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Fund Flows and Underlying Returns: The Case of ETFs

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ABSTRACT

I investigate the relation between exchange-traded fund (ETF) flows and their underlying securities' returns using a unique fund-level database covering U.S. equity ETFs, adjusted for the flow reporting bias. I document price pressure and price reversal patterns in ETF flow–return relation in panel and aggregate settings, suggesting an economically significant price pressure effect, even when controlling for mutual fund flows which do not exhibit price pressure. At an aggregate level, vector autoregressive (VAR) tests show that 38% of the price change associated with the flow shock corresponds to price pressure and is reversed after five days. These results extend the research concerning the price impact of institutional trades to the novel ETF framework and highlight differences in the market roles of mutual funds and ETFs.

JEL Classifications: *G12, G14, G23*

Keywords: *ETF; arbitrage; fund; flows; VAR; asset basket; mutual funds*

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I. INTRODUCTION

On September 18, 2007, the S&P 500 ETF (SPY) had net inflows of $15.6 billion, which represented 21% of its shares outstanding, while on the previous day, the same S&P 500 ETF (SPY) attracted only $2.2 billion. Unlike mutual funds, however, ETF flows are not in the form of money, but rather in the form of the underlying assets. Essentially, the $15.6 billion net inflow on September 18, 2007, meant that specialized market participants[1] bought the equivalent amount of the underlying S&P 500 stocks on the market[2] and exchanged them with the funds for their newly created ETF shares. Since the magnitude and variability of daily ETF flows are substantial, the amount of buying and selling of underlying stocks will vary significantly from day to day. While prior researchers have studied the relation of mutual fund flows with their underlying asset returns (e.g., see Warther, 1995; Edelen and Warner, 2001; Coval and Stafford, 2007; Ben-Rephael et al., 2011), relatively little is known about the relationship between ETF flows and the underlying assets. There are recent studies by Ben-David et al. (2014), Clifford et al. (2014), and Fulkerson et al. (2014) that look at the flow–return relation but do not specifically study the price impact associated with high-frequency ETF flows. To my knowledge the ETF flow–price impact relation has been examined only once in a paper by Kalaycıoğlu (2004) on the sample of four ETFs. However, the dramatic growth of the ETF market, and hence, the size of absolute fund flows and daily trading volume, increase in the number of funds and improvement in data quality warrant further study.

This relation is important given that exchange-traded funds have enjoyed an accelerated rise to economic prominence since their introduction in 1993, with annual growth rates in the U.S. in excess of 27%. In 2010, all U.S. ETFs had $991 billion in assets under management while equity ETFs had assets of $476 billion (compared to U.S. equity mutual funds' assets of $2,524 billion). In comparison, in 2006, U.S. ETFs only totaled $422 billion in assets, of which $276 billion was in equity ETFs. Moreover, 14% of institutional investors and 17 of the 20 largest mutual fund complexes report ETFs in their portfolios[3]. The increase in the popularity of ETFs is due to their inherent advantages in index tracking, such as lower expenses, tax efficiency and intraday tradability (Poterba and Shoven, 2002), especially when compared with mutual funds (Huang and Guedj, 2009).

The key to understanding the difference between mutual fund and ETF flows is the combination of "creation-redemption" activity with "in-kind" transactions. "Creation" occurs when an Authorized Participant (AP), usually a large broker-dealer or institution, gives the fund a basket of underlying securities and, in exchange, the AP receives an equivalent share of the ETF. "Redemption" is the opposite process. The AP gives the fund a share of the ETF and, in return, receives the equivalent basket of underlying securities. These transactions are known as "in-kind" because the exchange is essentially a barter of equivalent securities.

Due to the "in-kind" nature of creations and redemptions, APs are required to buy (sell) the underlying assets to create (redeem) ETF shares. Thus, the process itself involves an intervention in the underlying market. The relation of institutional trading and stock prices has been studied extensively in Harris and Gurel (1986), Lakonishok et al. (1992), and Chan and Lakonishok (1993), who find a sizeable but short-lived price impact. While the institutional trading studies report results confirming price pressure, the empirical findings documented in the mutual fund literature are mixed. Edwards and Zhang (1998), Warther (2002), Goetzmann and Massa (2003), Rakowski and Wang (2009), and Watson and Wickramanayake (2012) find no conclusive evidence of price pressure associated with mutual fund flows. On the other hand, Edelen and Warner (2001) document a statistically significant but weak price pressure using intraday data. Coval and Stafford (2007) find evidence of price pressure associated with forced mutual fund redemptions ("fire sales"). Ben-Rephael et al. (2011) analyze daily mutual fund flows from Israel and discover a significant price pressure effect.

The positive contemporaneous relation between fund flows and underlying returns cannot necessarily be interpreted as unambiguous evidence for price pressure. There are several hypotheses for the contemporaneous flow and return relation (Edelen and Warner, 2001). The first competing explanation is the information hypothesis where positive (negative) information shocks positively (negatively) affect both flows and returns simultaneously manifesting in a positive relation between current flows and returns. The second possible explanation is based on return–chasing investor behavior: Past positive (negative) returns lead investors to invest more (less) in ETFs resulting in positive (negative) flow indicated by the positive relation between lagged returns and current flows. In contrast, the price pressure explanation implies that the price impact expressed as a positive relation between contemporaneous flows and returns will be followed by a price reversal (Coval and Stafford, 2007) corresponding to a negative relation between lagged flows and returns.

To test these predictions, I analyze the relation between ETF flows and their underlying stock returns using a sample of 286 U.S. equity ETFs for the 2000–2010 period[4]. Given that ETFs are specifically constructed to track indices, the association of flows with the underlying stocks, if it exists, should be in proportion to the stocks' weight in the indices. Hence, the underlying index return is an intuitive measure to test the relation between flows and the underlying stock returns. I use data obtained from Bloomberg, Center for Research in Security Prices (CRSP) and directly from fund families to construct a database containing index returns and daily shares outstanding. I then adjust the dataset for the flow reporting bias discussed in Quinn et al. (2006) and Rakowski and Wang (2009)[5].

To test the price pressure hypothesis, I perform panel regressions with daily index returns as the dependent variable and contemporaneous and lagged ETF flows as the main independent variables with a set of controls. Additionally, given that several funds with similar features can track the same index, I examine commonalities between flows of funds tracking the same index. Next, I look at the flow–return relation in the time-series setting using vector autoregressive analysis (VAR). Finally, I assess the extent to which the ETF flow–return relation could be explained by the mutual fund flows.

Using panel regressions, I find that the price impact evidence is consistent across subsamples and subperiods, but the price reversal evidence is most prominent in the latter periods and in the top 10 ETFs representing half of U.S. equity ETF assets. Specifically, I find that a one standard deviation shock in the flows to top 10 ETFs is associated on average with price impacts of 18 and 26 basis points in the market return for the 2007–2010 and 2009–2010 periods respectively. Significant price reversals of 5 and 6 basis points corresponding to 27% and 22% of the initial price impact occur on the 2nd day in both subperiods. In contrast, the price impact for the whole sample is still significant across subperiods but is now three to ten times smaller with subsequent price reversal still present but now insignificant.

Employing a VAR analysis on the aggregate ETF flows and market returns for the 2007–2010 period, I again find a significant price reversal effect. Cumulative impulse response functions (CIRFs) show that after five days, there is a price reversal of 38% of the initial shock with the remaining 62% representing a permanent price change. Economically, a one standard deviation shock in aggregate ETF flow of 1.11% (in dollar terms $3 billion) is related to temporary and permanent shocks of 34 bps and 55 bps in market returns respectively. This evidence suggests that at least part of the ETF creation–redemption activity involves market intervention which introduces a transitory component into the market returns. Furthermore, this pattern persists after controlling for mutual fund flows which do not seem to exhibit price reversal suggesting that mutual fund flows and ETF flows are associated with market returns via different mechanisms.

My findings contribute to the literature in a number of ways. First, this paper explores a novel proxy for institutional trading based on the particular features of ETFs and is the first study to draw upon daily data for a large cross-section of funds over a 10 year period while adjusting for reporting bias. Second, it adds to the literature on the effect of institutional trading on prices, including providing evidence for the "price pressure" hypothesis (Edelen and Warner, 2001; Goetzmann and Massa, 2003; Coval and Stafford, 2007). The paper also contributes to the investment industry studies (e.g., Agapova, 2011) by examining differences in the flow-related price pressure of mutual funds and ETFs suggesting a clientele effect reflected in the informational content of the flows. Third, the results of this paper are also related to the microstructure literature, particularly to price deviations from fundamentals due to trading (Biais et al., 2005). Exchange-traded funds could be considered as derivatives or contingent claims on other securities, in this case, the underlying stocks comprising the index (Roll et al., 2010).

Consequently, the results provide evidence to the long-standing debate about shock propagation between linked assets (Subrahmanyam, 1991; Roll et al., 2012), especially in the context of emerging research on ETFs (Ben-David et al., 2014; Da and Shive, 2016).

II. RELATED LITERATURE

My paper adds to the rich literature on the role of institutional trading on returns of the related assets. Classical finance assumes flat demand curves (Shleifer, 1986), but the mounting evidence suggests otherwise. Demand shocks in this literature have been represented by variables such as excess order flow (Boehmer and Wu, 2008), "fire sales" by mutual funds (Coval and Stafford, 2007), block trades (Lakonishok et al., 1992; Chan and Lakonishok, 1993) and institutional flows (Wermers, 1999; Cai and Zheng, 2004). On the aggregate level, the relation between investor flows and returns is studied by Boyer and Zheng (2009) who find a significant positive association between quarterly cash flows for particular investor groups and market returns but discover no conclusive evidence of price pressure. Warther (1995), Edwards and Zhang (1998), Franklin Fant (1999), and Goetzmann and Massa (2003) focus on a relation between mutual fund flows and returns and also do not find significant evidence of price pressure. Edwards and Zhang (1998) examine flows into equity and bond mutual funds and their relation with market returns and find no evidence of price pressure except during the 1971–1981 period when massive redemptions negatively affected market returns. Furthermore, Rakowski and Wang (2009) employ vector-autoregressive regressions (VAR) to study short-term U.S. mutual fund flows and fail to find significant price reversal which indicates absence of price pressure.

In the international context, Froot et al. (2001) apply VAR to cross–border flows and local returns, while Oh and Parwada (2007) and Watson and Wickramanayake (2012) employ VAR to study the mutual fund flow-return relation in Korea and Australia respectively. Interestingly, none of these studies evince a significant price pressure effect.

On the other hand, a smaller group of papers does find evidence of price pressure. Edelen and Warner (2001) document a significant relation between lagged flows and intraday returns indicating evidence for price pressure which becomes weaker for the daily returns. Furthermore, Coval and Stafford (2007) investigate the effects of fire sales by the mutual fund managers facing large unexpected redemptions and find evidence of price pressure for large absolute flows. Continuing this line of research, Lou (2012) use mutual fund flow–induced price pressure to explain return predictability, "smart money" and momentum phenomena. Ben-Rephael et al. (2011) examine the association between aggregate Israeli mutual fund flows and underlying market returns using daily data. The authors find a significant correlation between concurrent market returns and mutual fund flows and a negative relation between lagged fund flows and returns consistent with price reversal and, therefore, price pressure.

Liquidity in ETFs has emerged as another branch of the ETF literature. For instance, Hamm (2010) analyze the link between ETFs and component liquidity, while Richie and Madura (2007) explore the impact of the introduction of new ETFs on the underlying stock liquidity. Broman and Shum (2015) study short-term trading and liquidity clienteles, while Malamud (2015) develop a model that links creation–redemption and liquidity shock propagation to the underlying assets. Ultimately, Ben-David et al. (2014) examine empirically the propagation of liquidity shocks through ETFs to the volatility of the underlying assets.

There has been a paucity of academic research focusing exclusively on the relation between ETF flows and returns. The closest study to this paper is that of Kalaycıoğlu (2004) who uses weekly, monthly and daily data for four ETFs during 2000–2003 to investigate the general determinants of the flow–return relation for the first time. The authors used pooled OLS regressions of the flow on return and vice versa to test the direction of the causality between flows and returns without any strongly conclusive results most likely due to flow reporting issues, sample size, and methodology limitations. In comparison with Kalaycıoğlu (2004), I focus expressly on the effect of the flows on returns in the vein of institutional trading literature using a substantially longer period (10 vs. 3 years), larger sample (286 vs. 4 ETFs) and statistically robust tests using cross-sectional and aggregate data. I also control for weekly mutual fund flows which yields a better ETF flow–return identification and hence, stronger and more generalizable inferences, while allowing me to explore evidence suggesting an unexpected clientele effect in ETFs.

Furthermore, the current study differs markedly from Clifford et al. (2014) who use monthly data to look at the determinants of the ETF flows highlighting the return-chasing behavior exhibited by investors. In the context of Kalaycıoğlu (2004), Clifford et al. (2014) examine the effect of the returns on flows, while the present paper scrutinizes the effect of flows on returns.

There are several papers started at the same time which study the relation of the ETFs and the pricing of the underlying assets. In particular, these can be broadly characterized as examining the relation between ETF activity and the moments of the distribution of underlying asset returns. For instance, Da and Shive (2016) investigate ETF activity and the correlations of the underlying assets. In contrast, Ben-David et al. (2014) document the link between ETF activity and the volatility of the underlying assets. In the context of these two studies, the present paper focuses on the effect of the ETF activity expressed as ETF flows on the first moment of the underlying returns while also controlling for mutual fund flows which allows for more precise identification. The present paper furnishes evidence buttressing claims by Ben-David et al. (2014) and Da and Shive (2016) about the considerable spillover effects of ETF activity on the underlying assets.

III. ETF FLOWS AND RETURNS

Although this paper relates closely to the mutual fund flow and return literature, flows in the ETF and mutual fund industries are structured differently. In the mutual fund case, managers respond to daily creation and redemption requests, either by investing the money in the fund's portfolio in case of creation or by selling portfolio shares in the market and returning proceeds to the investor in case of redemption. In the ETF case, daily creation and redemption are transacted with underlying stocks grouped into so-called "creation units" instead of cash. These "in-kind" transactions occur in the primary market between the fund and Authorized Participants (APs), who are usually large institutional investors and market makers who have signed a special agreement with the fund. APs then operate in the stock market to buy or sell the transacted stocks underlying the ETF shares. Essentially, flow-related trading activity in ETFs is shifted towards APs and not the fund itself as in the case of mutual funds.

Furthermore, ETF flows originate via two main pathways (Abner, 2011; Agapova, 2011). In the first case, an institutional investor, who wants to buy ETF shares and wants to avoid adverse price impact, submits an order to buy ETF shares with the Authorized Participant (AP) who acts as an intermediary and buys the equivalent underlying assets on the market. At the end of the day, the AP exchanges the purchased underlying assets for the ETF shares directly with the fund, and then transfers the newly created ETF shares back to the institutional investor. In the case of selling ETF shares, the process is the reverse - the institutional investor transfers the ETF shares to the AP who then exchanges them with the fund for the underlying assets, sells the assets on the market and returns the proceeds to the investor. Usually, however, APs, after receiving the sell order for ETF shares, sell short the underlying and return the short sale proceeds to the investors. Later the same day, the APs then exchange the ETF shares for the underlying assets with the funds and cover the short sale.

In the second case, an excess of demand (or supply) of ETF shares in the market leads to an increasing premium (or discount) of the ETF price to NAV, which generates arbitrage opportunities for Aps[6]. The APs then create (or redeem) ETF shares using the underlying asset basket to exploit the arbitrage opportunity. Given that APs are usually market makers, broker/dealers or large institutions with access to low transaction cost trading, they can relatively easily buy (or sell) the underlying asset basket to create (or redeem) the ETF shares. This process occurs daily and APs stand ready to take advantage of the ETF price premium or discount.

Given that fund flows can move prices (Coval and Stafford, 2007), a large inflow (outflow) in an ETF should result in an upward (downward) pressure on the underlying stock prices. If the effect is transitory (Froot et al., 2001; Ben-Rephael et al., 2011), then the underlying stocks' prices will revert to their pre-shock levels. If the effect is permanent, perhaps due to the coincidental arrival of new information (Edelen and Warner, 2001) or a change in investor sentiment, then the prices will not revert. Price reversal, hence, can be identified by a negative relation between lagged flows and contemporaneous returns. These relationships form the basis of the two hypotheses tested herein:

Hypothesis 1: Price Impact. ETF flows are positively and significantly related to the contemporaneous underlying stock returns.
Hypothesis 2: Price Reversal. Lagged ETF flows are negatively and significantly related to the contemporaneous underlying stock returns.

The mutual fund literature uses two main approaches to study similar hypotheses. The first approach is based on analyzing flow-return relation for each fund or groups of funds. For example, Rakowski and Wang (2009) implement VAR regressions for each fund, while Warther (1995) group mutual fund flows into subcategories and analyze the relation between flows for each category and their underlying returns. The second approach is based on using aggregate flows for the mutual fund industry on different frequencies, from quarterly (Boyer and Zheng, 2009; Jank, 2012) to daily (Edelen and Warner, 2001). Aggregate flow studies usually cannot isolate the flow-return relation within a specific subset of the stock market. For instance, a negative flow correlation between different similarly sized funds will result in a low or zero net aggregate flow (Warther, 1995; Cao et al., 2008), but fund-level flows might still be related to their specific underlying stock returns. Hence, analysis of the cross-sectional behavior of ETF flows might provide additional evidence for the price pressure hypothesis.

To test Hypotheses 1 and 2, I combine the two aforementioned approaches. First, I run panel regressions on the cross-section of ETFs using a methodology similar to the one used by Goetzmann and Massa (2003) and Ben-Rephael et al. (2011). Next, I aggregate flows across ETFs and investigate flow–return relation using vector autoregressive regressions and in the last section I explore the extent to which this relation could be explained by mutual fund flows.

IV. DATA AND SUMMARY STATISTICS

To test flow–return relation, I focus on U.S. equity ETFs due to the size of the ETF industry, the transparency of the creation-redemption process and the prevalence of physical replication of the index. The ETF industry in Europe and Asia is also well-developed, but the regulatory requirements are less transparent and the majority of equity ETFs replicate indices via derivatives.

Following Kalaycıoğlu (2004) and Svetina and Wahal (2008), I use *Bloomberg* as the main source of ETF data for the period starting in January 2000 and ending in July 2010. At the end of the sample period, the global ETF universe consisted of 5,126 exchange-traded funds. Among them, 923 ETFs trade on the U.S. markets and out of them 349 are equity ETFs. The data on ETFs includes prices, net asset value (NAV), shares outstanding, underlying index tickers, returns, and asset-based style descriptions. Available data only covers funds that have survived until the end of the sample, hence the database excludes "dead" funds. However, this fact is unlikely to introduce a survivorship bias, as low assets under management (AUM) and consequently low flows are cited most often as the cause of ETF delisting. Furthermore, I do not investigate hypotheses pertaining to fund characteristics but instead center on the empirical patterns associated with the funds' activity.

The shares outstanding data for ETFs are also present in Center of Research in Stock Prices (CRSP), but the update frequency is usually monthly instead of daily with a few exceptions (e.g., NASDAQ 100 ETF during a subperiod). I cross-check the *Bloomberg* data on shares outstanding with the CRSP stock database and fill in the missing data where possible. I also parse ETF websites and verify the data by hand, especially for fund families following different flow reporting timing such as ProShares. For the daily NAV, I use CRSP Mutual Fund Database and *Bloomberg*. The shares outstanding and NAV data are adjusted for splits, reverse splits and distributions.

I use the underlying index returns to measure price impact on the underlying assets. Index returns are calculated in real-time; hence, any price impact in the underlying asset basket is reflected in the index almost immediately (Tse et al., 2006). As of July 2010, U.S. equity ETFs tracked 275 different indices. I obtain end of day values for these indices from *Bloomberg* and cross-check them with other publicly available sources to ensure data integrity.

ETFs can also employ leverage via swaps or futures (Charupat and Miu, 2011; Shum et al., 2016), switching from the "in-kind" creation-redemption process to the cash-for-shares exchange. Usually, leverage is used to provide long or short multiples of the underlying index returns and is explicitly stated in the ETF name and prospectus. I screen names and descriptions for ETFs in the sample for these keywords: "Bear", "Ultra", "Short", "Inverse", "2x", "3x", "-2x". After screening, 63 leveraged funds are removed and 286 non-leveraged U.S. equity ETFs remain in the sample. The final sample represents about 40% of the total net assets and 32% of the total number of funds in the U.S. ETF universe.

The decrease in the growth rate of the fund population and the number of tracked indices suggests that the number of ETFs has started to outpace the number of indices tracked (Svetina and Wahal, 2008). This is consistent with an increased competition between funds and a scarcity of available indices to track. After the end of the sample, U.S. equity ETFs continued growing at a slightly lower pace with the number of the funds reaching 656 and the total net assets surpassing $1.2 trillion in 2015 (Investment Company Institute, 2016).

Given the rapid growth and relatively young age of the ETF industry, the flow–return relation most likely varies across time. I divide the period from 2000–2010 into three subperiods: the 2000–2010, 2007–2010 and 2009–2010. The period of 2007–2010 is the first period when the upward trend in total net assets becomes less prominent and flows become more stationary. Furthermore, this period also contains a period of market instability which might affect the inferences from the flow-return relation analysis. Consequently, I also include a shorter 2009–2010 subperiod. My choice of subperiod lengths is comparable to mutual fund studies, such as Goetzmann and Massa (2003), who use two years of daily data in their analysis.

To analyze the total net asset distribution of my sample, I take the last month of the sample, average daily total net assets for each ETF and sort the resulting averages into deciles. As documented in Table 1, total net asset distribution exhibits a significant positive skewness. More specifically, the TNA for the 10^{th} decile totals \$251 billion, which corresponds to 72.9% of my sample's TNA, while the TNA for 1^{st} decile is only \$0.4 billion, which amounts to 0.1% of the sample. Furthermore, the maximum and minimum TNA for the 10^{th} decile exhibit a much wider range compared to the other deciles.

Table 1

Sample summary statistics

This table contains summary statistics for the U.S. equity ETFs sample as of July 2010. Funds are ranked from one to ten by the average total net assets (TNA) during July 2010. Minimum, Maximum, Average and Total TNA are in \$ millions. % of Total Sample TNA is the ratio of the decile TNA to the total sample TNA.

NA Rank	No of funds	Minimum TNA	Maximum TNA	Average TNA	Total TNA	% of Total Sample TNA
1	29	3	22	14	415	0.1%
2	28	23	37	31	879	0.3%
3	29	38	54	46	1,345	0.4%
4	28	54	99	71	2,000	0.6%
5	29	100	150	125	3,618	1.1%
6	28	152	225	181	5,061	1.5%
7	29	227	405	293	8,508	2.5%
8	28	407	1,055	602	16,858	4.9%
9	29	1,086	2,760	1,876	54,405	15.8%
10	28	2,781	68,415	8,957	250,794	72.9%
Total	285	3	68,415	1,207	343,882	100.0%

A. ETF Flows

Given daily data on ETF shares outstanding, the flow can be calculated directly as the percentage change in shares outstanding:

$$\mathrm{Flow_t} = \frac{\mathrm{Shrout_t} - \mathrm{Shrout_{t-1}}}{\mathrm{Shrout_{t-1}}} \tag{1}$$

where $\mathrm{Shrout_t}$ represents total ETF shares outstanding at t. I will refer to $\mathrm{Flow_t}$ as fund flow or flow. This formulation is independent of the index price, NAV or fund price and allows to compute flows via changes in shares outstanding instead of changes in assets under management adjusted for the NAV return as in the mutual fund literature (Rakowski and Wang, 2009). Funds with lower assets usually exhibit lower frequency of creation-redemption activity, higher proportion of zero flow days, and hence higher flow kurtosis. For instance, the S&P 500 ETF (SPY) has 2 days with no flows in 2009, while the next largest fund in the sample, iShares S&P 500 ETF (IVV), has 72 days with no flows in the same year. Furthermore, flow in equation (1) is the net flow which is different from creations and redemptions observed separately or the gross flow, as for instance in Clifford et al. (2014) who use monthly flows, indicating that there might be substantial creation and redemption activity which when netted out results in a zero net flow. Finally, I correct for outliers and erroneous data entries by checking the data by hand and removing observations with flows above 1 or below -0.3 corresponding to a daily increase of 100% and a decrease of 30% of the previous day's shares outstanding respectively.

Exchange-traded funds often report using "T+1" accounting, widely followed in the mutual fund industry as described in Quinn et al. (2006)[7], which means that the shares outstanding are reported with a one day lag. In practice, however, this lag is time-varying. In other words, if the actual flow that day is 2 million shares, that flow under the "T+1" accounting is registered as of the next day. Four months later, dating of the flow reporting may change and the inflow of 2 million shares will be registered as of the same day. To further complicate matters, changes in reporting lag are not public and within the data provided by the database (e.g., *Bloomberg* or OptionMetrics), there is no way to identify the lag[8]. For mutual fund literature, this distinction is not important because the data on daily flows is uncommon and, on a monthly level, this bias is not significant (Quinn et al., 2006), but for ETFs this bias is crucial. I correct my sample for this bias by cross-checking N-CSRS and N-30b-2 filings for each fund family and matching the dates for shares outstanding in the filings to the dates in the sample.

Given that ETF flows depend on investors' interest in the fund, which in turn is correlated with the fund size, it is reasonable to expect higher absolute flows for larger ETFs. Moreover, due to the skewness of the TNA distribution examined in Table 1, an analysis of a smaller subsample of the high TNA ETFs provides generalizable inferences. In Table 2, I show summary statistics for the top 10 ETFs ranked by TNA in July 2010. The largest and oldest fund in the sample, SPDR S&P 500 (SPY), has nearly 3 times the TNA of the 2nd largest fund, iShares S&P 500 (IVV). Similar to Table 1, top 10 ETFs hold 51% of the total net assets for the equity ETFs. Furthermore, flow activity varies from 38% to 99% across top 10 funds, which lowers statistical power of the tests involving daily flows. ETF price premiums are similar across funds and are insignificantly negative on average.

Table 3 provides summary statistics for the variables of interest including flows for different samples and subperiods. Non-Zero Flows is the proportion of the observations with non-zero net flow activity and it ranges from 39% to 79% for the top 10 ETFs and from 20% to 23% for the whole sample across subperiods. This prevalence of zero flow days across all funds reduces statistical power of flow–return hypothesis tests. Furthermore, average percentage flows are substantially smaller for the top 10 funds ranging from 0.025% to 0.075% and larger for the whole sample with the estimates ranging from 0.141% to 0.235%, but the dollar flows exhibit the inverse behavior with averages ranging from \$0.4 to \$6 million for the top 10 funds and \$0.2 to \$0.8 million for the whole sample. This is most likely due to the fact the median ETF has infrequent and low dollar flows with low TNA, which implies larger percentage flows, while the top 10 ETFs have higher total net assets and more frequent and larger dollar flows which translates into lower percentage flows. Daily dollar flow standard deviations are better indicators of the economic impact and these range from \$499 million to \$726 million and from \$101 million to \$147 million for the top 10 ETFs and the whole sample respectively.

The average premiums range from -1 to 0 basis points and from -5 to -2 basis points for the top 10 ETFs and the whole sample respectively. Standard deviations, however, are in the range of 7 to 82 basis points across subperiods and subsamples which dovetails with the results by Petajisto (2013) who identify significant time-varying deviations of the ETF prices from their respective NAVs.

Table 4 presents correlations between contemporaneous and lagged flows and a variety of pricing variables using daily observations of S&P 500 ETF for 2007–2010. Correlations between ETF price, index level and NAV are all 0.99; hence, only NAV is included in the table. Flow exhibits a small but significant positive correlation with the Index Return of 0.11 which suggests a price impact. Flow also evinces a weakly significant and positive autocorrelation of 0.08 which implies that standard errors should be adjusted for serial autocorrelation. Correlations for the period of 2000–2010 are similar but smaller in absolute value. For the rest of the sample, correlations between flows and other variables are reduced even further due to the larger proportion of the zero flow days as documented in Table 3.

Table 2

Top 10 US equity ETFs

Descriptive statistics for top 10 equity ETFs traded in U.S. market for July 2010. Inception is the date when the fund started trading. Average TNA is the average over last 5 trading days of the sample in $ Millions. Style is based on market capitalization of the tracked index components and is obtained from Bloomberg. The proportion of Fund TNA relative to the total TNA of the ETFs in the sample is denoted by % of TNA. Non-Zero Flows is the proportion of the non-zero net daily flows. Premium is the average difference between the daily ETF price and the NAV scaled by the NAV and expressed in basis points. Non-Zero Flows and Premium are calculated using 2007–2010 period. Total/Average is the sum for Average TNA, % of TNA, and average for Non-Zero Flows and Premium.

Fund Name	Ticker	Inception	Style	Index Ticker	Average TNA	% of TNA	Non-0 Flows	Premium
SPDR S&P 500	SPY	21-Jan-93	Large	SPX	67,249	19.6%	99%	-1.6
iShares S&P 500	IVV	15-May-00	Large	SPX	21,672	6.3%	73%	-0.9
PowerShares NASDAQ 100	QQQ	4-Mar-99	Large	NDX	17,989	5.2%	66%	-1.8
Vanguard Total Stock Market	VTI	14-Apr-05	Large	MSCIBM	13,838	4.0%	81%	1.6
iShares Russell 2000	IWM	22-May-00	Small	RTY	12,616	3.7%	54%	-2.2
iShares Russell 1000 Growth	IWF	22-May-00	Large	RLG	10,214	3.0%	45%	2.2
iShares Russell 1000 Value	IWD	22-May-00	Large	RLV	8,429	2.5%	38%	0.6
SPDR S&P Midcap 400	MDY	26-Apr-95	Mid	MID	8,313	2.4%	77%	-2.3
SPDR DJIA Trust	DIA	13-Jan-98	Large	INDU	7,698	2.2%	88%	-0.6
iShares S&P Midcap 400	IJH	22-May-00	Mid	MID	7,086	2.1%	47%	-1.5
Total/Average					175,106	50.9%	67%	-0.65

Table 3
Variable summary statistics

This table presents summary statistics for the main variables in the dataset. Mean, Std Dev, P25, P50, P75 represent average, standard deviation, 25th, 50th (median) and 75th quantiles correspondingly. $\mathrm{Flow_t}$ is the daily ETF flow as in equation (1) and expressed in percentages. Dollar Flow is the fund flow in $ millions and calculated as $(\mathrm{Shrout_t} - \mathrm{Shrout_{t-1}})\mathrm{NAV_t}$. $\mathrm{Non-zero\ Flows}$ is the proportion of the days with the non-zero flows and expressed in percentages. TNA is the total net assets of the funds in $ millions. $\mathrm{R^{index}}$ is the index return tracked by ETFs in the sample. Premium is the difference between the ETF price and the NAV scaled by the NAV expressed in basis points. Statistics are computed for two subsamples: Top 10 ETFs by net assets as of July 2010 and the whole sample of 286 ETFs, and three subperiods: 2000–2010, 2007–2010, 2009–2010.

Variable		Top10			All ETFs		
		2000–2010	2007–2010	2009–2010	2000–2010	2007–2010	2009–2010
$\mathrm{Flow_t}$	Mean	0.075	0.051	0.025	0.235	0.184	0.141
	Std Dev	2.042	1.819	1.531	3.589	3.335	2.541
	P25	0.000	-0.136	-0.19	0.000	0.000	0.000
	P50	0.000	0.000	0.000	0.000	0.000	0.000
	P75	0.000	0.205	0.258	0.000	0.000	0.000
Dollar Flow	Mean	6.414	12.06	0.457	0.822	0.921	0.239
	Std Dev	499.12	726.98	522.65	129.30	147.53	101.28
	P25	0.000	-12.74	-23.91	0.000	0.000	0.000
	P50	0.000	0.000	0.000	0.000	0.000	0.000
	P75	0.000	21.36	33.65	0.000	0.000	0.000
Non-zero Flows	Mean	38.9	66.96	78.85	19.24	23.13	23.79
	Std Dev	48.75	47.04	40.85	39.42	42.16	42.58
	P25	0.000	0.000	100	0.000	0.000	0.000
	P50	0.000	100	100	0.000	0.000	0.000
	P75	100	100	100	0.000	0.000	0.000
TNA	Mean	10,911	15,857	18,060	1,166	1,141	1,239
	Std Dev	16,257	20,321	18,826	4,859	5,061	4,941
	P25	352	6,807	8,385	44	34	40
	P50	6,322	9,270	11,439	146	135	147
	P75	11,358	15,863	17,427	593	570	599
$\mathrm{R^{index}}$	Mean	0.007	-0.019	0.065	0.013	-0.007	0.072
	Std Dev	1.544	2.018	1.273	1.915	2.346	1.461
	P25	-0.685	-0.981	-0.559	-0.769	-1.051	-0.664
	P50	0.062	0.080	0.130	0.065	0.062	0.117
	P75	0.706	0.935	0.778	0.813	1.040	0.876
Premium	Mean	0	-1	-1	-2	-5	-5
	Std Dev	57	22	7	64	82	65
	P25	-8	-8	-5	-10	-12	-9
	P50	1	-1	-1	0	-1	0
	P75	10	6	3	10	9	7

Table 4
Flow correlations

The table shows correlations between variables for the S&P 500 ETF (SPY) during years 2007–2010. The Flow_t and Flow_{t-1} are the contemporaneous and lagged daily percent change in shares outstanding from equation (1). NAV is Net Asset Value reported by the fund by the end of the day. Daily shares outstanding are denoted by Shrout. The S&P 500 index return is denoted by $\mathrm{R}^{\mathrm{index}}$. The difference between the ETF price and the NAV scaled by the NAV at time t is denoted by Premium. The p-values are in parenthesis below the correlation parameter estimates.

Variables	Flow_t	Flow_{t-1}	NAV	Shrout_t	$\mathrm{R}^{\mathrm{index}}$	Premium
Flow_t	1					
Flow_{t-1}	0.076	1				
	(0.035)					
NAV	0.057	0.048	1			
	(0.115)	(0.180)				
Shrout_t	0.044	0.054	-0.794	1		
	(0.219)	(0.131)	(<0.001)			
$\mathrm{R}^{\mathrm{index}}$	0.108	-0.062	0.023	-0.014	1	
	(0.002)	(0.085)	(0.519)	(0.695)		
Premium	0.008	0.052	0.042	-0.034	-0.197	1
	(0.818)	(0.148)	(0.252)	(0.355)	(<0.000)	

One could argue that an increase in the index level is associated with the increase in the NAV and is negatively correlated with the premium with a correlation of -0.197. Next step in the argument is that the decrease in the premium (ETF price less than the NAV) induces APs to exploit this arbitrage opportunity (if the absolute premium exceeds transaction costs) resulting in redemption of ETF shares expressed as fund outflows. Hence, the premium should exhibit significant positive correlation with the flow (Petajisto, 2013). However, Table 4 shows that neither the contemporaneous or lagged flows are either statistically or economically correlated with the premium with the correlations of 0.008 and 0.052 respectively. This provides evidence against the argument that fund flows are related to the index return through the premium.

It is important to note that the end of day premium is not necessarily correlated with the intraday premium which is linked to the arbitrage activity of the APs in the absence of limits to arbitrage and, hence, end-of-day flows. Furthermore, Da and Shive (2016) also indicate that the large premium may represent arbitrage opportunities or presence of limits to arbitrage and suggest that without additional identification its usefulness is limited. Furthermore, the authors mention the non–synchronicity issue where the end of day NAV may be stale and a substantial premium may not represent the actual arbitrage opportunities even in the absence of limits to arbitrage. This is most likely the case for the ETFs with illiquid (Petajisto, 2013; Fulkerson et al., 2014) or international holdings. I surmise that it is less likely the case for the largest U.S equity ETFs with the highest flow activity which tend to hold more liquid stocks (see Table 3). Given mixed evidence, I include contemporaneous and lagged daily premiums in the regressions in Section 5.1 to account for the possible omitted variable bias.

Shares outstanding have negative correlation with NAV of -0.794 which is similar to the average correlation for the top 10 ETFs of -0.455. These correlations vary widely year to year but remain slightly negative on average. One possible explanation for the negative correlation is a sample bias driven most likely by a combination of a persistent positive trend in shares outstanding and strong cyclical and trend components in the long-term market prices. Interestingly, however, correlation between first difference of the shares outstanding and NAV is much lower in absolute terms at 0.053. Given the possibility of a time trend generating spurious inferences, I include year-month dummies as a robustness test in the upcoming section.

V. EMPIRICAL ANALYSIS

A. Panel Regressions

To test Hypothesis 1, I perform panel regressions of daily index returns on ETF flows. I follow approach similar to the one used by Edelen and Warner (2001) and Ben-Rephael et al. (2011) and regress index returns on five index return lags, a contemporaneous flow and its five lags. Due to the auto- and cross-correlation of daily index returns (Ackert and Tian, 2008), I adopt panel corrected standard errors (PCSE) with adjustments for cross-panel correlation and a panel-specific AR(1) process which is similar to heteroscedasticity and cross-correlation robust standard errors (Haas and Lelyveld, 2006; Kacperczyk and Seru, 2007).

Petajisto (2013) and Clifford et al. (2014) find that the daily premium is positively associated with subsequent flows. If the premium is causally related to flows and correlated with index returns, then including the premium as a control variable should correct the omitted variable bias (see Section A)[9]. Consequently, I include the daily premium and its one day lag as the controls.

I divide the sample into two subsamples: the first comprising the top 10 ETFs and the second comprising the entire sample of 286 ETFs. Time-wise, I partition the sample period into three subperiods: 2000–2010, 2007–2009, 2009–2010. The regression specification is as follows:

$$\mathrm{R}_{\mathrm{i,j,t}}^{\mathrm{index}} = \alpha + \sum_{\mathrm{l}=1}^{5} \beta_{\mathrm{R^{index}},\mathrm{l}}\, \mathrm{R}_{\mathrm{i,j,t-l}}^{\mathrm{index}} + \sum_{\mathrm{l}=0}^{5} \beta_{\mathrm{Flow,l}}\, \mathrm{Flow}_{\mathrm{i,j,t-l}} + \sum_{\mathrm{l}=0}^{1} \beta_{\mathrm{Premium,l}}\, \mathrm{Premium}_{\mathrm{i,j,t-l}} + \varepsilon_{\mathrm{i,j,t}} \tag{2}$$

where $\mathrm{R}_{\mathrm{i,j,t}}^{\mathrm{index}}$ corresponds to the daily return of the $\mathrm{j^{th}}$ index tracked by the $\mathrm{i^{th}}$ fund at t, $\mathrm{R}_{\mathrm{i,j,t-l}}^{\mathrm{index}}$ is the l-lagged $\mathrm{j^{th}}$ index return tracked by the $\mathrm{i^{th}}$ fund, $\mathrm{Flow}_{\mathrm{i,j,t-l}}$ is the l-lagged flow of the $\mathrm{i^{th}}$ fund which tracks the $\mathrm{j^{th}}$ index, $\mathrm{Premium}_{\mathrm{i,j,t-l}}$ is the l-lagged percentage difference between $\mathrm{i^{th}}$fund's ETF price and NAV tracking $\mathrm{j^{th}}$ index. The lag indicator l varies from 0 to 5 for the flows, from 1 to 5 for the index returns and from 0 to 1 for the premium. In the sample, by definition $\mathrm{i} \geq \mathrm{j}$ as there are more funds than indices.

Table 5
Panel regressions

The regression table reports estimation results for panel regressions of index return on flow for several subsamples and subperiods. First subsample contains top 10 ETFs ranked by net assets and second subsample is the whole U.S. equity ETFs sample. The estimation is conducted for three subperiods: 2000–2010, 2007–2010 and 2009–2010. $\mathrm{Flow_t}$ and $\mathrm{Flow_{t-1}}$ are the contemporaneous and l-lagged flows from equation (1). Contemporaneous and l-lagged index returns are denoted as $\mathrm{R_{index,t}}$ and $\mathrm{R_{index,t-1}}$. $\mathrm{Premium_{i,j,t-1}}$ is the percentage difference between the ETF price and the NAV. Standard errors are Panel Corrected Standard Errors (Kacperczyk and Seru, 2007) corrected for heteroscedasticity, cross-panel correlation and panel-specific autocorrelation specified as AR(1) process (z-stats are in parenthesis). *, **, *** measure significance at the 10%, 5%, and 1% level, respectively.

	Top 10 ETFs			Full Sample		
Variables	2000–2010	2007–2010	2009–2010	2000–2010	2007–2010	2009–2010
$\mathrm{R_{index,t-1}}$	-0.074***	-0.119***	-0.009	-0.056***	-0.087***	-0.011
	(-3.728)	(-3.465)	(-0.164)	(-2.728)	(-3.016)	(-0.201)
$\mathrm{R_{index,t-2}}$	-0.067***	-0.078**	-0.013	-0.073***	-0.079***	-0.033
	(-3.352)	(-2.267)	(-0.218)	(-3.528)	(-2.706)	(-0.611)
$\mathrm{R_{index,t-3}}$	0.038*	0.051	-0.020	0.027	0.029	-0.004
	(1.899)	(1.486)	(-0.357)	(1.294)	(0.988)	(-0.077)
$\mathrm{R_{index,t-4}}$	-0.023	-0.035	0.009	-0.022	-0.029	0.000
	(-1.138)	(-1.005)	(0.155)	(-1.042)	(-1.003)	(0.003)
$\mathrm{R_{index,t-5}}$	-0.030	-0.021	0.003	-0.030	-0.030	-0.007
	(-1.506)	(-0.624)	(0.057)	(-1.464)	(-1.027)	(-0.138)
$\mathrm{Flow_t}$	0.026***	0.092***	0.177***	0.009***	0.014***	0.017***
	(4.945)	(6.764)	(9.373)	(6.896)	(5.371)	(4.550)
$\mathrm{Flow_{t-1}}$	-0.001	0.006	0.013	0.000	-0.000	0.000
	(-0.182)	(0.441)	(0.752)	(0.097)	(-0.149)	(0.114)
$\mathrm{Flow_{t-2}}$	-0.007	-0.025*	-0.037**	-0.000	-0.002	-0.004
	(-1.271)	(-1.853)	(-2.136)	(-0.095)	(-0.780)	(-0.960)
$\mathrm{Flow_{t-3}}$	0.006	0.012	0.005	0.000	0.001	-0.000
	(1.091)	(0.919)	(0.312)	(0.312)	(0.599)	(-0.131)
$\mathrm{Flow_{t-4}}$	-0.007	0.007	-0.016	-0.002*	-0.003	-0.004
	(-1.240)	(0.513)	(-0.956)	(-1.661)	(-1.317)	(-1.189)
$\mathrm{Flow_{t-5}}$	0.002	-0.004	-0.000	-0.003**	-0.005**	0.001
	(0.442)	(-0.323)	(-0.025)	(-2.001)	(-2.022)	(0.299)
$\mathrm{Premium_t}$	-0.052***	-0.074***	-2.440***	-0.260***	-0.437***	-0.109***
	(-3.292)	(-3.691)	(-4.881)	(-24.250)	(-22.605)	(-9.250)
$\mathrm{Premium_{t-1}}$	0.019	-0.020	-0.019	0.260***	0.189***	0.045***
	(1.213)	(-1.022)	(-0.039)	(24.251)	(12.076)	(4.240)
Constant	0.000	-0.000	0.000	0.000	-0.000	0.001
	(0.282)	(-0.425)	(0.466)	(0.392)	(-0.258)	(0.887)
Obs	22,043	7,541	2,520	374,060	194,219	70,335
R^2	0.016	0.035	0.075	0.028	0.048	0.007
Funds	10	10	10	285	285	284

The coefficients for the contemporaneous ETF flow are positive and strongly significant for all subsamples and subperiods (with t-stats ranging from 4.550 to 9.351). The coefficients for the lagged flows are significantly negative at the second lag for top 10 ETFs for the subperiods of 2007–2010 (t-stat = -1.853) and 2009–2010 (t-stat = -2.106) indicating price reversal on the second day after the price impact. For the 2007–2010 period, a one standard deviation in flows for the top 10 ETFs is about 2%, which is associated with an 18 basis points (bps) increase in the corresponding index return and the subsequent reversal of 5 basis points. For the 2009–2010 period, the magnitude of the relation between one standard deviation shock and index return is about two times larger with a corresponding return increase of 26 bps (σ_{flow} = 1.5%) and a posterior reversal of 6 basis points.

For the whole sample, the flow coefficients are less significant mainly due to the prevalence of the zero flow days for many smaller ETFs as discussed in Section IV-A. For the periods of 2000–2010, 2007–2010 and 2009–2010, across all ETFs zero flow days account for 81%, 78% and 75% of the fund-day observations correspondingly which is much higher than 61%, 40% and 30% for the top 10 ETFs for the same periods. Flow coefficients for second and fifth lags are negative, with the latter becoming significant for the whole period and the 2007–2010 subperiod which could be interpreted as evidence of price reversal occurring at longer lags due to lower liquidity of holdings for some ETFs (Petajisto, 2013). For the whole sample, one standard deviation change in total flows during 2007–2010 (σ_{flow} = 3.3%) and 2009–2010 (σ_{flow} = 2.5%) are associated with an increase in daily returns of 5 and 4 basis points respectively.

The coefficients for the contemporaneous premium are all significantly negative across the samples and subperiods with the lags showing up as mostly positive. Interestingly, one day lag of the premium is positive for almost all subsamples and subperiods but becomes significant only for the whole sample, which is reasonable given higher illiquidity of the underlying assets for some ETFs and, hence, persistence of the premium relation with the index return[10].

It is important to note that panel tests based on the full sample have low explanatory power as the vast majority of funds have low total net assets (90% of the ETFs account for 16% of the total TNA) and relatively infrequent creation-redemption activity resulting in a high ratio of observations with zero net flows. For instance, during 2009, the top 10 ETFs had zero net flow activity during 20% of the total trading days, while the remaining 276 ETFs had zero net flow activity during 77% of the days. Furthermore, even within the largest TNA decile, there is a substantial difference in TNA and non-zero flow days between the top 10 ETFs and the remaining 28 ETFs. In the 2009–2010 subperiod, the remaining 28 ETFs in the largest TNA decile had zero net flow activity in 42% of the trading days as compared to the 20% for the top 10 ETFs. In these conditions, fund regression tests based on a larger sample will necessarily have a downward bias in the coefficients.

To verify the robustness of the inferences, I reestimate results in this section using Petersen (2009)'s two-way clustering with any changes in inferences. I also apply random and fixed effect panel estimators and obtain quantitatively similar results. Furthermore, I test different combinations of index return and flow lags and obtain quantitatively similar results. To avoid fund incubation bias (Evans, 2010; Clifford et al., 2014), I exclude the first year of flows without major changes in my findings. Given negative time-series correlations between shares outstanding and NAV for the top 10 funds reported in Table 4, I rerun the panel regressions in Table 5 with year-month dummies without any major changes in my findings.

1. Aggregate Flows and Returns: VAR Analysis

In the mutual fund literature flow-return hypotheses are usually tested using aggregate flows given that long-term daily fund-level flows data are hard to obtain. Moreover, high-frequency aggregate data, even if available, is also often constrained to a certain period; for instance, the length of the sample period is two years in Ben-Rephael et al. (2011), four years in Goetzmann and Massa (2003) and one year in Edelen and Warner (2001). Testing Hypotheses 1 and 2 using daily aggregate flows allows for a direct comparison with the mutual fund flow literature.

For the aggregate flow–return analysis, I employ vector-autoregressive regressions (VAR) which are frequently used in the institutional flows and returns literature. For instance, Froot et al. (2001) have applied VAR to portfolio flows in international context, while Oh and Parwada (2007), Watson and Wickramanayake (2012) and Ben-Rephael et al. (2011) study the mutual fund flow-return relation using VAR in Korea, Australia and Israel respectively. Rakowski and Wang (2009) employ VAR to study short-term U.S. mutual fund flows. Interestingly, out of the four studies mentioned, only Ben-Rephael et al. (2011) find significant evidence of price pressure.

I aggregate the fund flows across ETFs using lagged and contemporaneous shares outstanding and the current NAV with the following specification,

$$\mathrm{Flow}_t^{\mathrm{aggr}} = \frac{\sum_{j=1}^{k}\sum_{i=1}^{n}(\mathrm{Shrout}_{i,j,t} - \mathrm{NAV}_{i.j.t})}{\sum_{j=1}^{k}\sum_{i=1}^{n}(\mathrm{Shrout}_{i,j,t-1} - \mathrm{NAV}_{i.j.t})}\text{-}1 \tag{3}$$

where $\mathrm{Shrout}_{i,j,t}$ and $\mathrm{NAV}_{i,j,t}$ are the shares outstanding and net asset value respectively for fund i tracking index j at time t, n is the number of funds tracking index j at time t, and k is the total number of indices. Using contemporaneous NAV to determine assets under management for both days helps to avoid implicitly including fund returns in aggregate flow. I also test one and two day lags of NAV with similar results.

To maintain comparability with the previous section, a period from 2007 to 2010 comprising 756 trading days is selected. This sample size is similar to other short-term mutual fund flow studies (e.g., Goetzmann and Massa (2002)). The flow-return VAR model is specified as follows,

$$\begin{bmatrix} R_t^{\mathrm{VWRETD}} \\ \mathrm{Flow}_t^{\mathrm{aggr}} \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} \beta_{1,R^{\mathrm{VWRETD}}}(L) & \beta_{1,\mathrm{Flow}^{\mathrm{aggr}}} \\ \beta_{2,R^{\mathrm{VWRETD}}}(L) & \beta_{1,\mathrm{Flow}^{\mathrm{aggr}}} \end{bmatrix} \begin{bmatrix} R_t^{\mathrm{VWRETD}} \\ \mathrm{Flow}_t^{\mathrm{aggr}} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix} \tag{4}$$

where $\mathrm{Flow}^{\mathrm{aggr}}$ is the aggregate equity ETF flow following equation (3) and R^{VWRETD} is Value-Weighted Index Return (CRSP). The number of lags, $L = 4$, is calculated using Akaike criterion ($\mathrm{AIC}_{\min} = -11.3$). The contemporaneous shock and four lags represent the entire trading week and are comparable to the panel and aggregate regressions in Section 5.1. Furthermore, lag order selection test results are similar to Edwards and Zhang (1998) and Ben-Rephael et al. (2011) who also use four lags in their VAR models. In the estimation results, for convenience, I denote the regression with R_t^{VWRETD} as the dependent variable as Equation 1 and the regression with $\mathrm{Flow}_t^{\mathrm{aggr}}$ as the dependent variable as Equation 2.

Table 6
Aggregate flow VAR regressions

This table presents vector autoregressive (VAR) regressions of aggregate ETF flow ($\mathrm{Flow}^{\mathrm{aggr}}$) and index return ($\mathrm{R}_{\mathrm{index}}$) using specification (4). The estimation period is from 2007 to 2010. Aggregate ETF flow is specified as percentage change in aggregate assets under management using contemporaneous NAV as referenced in equation (3). Index return is Value-Weighted Index Return (CRSP). Means and standard deviations of the dependent variables are reported in basis points. Lagged flows are denoted as $\mathrm{Flow}_{t-l}^{\mathrm{aggr}}$ with l varying from one to four. Lagged index returns are denoted as $\mathrm{R}_{\mathrm{index},t-l}$ with l varying from one to four. The t-stats are in parenthesis. The asterisks *, **, *** represent statistical significance at the 10%, 5%, and 1% level, respectively.

Variables	Equation 1: Dep Var = $\mathrm{R}_t^{\mathrm{VWRETD}}$	Equation 2: Dep Var =$\mathrm{Flow}_t^{\mathrm{aggr}}$
Mean	-2	10
Std Dev	194	111
$\mathrm{Flow}_{t-1}^{\mathrm{aggr}}$	0.001	0.041
	(0.015)	(1.109)
$\mathrm{Flow}_{t-2}^{\mathrm{aggr}}$	-0.160**	0.033
	(-2.486)	(0.884)
$\mathrm{Flow}_{t-3}^{\mathrm{aggr}}$	0.044	0.023
	(0.686)	(0.603)
$\mathrm{Flow}_{t-4}^{\mathrm{aggr}}$	-0.013	0.013
	(-0.199)	(0.343)
$\mathrm{R}_{t-1}^{\mathrm{VWRETD}}$	-0.104***	-0.007
	(-2.755)	(-0.301)
$\mathrm{R}_{t-2}^{\mathrm{VWRETD}}$	-0.076**	-0.081***
	(-2.016)	(-3.710)
$\mathrm{R}_{t-3}^{\mathrm{VWRETD}}$	0.053	0.002
	(1.409)	(0.070)
$\mathrm{R}_{t-4}^{\mathrm{VWRETD}}$	-0.040	-0.089***
	(-1.051)	(-4.042)
Constant	-0.000	0.001*
	(-0.103)	(1.894)
Observations	756	756

The results of the VAR estimation and dependent variable summary statistics are presented in Table 6. Aggregate ETF flow has a mean of -10 bps and a standard deviation of 111 bps corresponding in dollar terms to \$0.26 billion and \$3.03 billion respectively, which is comparable to mutual fund flows. The lagged aggregate flow coefficient estimates for Equation 1, $\beta_{1,\mathrm{Flow}^{\mathrm{aggr}}}$, exhibit generally negative and significant or insignificantly positive values with the two-day lagged coefficient magnitude of -0.160 with a t-stat of -2.486 (p-value=0.013). The return coefficient estimates for the same equation, $\beta_{1,\mathrm{R}^{\mathrm{VWRETD}}}$, are significantly negative for lags one and two, which indicates a negative serial autocorrelation in returns. In Equation 2, lagged flow coefficient estimates do not exhibit statistical significance which is reasonable given the absence of significant autocorrelation in the aggregate ETF flows, while lagged returns are negatively related to the contemporaneous flows which suggests that ETF investors are somewhat contrarian (Warther, 2002) which is similar to the findings from the mutual fund flow studies (Rakowski and Wang, 2009) who find either no performance chasing or slightly contrarian behavior on the daily level. Interestingly, Clifford et al. (2014) find evidence of return–chasing in ETFs with a positive relation between previous 12-month returns and monthly flows while Fulkerson et al. (2014) find performance chasing in bond ETF funds on the monthly frequency which suggests that investor behavior varies with the flow–return horizon.

Cumulative impulse response functions (CIRF) for the VAR model in equation (4) are illustrated in Figure 1. Figure 1a depicts the response of a one-unit flow shock on index returns. The contemporaneous flow-return shock with magnitude of 0.462 (t-stat of 7.65) is placed at lag one in the graphs. In economic terms, a one standard deviation shock of $3 billion in dollar ETF flow is associated with a market return impact of 89 basis points. During day one (lag two in the graphs), the cumulative response shows a slight decrease of the contemporaneous price impact from 0.462 to 0.409 (t-stat of -0.65) which most likely signals a combination of two countervailing forces: price pressure and consequent price reversal. On day two, the accumulated price impact falls to 0.219 with a highly significant difference of 0.243 (t-stat of 2.52) between the contemporaneous shock and the day two cumulative impact. In other words, approximately 53% of the contemporaneous price impact corresponding to 47 bps is reversed by day two. On day three, the cumulative impact increases to 0.302 with the difference between contemporaneous shock and day three cumulative impact being 0.160 (t-stat of -1.46).

Figure 1a

Response of index return to one unit innovation in aggregate flow

Figure 1a outlines the cumulative impulse response of index return (Value-Weighted Index Return) to one standard deviation shock in aggregate flow as measured in equation (3). The contemporaneous relation between index return and aggregate flow is calculated with index return depending on flows specification and is located at lag one. There are 20 lags (days). Confidence intervals of 95% are shown in dashed grey lines.

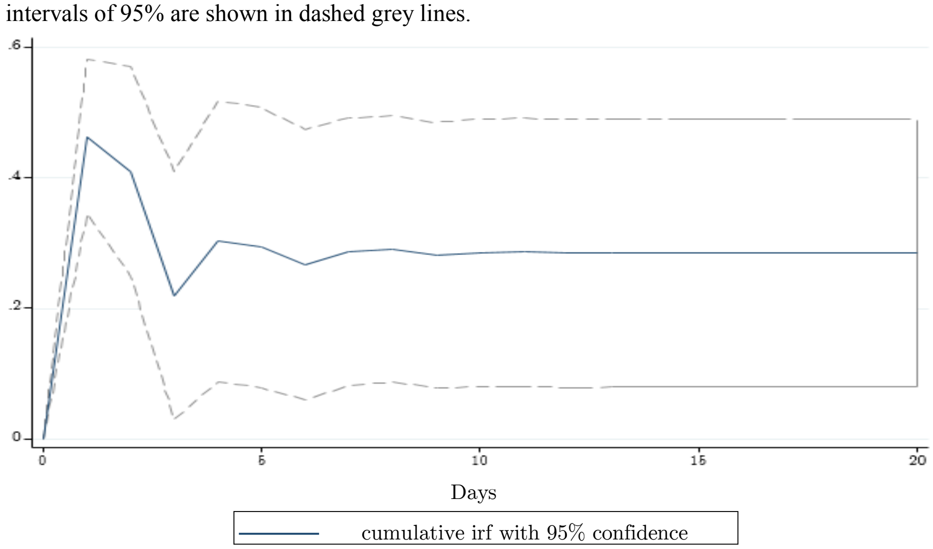


Figure 1b

Response of aggregate flow to one unit innovation in aggregate flow

Figure 1b outlines the cumulative impulse response of aggregate flow to one standard deviation shock in aggregate flow following in equation (3). The contemporaneous relation between index return and aggregate flow is calculated with index return depending on flows specification and is located at lag one. There are 20 lags. Confidence intervals of 95% are shown in dashed grey line.

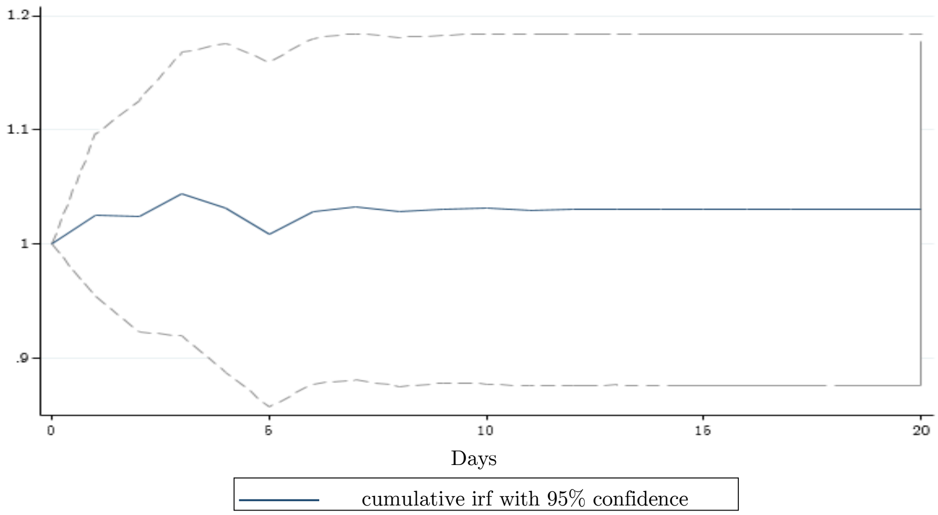


Figure 1c

Response of aggregate flow to one unit innovation in index return

Figure 1c outlines the cumulative impulse response of aggregate flow to one standard deviation shock in index return where aggregate flow is described in equation (3). The contemporaneous relation between index return and aggregate flow is calculated with index return depending on flows specification and is located at lag one. There are 20 lags. Confidence intervals of 95% are shown in dashed grey lines.

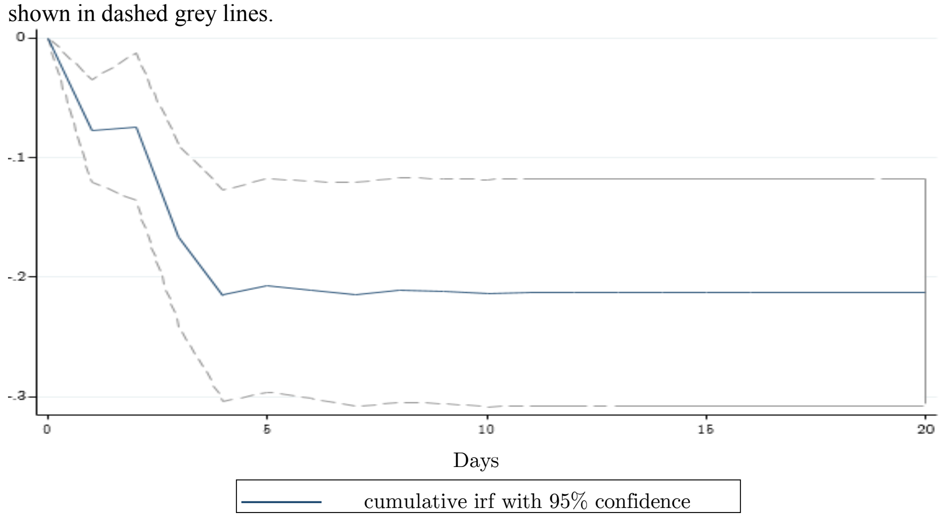
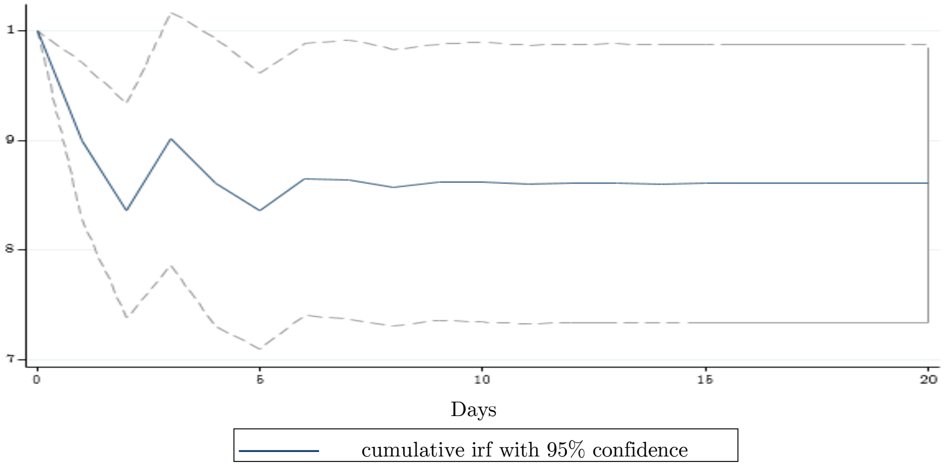


Figure 1d

Response of index return to one unit innovation in index return

Figure 1d outlines the cumulative impulse response of index return to one standard deviation shock in index return. The contemporaneous relation between index return and aggregate flow is calculated with index return depending on flows specification and is located at lag one. There are 20 lags. Confidence intervals of 95% are shown in dashed grey lines.



In the following days, cumulative price impact stabilizes at 0.28 with the differential between contemporaneous shock and long-run equilibrium at 0.178 (t-stat of 1.71) which is equivalent to 38% of the day zero impact. Given partial reversion, in the long run, 62% (55 bps) and 38% (34 bps) of the initial shock are permanent and transitory respectively lending support to Hypothesis 1 and providing evidence of the disequilibrating association of ETF flows and the underlying returns. Furthermore, my findings resonate with the results of Ben-Rephael et al. (2011) who find that in the case of Israeli mutual funds approximately half of the contemporary return shock is reversed within 10 days.

Figure 1b presents the response of aggregate flow to a one standard deviation shock in aggregate flow, or the persistence in flows. The long-run cumulative response is 1.030; however, it is insignificantly different from one with a t-stat of 0.38, thereby indicating very weak shock persistence which is reasonable given negligible flow autocorrelation. The response of aggregate flows to one-unit shock in index returns is depicted in Figure 1c. Flows respond negatively and significantly to the contemporaneous shock in index returns with the long-run equilibrium achieved at -0.213 with a t-stat of -4.38 which is consistent with contrarian investor behavior but as mentioned earlier is in sharp contrast with return–chasing found by Clifford et al. (2014) using monthly data. One possible explanation is that the flows–return relation varies with horizon with return–chasing prevalent on lower frequencies. In Figure 1d, the response of the index return to one-unit shock in index returns is plotted demonstrating a negative serial correlation between contemporaneous and lagged returns. Over a period of 20 days, the response to the shock reaches a maximum of roughly 0.835 at days two and five and then stabilizes at a cumulative response of 0.860 with a t-stat of 2.15.

As a robustness check, I estimate orthogonalized impulse response functions (Hamilton, 1994) using the same VAR specification as in equation (4) and obtain results closely matching those in Figure 1 and Table 6. Furthermore, I also test a range of four to ten lags in VAR and four to twenty periods in the impulse response functions with qualitatively similar results. Although with a high number of lags in VAR and a low number of periods, the CIRF graphs show a longer convergence to a steady state, the shape and confidence interval bounds of the impulse function in the first four periods are similar to the ones presented in Figure 1. I also re-estimate VAR equations using aggregate dollar flow instead of aggregate percentage flow and obtain similar inferences.

2. Aggregate Flows and Returns: ETFs and Mutual Funds

Given the ongoing debates about price pressure in mutual fund flows[11] and similarities between ETF and mutual fund investor behavior expressed via flows (Clifford et al., 2014), in this section I assess the extent to which mutual fund flows might be responsible for the ETF flow price pressure evidence.

Mutual fund and ETF clienteles could face similar investment objectives and constraints and thus react to the information arrival by the correlated flows in and out of the both types of funds[12]. Furthermore, the domestic equity mutual funds in 2010 had the total net assets of \$4,055 billion, while domestic equity ETFs had only \$476.18 billion, and if the flows are proportional to the total net assets then mutual fund flows should be larger than the ETF flows leading to the identification problem in the case of correlated flows.

I obtain weekly aggregate domestic equity mutual fund flows from Investment Company Institute (ICI). For the ETF flows, I construct aggregate weekly flows by taking weekly change in shares outstanding for each fund and multiplying it by that fund's NAV calculated at the beginning of each week, and then aggregating weekly flows across funds.

It is important to highlight the difference between the weekly flows in this section and the daily flows used in the rest of the paper. The price pressure evidence from the panel and VAR regressions indicate that the price impact occurs contemporaneously with the flows and the price reversal happens 1-2 days later in the panel regressions and 2 days later in the VAR regressions. Quick decay of the price impact and reversal associated with a shock in the daily flows implies that the evidence for the price reversal is negligible on the horizons longer than 5-6 days as shown in the Figure 1a. Hence, using weekly or monthly horizon regressions to find evidence of price pressure may not necessarily lead to correct inferences. Therefore, my purpose in this section is not replicating the ETF flow–return regressions with mutual fund flows as controls, which is impossible given the data constraints, but rather determining the extent to which the mutual fund flow could be a confounding variable in the ETF flow–return analysis.

Table 7 displays statistics in Panel A and pairwise correlations in Panel B for weekly ETF and mutual fund flows and the index returns for the 2007–2010 subperiod used in the VAR regressions in Section 5.1.1. Time-series means of the flows in Panel A indicate that mutual funds during that period had on average negative flows compared to the more volatile positive ETF flows with the range statistics confirming that notion. More importantly, the correlation between weekly ETF and mutual fund flows is negative meaning that higher flows into ETFs may not necessarily be accompanied by higher flows into mutual funds which is consistent with other studies (Agapova, 2011) on the monthly level. The correlation between weekly ETF flow and the index return is close to zero which is expectable given that the price impact from a flow shock dissipates within 5 days and the daily ETF flows do not exhibit significant autocorrelation. Interestingly, mutual fund flows do have positive correlation with the weekly index return suggesting an intra-week price impact without a posterior reversal which implies a permanent price innovation found in mutual fund flows by, for instance, Edelen and Warner (2001) and Rakowski and Wang (2009)[13].

Table 7

Weekly ETF and mutual fund flow statistics and correlations

This table presents statistics in Panel A and pairwise correlations in Panel B for the weekly ETF and mutual fund flows and the weekly index returns denoted as Flow_w^{MF}, Flow_w^{ETF} and R_w^{VWRETD} respectively. Weekly mutual fund flows are from Investment Company Institute (ICI). Weekly ETF flows are constructed from the daily data using previous week's NAV and the weekly change in shares outstanding for each fund and then aggregated across funds for each week. Both ETF and mutual fund flows are measured in millions of dollars for ease of interpretation. Weekly index return is Value-Weighted Index Return (CRSP) expressed in percent. The sample period is from July 2007 to July 2010. * denotes significance at the 5%.

Panel A

Variable	Obs	Mean	Std. Dev.	Min	Max
Flow_w^{MF}	157	-1,865.41	4,278.43	-21,734.00	5,606.00
Flow_w^{ETF}	157	1,020.21	7,048.24	-13,454.19	42,486.45
R_w^{VWRETD}	157	-0.112%	3.403%	-16.121%	9.957%

Panel B

Variables	Flow_w^{MF}	Flow_w^{ETF}	R_w^{VWRETD}
Flow_w^{MF}	1.000		
Flow_w^{ETF}	-0.317*	1.000	
R_w^{VWRETD}	0.045	0.240*	1.000

To gain more insight into the effect of the flows on the daily returns, I run several regressions where I fit different leads of daily returns on the weekly ETF and MF flows with a varying set of controls. The objective is to identify the relation of the ETF and mutual fund flows and the posterior daily returns. The regressions follow this specification:

$$R_{t+1,t+k}^{VWRETD} = \alpha + \sum_{t}^{t+k-1} \beta_{R,t} R_t^{VWRETD} + \mathrm{Flow}_w^{ETF} + \mathrm{Flow}_w^{MF} + R_w^{VWRETD} + \varepsilon_t \qquad (5)$$

where $R_{t+1,t+k}^{VWRETD}$ are the daily index returns for the first day after the date of the weekly ETF and mutual fund flows respectively, $\sum_t^{t+k-1} R_t^{VWRETD}$ are the leading daily index returns from the first lead t up to the lead before the daily return being regressed $t+k-1$ and R_w^{VWRETD} is the weekly index return. The leading daily and the weekly index returns on the RHS of the regression control for the daily return autocorrelation and the contemporaneous weekly impact of the flows respectively. I use returns for the subsequent 7 days after each weekly flow.

Table 8

ETF and mutual fund weekly flow regressions

The regression table reports estimation results for regressions of posterior daily index returns for days from $t+1$ to $t+7$ on ETF and mutual fund flows with controls. Each column corresponds to a separate regression with a different dependent variable each one an index return on the k^{th} day, R_{t+k}^{VWRETD}, after the weekly flow. Each regression has a set of control variables comprised of the daily returns for the days from t and to $t+k-1$ to control for the daily return autocorrelation. Weekly ETF and mutual fund flows and the weekly index returns are denoted as $Flow_w^{ETF}$, $Flow_w^{MF}$ and R_w^{VWRETD} respectively. Weekly mutual fund flows are from Investment Company Institute (ICI). Weekly ETF flows are constructed from the daily data using previous week's NAV and the weekly change in shares outstanding for each fund and then aggregated across funds for each week. Both ETF and mutual fund flows are measured in billions of dollars for convenience. Weekly index return is Value-Weighted Index Return (CRSP) and is expressed in percent. The sample period is from July 2007 to July 2010. Standard errors are corrected for heteroscedasticity and autocorrelation up to five lags with Newey and West (1987) standard errors (t-stats are in parenthesis). *, **, *** measure significance at the 10%, 5%, & 1% level, respectively.

Variables	Dependent Variable						
	R_{t+1}^{VWRETD}	R_{t+2}^{VWRETD}	R_{t+3}^{VWRETD}	R_{t+4}^{VWRETD}	R_{t+5}^{VWRETD}	R_{t+6}^{VWRETD}	R_{t+7}^{VWRETD}
R_{t+1}^{VWRETD}		-0.081	-0.318***	-0.031	-0.015	-0.123	0.131
		(-0.621)	(-2.582)	(-0.349)	(-0.187)	(-0.837)	(1.226)
R_{t+2}^{VWRETD}			0.027	-0.163	0.165	0.233**	-0.262**
			(0.226)	(-1.599)	(1.573)	(2.040)	(-2.531)
R_{t+3}^{VWRETD}				-0.267***	-0.005	0.070	-0.080
				(-4.911)	(-0.050)	(0.594)	(-1.084)
R_{t+4}^{VWRETD}					0.022	0.116	0.090
					(0.403)	(1.028)	(1.525)
R_{t+5}^{VWRETD}						-0.166*	-0.079
						(-1.748)	(-0.930)
R_{t+6}^{VWRETD}							-0.065
							(-0.601)
$Flow_w^{ETF}$	0.013	0.017	0.039	-0.034*	-0.055***	-0.009	0.011
	(0.441)	(1.465)	(1.281)	(-1.760)	(-2.809)	(-0.491)	(0.511)
$Flow_w^{MF}$	0.036	0.017	0.044	-0.026	0.014	0.064	0.024
	(0.881)	(0.889)	(0.756)	(-0.550)	(0.314)	(1.276)	(0.663)
R_w^{VWRETD}	1.015	2.473	-11.534	-4.099	10.091*	1.449	2.620
	(0.163)	(0.581)	(-1.072)	(-1.160)	(1.766)	(0.254)	(0.670)
Constant	0.043	-0.027	-0.105	0.177	0.006	0.055	-0.079
	(0.307)	(-0.242)	(-0.582)	(1.221)	(0.047)	(0.316)	(-0.583)
Obs	156	156	156	156	156	155	155
R^2	0.007	0.021	0.110	0.139	0.114	0.091	0.163

Table 8 shows the results of the regression analysis. Interestingly, the coefficients on the weekly ETF flow exhibit a distinctive pattern similar to the daily VAR regressions from Table 6 — the coefficients for the first 3 days after the weekly flow are decreasing and insignificantly positive and then turn significantly negative on the 4th and 5th days and then back to insignificant on the 6th and 7th days. This pattern is consistent with the impulse response function behavior from Figure 1a where the positive contemporaneous price impact is followed by price reversal and the consequent dampening of the original shock. In economic terms, an increase of the weekly ETF flow of $1 billion is associated with a price reversal on the 5th day of 5 basis points and one standard deviation shock in ETF flows ($\sigma_{\mathrm{flow}_w^{ETF}}$ = $7.04bln) corresponds to a reversal of 35 basis points which is similar to the estimates in the VAR regressions. Furthermore, the price reversal pattern in the ETF flow coefficients while controlling for the MF flows suggests that the price pressure evidence from the VAR regressions is most likely due to ETF flows and not the unobserved daily MF flows.

Interestingly, the coefficients for the mutual fund flows are consistently insignificant suggesting no evidence of price reversal that I find in ETF flows. Following Edelen and Warner (2001), positive contemporaneous relation between mutual fund flows and returns with no price reversal implies that flows are a response to "new information" being permanently impounded in the prices which is consistent with other studies (Rakowski and Wang, 2009). This difference in information content of the flows implies a clientele effect which merits further investigation. Conventionally, mutual funds are held by individual investors who are considered uninformed; the ETFs, however, are held by a mix of retail and institutional investors who are considered uninformed and informed respectively. Hence, one would expect the mutual fund flows to be more prone to uninformed trading and more likely to push prices away from fundamentals with a subsequent price reversal than ETF flows. The evidence in Table 8, however, points to the contrary. Furthermore, a recent paper by DeVault et al. (2014) shows that institutional investors might be also subject to sentiment shocks which makes the ETF flows driven by the institutional investor demand more likely to be associated with transitory price pressure.

Examining the coefficients for control variables reveals the need to account for the autocorrelation of daily returns given that some of the leading daily returns on the RHS of the regression have high t-stats, in particular in the 4th day return regression. Furthermore, the weekly return, R_w^{VWRETD}, is slightly significant for the 5th day return regression. As a robustness test, I evaluate different combinations of the control variables without any notable changes in the inferences — ETF flows still show price reversal and MF flows are persistently insignificant[14].

VI. CONCLUSIONS

Using a unique database of fund-level flows and their respective daily index returns for the sample of 286 U.S. equity ETFs, I find that exchange-traded fund flows exhibit a statistically significant and cross-sectionally consistent positive association with contemporaneous underlying index returns across several specifications, subperiods and aggregation levels. The magnitude of the relation as a response to one standard deviation flow shock varies in different specification and subsamples from 7 to 89 basis points, with coefficient estimates increasing in the latter part of the sample. Furthermore, I find substantial evidence of price reversal in the top 10 ETFs using panel regressions and on the aggregate level using vector autoregressive (VAR) with price reversal accounting for 38% of the contemporaneous return shock due to flows. Price reversal is also economically significant with a one standard deviation shock in flows of $3 billion associated with a posterior 34 basis points price reversal. Given that transitory price pressure is identified by the subsequent price reversal (Goetzmann and Massa, 2003; Ben-Rephael et al., 2011), this significant negative relation between lagged fund flow and returns is consistent with the price pressure explanation.

These findings provide a novel contribution to the price pressure (Harris and Gurel, 1986) and institutional flow literature (Edelen and Warner, 2001; Goetzmann and Massa, 2003) by exploring the relation between fund flows and the underlying returns in the ETF context. Authorized Participants (APs) driven by the intraday arbitrage opportunities and large orders from clients engage in creation-redemption with the ETF potentially yielding a concomitant intervention in the market. The permanent component of the effect of this intervention on prices is interpreted as market efficiency improving price discovery; but, the transitory component suggests a possibly disequilibrating price pressure due, for instance, to noise traders (DeLong et al., 1990). I document the evidence suggesting that at least part of the ETF creation–redemption activity results in an economically significant price pressure. Given the recent and most likely continuing dramatic increase in the total amount of assets invested in ETFs, it is important to understand their impact on financial markets.

Furthermore, few studies have explored the cross-section of institutional flows as mostly aggregate flows are available. I study flow–return relation in the panel setting and find that even accounting for the potential cross-fund flow correlation, price reversal is driven in the latter subperiods by the flows to top 10 ETFs ranked by size. On the other hand, for the U.S. equity ETFs in general, the evidence of the price reversal is more muted suggesting that price pressure is more permanent in nature.

Moreover, price reversal persists even when controlling for mutual fund flows which do not exhibit price reversal indicating that ETF flows differ from their mutual fund counterparts in the nature of the information they impound and their association with the market returns, suggesting a clientele effect. Additionally, I find that horizon is an important factor in the flow–return studies as ETF flows contradictorily exhibit contrarian and performance–chasing behaviors on the daily level and monthly levels respectively (Clifford et al., 2014).

ENDNOTES

1. Authorized Participants (APs) who have signed an agreement with the fund and usually comprise institutional investors and market makers.
2. If the Authorized Participant already holds the underlying securities; they can exchange those securities for the ETF shares without having to buy them on the market. However, according to practitioners (Abner, 2011), APs usually transact flow-related orders on the market.
3. "Exchange Traded Funds: Maximizing the Opportunities for Institutional Investors", *Viewpoints*, SSGA, December, 2009.
4. I discard the 1993–2000 period due to higher incidence of the zero flow fund-day observations.

5. A majority of ETFs report their flows next day after the actual flows occur; however, some funds report flows with variable leads and lags. Within the data provided by the *Bloomberg* there is no clear way to identify the exact timing of the flows. Also see Section 4 for discussion.
6. The mispricing can be exploited by any trader on the secondary market, by selling short the overpriced asset and buying the underpriced and reverse the trade when mispricing disappears. However, only the APs are uniquely positioned to transact directly with the ETF to ensure the end-of-day equivalence between the two legs of the arbitrage trade.
7. Interview with Mr. Don Suskind (PIMCO) and phone interviews with other ETF families.
8. In fact, Bloomberg was not aware of this issue when contacted by the author in May 2010. As of 2015, the data on daily flows provided by the ETFs directly and the data provided by OptionMetrics differ by a varying number of lags.
9. I analyze the flow correlations for the equity non-leveraged funds tracking the same index and find that there is little serial- and cross-correlation between flows to the funds tracking the same index. These results cast doubt on the existence of the common unobserved factor driving both returns and flows on the contemporaneous basis. Excluding leveraged funds, only 2 indices are tracked by more than 1 fund: SPY by State Street and IVV by iShares track S&P 500; MDY by State Street and IJH by iShares track S&P 400. Hence, given that the sample size is small these results are not included in the paper and are available upon request.
10. This pattern is confirmed in the untabulated panel regressions of the index returns on the premiums and their daily lags (1–5 lags) for the top 10 ETFs and the rest of the sample: lagged premiums are more significant for the non-top 10 ETFs.
11. See, for instance, Ben-Rephael et al. (2011) who find price pressure in Israeli daily mutual fund flows and Rakowski and Wang (2009) who do not find any in the US daily mutual fund flows.
12. It is important to reiterate the difference between the MF and ETF flows. Mutual fund flows are creation and redemption requests by the investors transacted directly with the fund, while ETF flows are creation and redemption requests either initiated by APs due to the arbitrage-induced trades profiting from the persistent ETF share demand-supply imbalances or by the same APs satisfying large creation and redemption requests submitted by the institutional investors (Abner, 2011).
13. Untabulated correlations show that weekly mutual fund and ETF flows have correlations of 0.113 and -0.092 with the following week's market return.
14. Robustness test results are available on request.

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