an error term.

The important feature of this model is that the dependent variable captures the geographical distribution of fund flow with respect to the total assets under management (AUM) of the home location, rather than the total flow. In other word, our dependent variable captures the allocation of fund flows within the whole ETFs in each geographic location. Since the daily flow (not change in AUM) is standardized by the total AUM at each day, our dependent variable is unaffected by market shocks changing the overall value of AUM and instead, captures the shift in flow from one group to another. As a result, we do not analyze the effect of COVID-19 per se, but only differences in the effect of changes in spread of the pandemic across funds using the interaction term.

\[
\text{Flow Share}_{ijt} = \frac{\sum \text{flow of ETFs listed in location } i \text{ with exposure to location } j \text{ at time } t}{\sum \text{AUM of ETFs in location } i \text{ at time } t - 1}
\]

In our model, a negative coefficient \( \alpha_1 \) implies that investors systematically tend to invest more in domestic funds, indicating that there is a home bias in investors’ portfolio. The coefficients of interaction terms, \( \alpha_2 \) and \( \alpha_3 \), allow us to capture any differential impact of COVID-19 spread in home and host countries on the share of foreign flow. The vector of control variables, \( \Psi_{ijt} \), includes time fixed effect, and in some specifications, home and host fixed effects. Furthermore, we control for the supply shock in home country by including the proportion of domestic flow to total AUM of all funds in home geographic location.

It can be seen from the data in Table 2.5 that there exists a home bias in aggregate investors of Asia, Europe, and U.S. because investors across all these locations found to extend systematically
fewer new money flow to ETFs with foreign exposure. The share of flow to an ETF with foreign exposure is lower by 0.01. This is consistent with a large body of literature that have documented home bias in international investment for investors from different countries. It emerges from the results, however, that investors do not show a tendency toward home location, when home is hit by the spread of the pandemic (column 1). This finding is more consistent with the flight to safety in which, investors shift their portfolio toward a safer assets and markets when exposed by a shock. One may argue that using OLS regression may not be the best choice when the dependent variable, Flow Share, fluctuates between zero and one. The main reason we use OLS in our model is the large number of dummy variables used in different specifications of the model. To alleviate this concern, we use a Tobit model assuming truncated dependent variable in column 2 (Giannetti and Laeven (2012)). Using the same set of control variables, the results remain similar to the OLS estimation. The results also remain intact, even after controlling for the home and host country (column 3).

Interestingly, the results change after we control for the contemporaneous spread of COVID-19 in the host location. If anything, this indicates that flight home effect depends on the situation of the home and host location, and the ability of each location to control the situation and spread of the COVID-19 pandemic. Judging from the coefficients of interaction terms, the results suggest that the impact on the proportion of foreign flow is significantly higher when investors perceive the uncertainty in host location than when they experience raise in the number of infected people at home.

If the direction of the flow depends on the geographical location and the ability of the countries in controlling the pandemic, then one can conclude that this effect is driven by flight to safety. To further investigate this issue, we divide our sample into three subsamples based on the home
geographic location. By differentiating the home geographic location, we seek to investigate the behavior of investors in each location in response to the spread of COVID-19 pandemic in their home, and rest of the world.

Table 2.5

Table 6 demonstrate the model estimation for each geographic location. The most surprising aspect of the data is the heterogeneous behavior of the investors across different locations. While the coefficient of Foreign Flow for Asian and U.S. funds signals a strong home bias, a positive and statistically significant coefficient for European investors shows a tendency for geographic diversification among European investors. This trend is most probably the byproduct of different sources of uncertainty including Brexit and COVID-19 pandemic, considering the fact that our study dates back to January 2019, a year before the pandemic begins. Another interesting finding of Table 2.6 is the coefficient of the interaction term, $Foreign\ Flow_{ij} \times COVID19\ Home\ Country_{it}$. When hit by the COVID-19 pandemic, Asian countries significantly reduce investing in foreign countries and redirect money to home location, where they believe have a better control over the situation. To the contrary, European investors increased their foreign investment following the spread of pandemic. Once again, this finding rules out the flight home hypothesis at the time of a worldwide catastrophe and endorses the flight to safety hypothesis. The inability of European countries to a timely and agile response to the pandemic drove the European investors to rebalance their portfolio away from the domestic funds to more international funds. Flow of the US funds also show the similar, but less pronounce behavior to Asian funds. US investors also do not appear overly concern about the shock in other locations. This can be observed by the statistically insignificant coefficient of the $Foreign\ Flow_{ij} \times COVID19\ Host\ Country_{it}$. A possible explanation for these results may be the
fact that US experience the pandemic with a lag after Asia and Europe, when investors did not have any other option to reallocate their portfolio. The result for the host interaction for Asia and Europe, however, remains negative and significant, showing the response of investors to the spread of the pandemic in other locations.

Table 2.6

**Conclusion**

The COVID-19 pandemic has given researchers a unique opportunity to study the effects of the pandemic on financial markets. Our study differs from previous studies in two major ways. First, as opposed to using returns, we *follow the money* by using actual dollars of fund flows where investors react to the pandemic by moving their funds between domestic and international focused funds. Our second contribution centers on investigation of the existence of two distinct regimes during this pandemic: (1) a “normal” regime when all ETFs receive positive flows and (2) a “panic” regime which emerges when the number of infected people surges in a global location and investors shift their funds from non-U.S. ETFs to U.S.-exposed ETFs.

We employ the general Markov switching model to examine the relationship between the aggregated flow of four groups of U.S ETFs with exposure to Asia, Europe, U.S., and the rest of the world during the COVID-19 pandemic crisis. We find mounting evidence that U.S. investors use international ETFs to geographically diversify their portfolios. We confirm the existence of two regimes during the first three quarters of 2020, concurrent with the prevalence of COVID-19 pandemic across the world. The first regime (normal) is characterized by lower volatility and positive flow for all ETF groups. By contrast, the second regime is labeled “panic”, as it is characterized by higher volatility that emerges by the surge in the number of COVID-19 new cases.
in each geographic area. Furthermore, during the panic regime, we find evidence of an increase in home bias and flight to quality from international ETFs to U.S. ETFs.

In a different setting and using OLS regression, we develop a measure to distinguish the response of different investors across the world to COVID-19 spread in their home region. We find a very different approach among European and Asian investors. While Asian investors generally have a home bias and increase investing in domestic funds during the pandemic, European investors tend to diversify their portfolio and increase their foreign exposure during the same period. This finding is consistent with the flight to safety and shows the heterogeneous behavior of investors depending on their geographic location.

Another interesting finding of this study is the speed of the investor’s portfolio adjustment in response to the risk of the pandemic in one geographic location. Liquidity provided by ETFs enables investors to react promptly to global news and causes investors to adjust their portfolio allocations accordingly. The first signs of the panic regime and new money outflow from Asian ETFs started less than a week after the number of infected people reached more than 100 in China. The investors response time to the new information about pandemic reduced and became more instantaneous for money outflows from European ETFs toward U.S. ETFs, as investors learn more about the severity of the pandemic. This portfolio rebalancing away from international funds toward U.S. ETFs, is consistent with the flight-to-safety effect and surge in “home bias” investing during the adverse economic shocks.

Our results have important implications for policymakers and portfolio managers. Despite all the progress in the world’s health improvements during the past century, human health is confronting new threats. As technology progresses, human communities become denser, and the entire world
become more interconnected. The dark side of this internationalization is the growth of pandemic infections during the past few years. SARS, Ebola, H5N1, H7N9 avian flu, and recently COVID-19 are examples of health issues that can disrupt the global supply chain and trigger a financial crisis. As a result, governments and policymakers need to set a new standard in effective control of contagion. From the viewpoint of portfolio management, using a measure of infection – similar to what is used in the present study, coupled with a dynamic asset allocation portfolio, can be used to rebalance the portfolio in a timely and efficient manner.

Even if the regime-switching process cannot be predicted by a factor, our findings are still relevant and useful for diversification. We show that during such global uncertainty, the “home bias” among investors increases, and portfolio distributions tilt toward domestic assets, where investors have less information disadvantage. Our results also show that there is a contagion between geographic locations and investors can use ETFs to hedge against local uncertainties.
References


Figure 2.1 Cumulative new money flows ($million) into ETFs, by geographic exposure

This figure shows the daily flow into ETFs with exposure to Asia, Europe, U.S., and rest of the world since January 2020. To facilitate comparison across series, the left y-axis shows the dollar value of flows for U.S. and Others, while the right y-axis represents the dollar value of flow for Asia and Europe. The sample period is from January 2020 to October 2020.
Figure 1. Smoothed probability of Panic Regime for univariate Markov switching models. The flow series considered are the aggregated flow of ETFs with exposure to Asia (panel A), Europe (panel B), and U.S. (panel C). The blue line represents the number of new COVID-19 cases in each geographic location during the period of study. The first time that the number of new infected people in each area surpassed 100 is indicated with an arrow. The sample period is from January 2020 to October 2020.
Figure 2.2 Smoothed probability of Panic Regime for multivariate MSIAH model.

The blue line represents the number of new COVID-19 cases in each geographic location during the period of study. The first time that the number of new infected people in each area surpassed 100 is indicated with an arrow. The sample period is from January 2020 to October 2020.
Table 2.1 Descriptive Statistics
Panel A and B present summary statistics and correlation matrix for aggregated ETF flows with exposure to Asia, Europe, U.S., and rest of the world. The sample period is from January 2020 to October 2020 (196 days).

<table>
<thead>
<tr>
<th>Panel A: Daily Flow</th>
<th>Asia</th>
<th>Europe</th>
<th>USA</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean</td>
<td>-34</td>
<td>-6</td>
<td>1100</td>
<td>339</td>
</tr>
<tr>
<td>std</td>
<td>165</td>
<td>157</td>
<td>4000</td>
<td>713</td>
</tr>
<tr>
<td>min</td>
<td>-670</td>
<td>-514</td>
<td>-10982</td>
<td>-2745</td>
</tr>
<tr>
<td>25%</td>
<td>-102</td>
<td>-67</td>
<td>-955</td>
<td>86</td>
</tr>
<tr>
<td>50%</td>
<td>-16</td>
<td>2</td>
<td>1071</td>
<td>443</td>
</tr>
<tr>
<td>75%</td>
<td>52</td>
<td>52</td>
<td>3342</td>
<td>743</td>
</tr>
<tr>
<td>max</td>
<td>363</td>
<td>835</td>
<td>18719</td>
<td>2006</td>
</tr>
</tbody>
</table>

Panel B: Correlation Matrix

<table>
<thead>
<tr>
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<th>Asia</th>
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<th>USA</th>
<th>Other</th>
</tr>
</thead>
<tbody>
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<td>Asia</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Europe</td>
<td>0.24</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>USA</td>
<td>0.04</td>
<td>0.07</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Other</td>
<td>0.16</td>
<td>0.26</td>
<td>0.12</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2.2 Performance measures for univariate Markov switching models.
For each geographic location, the first column shows the Akaike’s Information Criteria (AIC), and the second column represents the Bayesian Information Criteria (BIC). The sample period is from January 2020 to October 2020.

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
<th>Europe</th>
<th>USA</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>AIC</td>
<td>BIC</td>
<td>AIC</td>
</tr>
<tr>
<td>2-State MSIAH</td>
<td>464</td>
<td>497</td>
<td>507</td>
</tr>
<tr>
<td>3-State MSIAH</td>
<td>486</td>
<td>555</td>
<td>432</td>
</tr>
<tr>
<td>2-State MSIH</td>
<td>501</td>
<td>528</td>
<td>483</td>
</tr>
<tr>
<td>3-State MSIH</td>
<td>518</td>
<td>577</td>
<td>492</td>
</tr>
</tbody>
</table>
Table 2.3 Parameter estimates for univariate models.
This table reports the parameter estimates of the univariate 2-state Markov switching models for the daily flow of ETFs with exposure to Asia, Europe, and U.S. The model choice (MSIAH Vs. MSIH) is based on the lowest AIC and BIC score from Table 2.2. The general MSIAH model is specified as $y_t = \mu_{S_t} + \beta_{S_t} y_{t-1} + \epsilon_t$, where $y_t$ refers to a vector of individual location flows, $\mu_{S_t}$ represents the conditional mean in each state (1 and 2), and $\sigma_{S_t}$ shows the conditional volatility of each state. $\beta_{S_t}$ denotes the first-order autoregressive term and $\epsilon_t$ shows the residuals. The MSIH model is a special form of MSIAH where $\beta_{S_t} = 0$. Duration shows the respective duration of being in one regime during the period of the study. The sample period is from January 2020 to October 2020. The parentheses contain the standard error. *, **, and ***, respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
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<th>Model</th>
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<th>Europe</th>
<th>USA</th>
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</thead>
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<tr>
<td>2S-MSIAH</td>
<td>2S-MSIAH</td>
<td>2S-MSIAH</td>
<td>2S-MSIAH</td>
</tr>
<tr>
<td>$\mu_1$</td>
<td>0.10* (0.06)</td>
<td>0.18*** (0.04)</td>
<td>-0.03 (0.06)</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>-0.72*** (0.26)</td>
<td>-0.17 (0.14)</td>
<td>0.03 (0.15)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.58*** (0.07)</td>
<td>-0.17 (0.14)</td>
<td>0.10 (0.10)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.12 (0.16)</td>
<td>0.10 (0.10)</td>
<td>0.29*** (0.11)</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.40*** (0.04)</td>
<td>0.12*** (0.02)</td>
<td>0.35*** (0.06)</td>
</tr>
<tr>
<td>$\sigma_2$</td>
<td>1.48*** (0.33)</td>
<td>1.80*** (0.26)</td>
<td>1.78*** (0.32)</td>
</tr>
<tr>
<td>Duration 1</td>
<td>143.38</td>
<td>9.11</td>
<td>10.33</td>
</tr>
<tr>
<td>Duration 2</td>
<td>32.69</td>
<td>2.72</td>
<td>7.68</td>
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Table 2.4 Parameter estimates for multivariate MSIAH model

This table reports the parameter estimates of the multivariate 2-state Markov switching models for the daily flow of ETFs with exposure to Asia, Europe, U.S., and rest of the world. The model choice (MSIAH) is based on the lowest AIC and BIC score. The MSIAH model is specified as $y_t = \mu_{S_t} + \beta_{S_t} y_{t-1} + \epsilon_t$, where $y_t$ refers to a matrix of four flow series, $\mu_{S_t}$ represents a vector of mean flow in each state (1 and 2), and $\sigma_{S_t}$ shows the conditional volatility of each state. $\beta_{S_t}$ is a $4 \times 4$ matrix of autoregressive term in each state and $\epsilon_t$ shows the error term. Duration shows the respective duration of being in one regime during the period of the study. The sample period is from January 2020 to October 2020. The parentheses contain the standard error. *, **, and *** respectively, denote significance at the 10%, 5%, and 1% levels.

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
<th>Europe</th>
<th>USA</th>
<th>Other</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\mu_1$</td>
<td>0.12** (0.06)</td>
<td>0.03 (0.06)</td>
<td>0.03 (0.08)</td>
<td>0.19*** (0.06)</td>
</tr>
<tr>
<td>$\mu_2$</td>
<td>-1.11*** (0.21)</td>
<td>-0.14 (0.21)</td>
<td>0.43* (0.24)</td>
<td>-0.73** (0.30)</td>
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<tr>
<td>$\beta_{1_Asia}$</td>
<td>0.38*** (0.07)</td>
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<td>-0.14 (0.09)</td>
<td>0.02 (0.07)</td>
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<tr>
<td>$\beta_{2_Asia}$</td>
<td>-0.00 (0.01)</td>
<td>-0.09 (0.13)</td>
<td>0.29*** (0.01)</td>
<td>-0.09 (0.17)</td>
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<td>-0.00 (0.02)</td>
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<td>0.40* (0.21)</td>
<td>0.42* (0.23)</td>
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<tr>
<td>$\beta_{1_USA}$</td>
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<td>0.03 (0.06)</td>
<td>0.24*** (0.07)</td>
<td>0.07 (0.06)</td>
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<tr>
<td>$\beta_{2_USA}$</td>
<td>0.31** (0.16)</td>
<td>0.13 (0.15)</td>
<td>0.14 (0.18)</td>
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</tr>
<tr>
<td>$\beta_{1_Others}$</td>
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<td>-0.04 (0.09)</td>
<td>0.28*** (0.08)</td>
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<tr>
<td>$\beta_{2_Others}$</td>
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<td>0.27** (0.14)</td>
<td>0.03 (0.18)</td>
<td>0.13 (0.18)</td>
</tr>
<tr>
<td>$\sigma_1$</td>
<td>0.35*** (0.04)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\sigma_2$</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>Duration 1</td>
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<tr>
<td>Duration 2</td>
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### Table 2.5 Foreign Flow and Home Bias Effect

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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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</thead>
<tbody>
<tr>
<td>Foreign Flow</td>
<td>-0.017***</td>
<td>-0.005***</td>
<td>-0.017***</td>
<td>-0.016***</td>
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<tr>
<td>COVID-19 Home Country * Foreign Flow</td>
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<td>-0.012*</td>
<td>-0.011</td>
<td>-0.018**</td>
</tr>
<tr>
<td>COVID-19 Host Country * Foreign Flow</td>
<td></td>
<td></td>
<td></td>
<td>-0.044***</td>
</tr>
<tr>
<td>Domestic Flow</td>
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<td>0.343***</td>
<td>0.336***</td>
<td>0.335***</td>
</tr>
<tr>
<td>Time FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Home and Host FE</td>
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<td>No</td>
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<td>No</td>
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<td>Observations</td>
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<td>5670</td>
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<tr>
<td>R-squared</td>
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<td>0.353</td>
<td>0.345</td>
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</tr>
<tr>
<td>Adjusted R-squared</td>
<td>0.259</td>
<td>0.271</td>
<td>0.263</td>
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</tr>
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### Table 2.6 Foreign Flow and Home Bias by Geographic Location

<table>
<thead>
<tr>
<th></th>
<th>Asia</th>
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<th>US</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign Flow</td>
<td>-0.019***</td>
<td>0.004***</td>
<td>-0.031***</td>
</tr>
<tr>
<td>COVID-19 Home Country * Foreign Flow</td>
<td>-0.491***</td>
<td>0.012**</td>
<td>-0.035*</td>
</tr>
<tr>
<td>COVID-19 Host Country * Foreign Flow</td>
<td>-0.098***</td>
<td>-0.012**</td>
<td>0.019</td>
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<tr>
<td>Domestic Flow</td>
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</tr>
<tr>
<td>Time FE</td>
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<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Home and Host FE</td>
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<td>No</td>
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<tr>
<td>Observations</td>
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<td>1890</td>
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<td>0.406</td>
<td>0.381</td>
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<tr>
<td>Adjusted R-squared</td>
<td>0.062</td>
<td>0.107</td>
<td>0.07</td>
</tr>
</tbody>
</table>
Appendices

Appendix 1: Essay 1 Variable Definition

Net Flow: Net flow into or out of the fund in $M. This variable is aggregated from the daily value. Source: Bloomberg and ETFG

Net Asset Value: Fund's total net assets divided by the number of shares outstanding, minus fees and expenses. This variable is averaged from the daily value. Source: Bloomberg and ETFG

Shares Outstanding: The number of ETF shares issued as of the closing on the previous trading day. It is the number used to calculate the NAV. This variable is averaged from the daily value. Source: ETFG and CRSP

Volume: Sum of the trading volumes during the month. Source: CRSP

Returns: Change in the total value of an investment in a common stock over some period of time per dollar of initial investment. Source: CRSP

Assets Under Management: Total assets under management in $M. Source: Bloomberg and ETFG

Leveraged: A dummy variable that takes the value of 1 if a fund is leveraged. Source: ETFG

Active: A dummy variable that takes the value of 1 if fund is managed actively. Source: ETFG

Option Availability: A dummy variable that takes the value of 1 if an option is available for the ETF. Source: ETFG

Option Volume: Volume of the available option. Source: ETFG

Number of Constituents: Number of underlying constituents. Source: ETFG (Derived)

Bid-Ask Spread: The difference between the closing bid and ask quotes for a security. Source: CRSP and ETFG
**Fund Age:** The difference between the data date and the inception date in years. Source: CRSP and ETFG (Derived)

**Price Ratio:** Price over the net asset value. CRSP and ETFG (Derived)

**Expense Ratio:** The amount an investor pays after accounting for the impact of reimbursements and contractual waivers. Source: ETFG

**Management Fee:** A recurring payment, typically expressed as a percentage of the fund's AUM, charged by an investment manager for managing a fund's investment portfolio. Source: ETFG

**Family Size:** Total assets under management for all the members of a family. A family is all funds for which the first 6 digits of the CUSIP number are similar. ETFG (Derived)

**Family Count:** Total number of all the members of a family. A family is all funds for which the first 6 digits of the CUSIP number are similar. ETFG (Derived)

**Share Turnover:** Volume over the number of shares outstanding. CRSP and ETFG (Derived)

**Size:** Logarithm of total assets under management. CRSP (Derived)

**Previous Holding:** the average ETF ownership prior to the flow shock