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ARE FLOWS COSTLY TO ETF INVESTORS?

- As we seek to further expand our expertise on the ETF marketplace, members of our investment committee continue to research more deeply the structure and trading of these unique securities.
- This month's commentary is a contemporary white-paper written by Dr. Brian Henderson and Dr. Jeff Buetow that discusses potential influences of the manner of the creation/redemption process employed by distinct groups of ETFs.
- More specifically, Drs. Henderson and Buetow ask whether there are definable performance differentials between those ETFs that employ *in-kind* creation/redemptions, versus those that allow for *cash* creations/redemptions (the differences between the two approaches are explained in the paper).
- The main results include:
    - We find no evidence that fund-level flows predict returns, but find evidence of fund flows "chasing" returns.
    - We find no evidence that ETFs are particularly susceptible to opportunistic trading behavior based on market-timing strategies.
    - Our cross-sectional performance analysis, however, implies that among ETFs tracking international benchmarks, funds featuring cash creations and redemptions underperform their benchmark indexes by an average 1.76% more than in-kind funds, annually.
    - Overall, our empirical analysis provides limited evidence that fund flows are costly to ETF investors. Any evidence of costly flows are relegated to funds featuring cash creations and redemptions and tracking international indexes.

Are Flows Costly to ETF Investors? *

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Abstract

Authorized Participants (APs) create and redeem ETF shares in response to supply and demand imbalances for the shares in the secondary market. For the majority of ETFs, share creations and redemptions take place as in-kind transactions, but a growing number of ETFs feature cash creations and redemptions. We investigate whether ETF flows are costly to investors. Using a reasonable proxy for the potential cost of fund flows, we find evidence of under-performance associated with flows to ETFs featuring cash creations and redemptions and tracking international benchmarks. Since ETF flows do not predict subsequent returns and we do not find evidence the funds are susceptible to market timing strategies, the costs likely stem from the transactions costs associated with portfolio trades necessary to accommodate cash liquidity.

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1 Introduction

Exchange Traded Funds (ETFs) have been one of the most successful financial market innovations in recent years. Since 1993, when State Street introduced the first U.S. ETF, the number of funds has increased to 1,159 with approximate total assets of $1.3 trillion under management.[1] ETFs owe their success largely to some combination of their generally low fees and the close tracking of their realized investment returns with those of the target benchmark index. The ETF product space has grown to include many, targeted exposures previously unavailable to most investors in any form, much less through vehicles available for trading intra-day. To facilitate close tracking of the ETF shares with the value of fund assets, the product design features two layers of liquidity. ETF shares are listed and traded on exchanges, providing intraday liquidity. ETFs offer an additional layer of liquidity through the primary market allowing for the creation of new and redemption of existing fund shares. In contrast, other investment companies typically offer only one layer of liquidity. For example, open-end mutual funds offer once-daily liquidity at the fund's net asset value (NAV). Traditional closed-end funds trade in the secondary market at prices which often differ meaningfully from the funds' NAV (Pontiff, 1996). Numerous empirical studies find that ETF returns closely track those of the benchmark index, implying that the dual layers of liquidity, combined with proper fund management, succeed at creating intra-day tradeable vehicles replicating the returns to the benchmark index (Elton, Gruber, Comer, and Li, 2002; Buetow and Henderson, 2012).

Critical to ETF return tracking and liquidity is the primary market where Authorized Participants (APs) create and redeem shares, alleviating imbalances between the supply of and demand for the ETF shares in the secondary market. Typically, APs are quantitative trading firms. For the majority of ETFs, primary market creations and redemptions of fund shares take place through *in-kind* exchanges. Each ETF publishes daily a list of underlying securities and their respective quantities constituting "the basket" of securities equaling one creation unit.[2] In response to excess demand for the ETF shares in the secondary market, APs act to create additional ETF shares by purchasing the basket of underlying securities. The APs hedge their position in the basket by selling short the ETF shares. Although the actual share creation takes place after the close of trading when the AP delivers the basket securities along with a cash fee to the trustee, the APs' trades

[1] Source: Morningstar Direct database on March 7, 2013.

[2] In addition to the basket securities, creation units typically include a cash amount. Further, the AP must pay a transaction fee associated with the exchange. Sponsors determine the size of "creation baskets." The size ranges from 10 to 100 thousand shares, with a median of 50 thousand, according to Morningstar Direct.

alleviate the secondary market supply and demand imbalances.[3] The share redemption process works in the reverse order. The *in-kind* exchange process facilitates the tax efficiency of ETFs as these exchanges avoid portfolio turnover and do not result in the funds' realization of capital gains or losses. Additionally, the *in-kind* exchange delegates the trading associated with fund flows, including direct and indirect costs, to the APs.

As the ETF product space evolved in recent years, innovation reached beyond traditional asset classes to investment assets having characteristics that render difficult or impossible *in-kind* primary market exchanges. Thus, many funds offering innovative exposures allow *cash*, instead of *in-kind*, exchanges. For example, many international emerging market funds encounter restrictions on non-domestic holdings as evidenced by Russia's legal restrictions on foreign direct ownership stakes in domestic companies or the imposition of significant transaction taxes by Brazil. *Cash* exchanges even extend beyond the more exotic exposures as some sponsors such as PIMCO utilize *cash* exchanges in the primary market given the sponsor's purported, superior access to security inventories, which renders *cash* exchanges more efficient for the funds. Unlike *in-kind* exchanges, *cash* exchanges require that the fund itself, as opposed to the APs, transact in the underlying securities.

ETF *cash* creations and redemptions are similar to mutual funds' daily liquidity provision. Open-end mutual funds provide cash liquidity at the closing NAV, requiring the fund to transact the portfolio securities. Additionally, outflows result in open-end mutual funds' realization of capital gains or losses. The extant literature connects such flows to costs born by long-term shareholders. For example, Greene and Hodges (2002) find evidence of costly flows to investors in U.S. mutual funds holding primarily international assets, resulting in significant dilution of long-term investors' wealth due to short-term trading. This result is concentrated among mutual funds holding international securities, but may apply generally to situations in which there exists a lag between the cash transaction and the deployment of that cash when next-day returns are predictable. Similarly, Goetzmann, Ivkovic, and Rouwenhorst (2001) document the existence of profitable trading strategies stemming from international mutual funds' use of "stale" prices when computing daily NAVs. Additionally, when funds face net redemptions and must liquidate portfolio holdings, an overhang of unrealized capital gains may become costly for taxable investors (Barclay, Pearson, and Weisbach, 1998).

In light of the extant research highlighting multiple channels through which fund flows are deleterious to buy-and-hold mutual fund investors, a natural question arises as to whether or

[3] Typically the AP must notify the Trustee by 4pm E.S.T. of their intent to create or redeem shares.

not ETF flows impact investment performance. We focus on the ETFs with *cash* creations and redemptions as the most likely group to suffer costs associated with flows. Costs to shareholders of funds having *cash* exchanges may come through trading costs associated with the flows, or opportunistic fund flows when there is a lag between determination of the NAV and when the fund transacts in the underlying. Among ETFs tracking indexes comprised of less liquid or non-U.S. securities, there may be considerable lags between the share creations and redemptions and the time when the fund transacts in the underlying due to time-zone differences or simply the time necessary to execute the order flow in the market for the underlying. Thus, it is possible that *cash* exchanges are costly to long-term shareholders through either of two channels: transactions costs, or the lag time between the NAV computation and fund portfolio transactions. To minimalize the potentially adverse impact of flows on existing shareholders, many funds having *cash* creations may "pass back" a portion of these costs if transacting in the portfolio securities is more expensive than indicated by the NAV.[4] While pass-back fees present risk to APs and potentially deter timing activities, the extent to which such fees are utilized is unknown, and APs are likely to pass such risk back to investors through the spread. The extent to which the ETF creation and redemption processes, whether they feature *cash* or *in-kind* exchanges, impact fund performance and benchmark tracking is an open empirical question.

While there is a substantial extant literature on the relation between flows and returns among open-end mutual funds, to our knowledge, ours is the first to examine the relation between ETF flows and returns. We find evidence of return chasing behavior among ETF flows since ETF outflows (share redemptions) follow negative index returns and ETF inflows (share creations) follow positive index returns. This finding is consistent with the findings of Edelen and Warner (2001) and Goetzmann and Massa (2003) that daily mutual fund flows correlate positively with one-day lagged returns. Additionally, we find no statistical relation between flows and either contemporaneous or next-day index returns. These patterns are consistent with the interpretation that ETF flows respond to returns, or to the information driving returns, and that these flows do not drive or predict returns. Additionally, we consider a simple market-timing strategy to determine whether ETFs, particularly those featuring *cash* exchanges are susceptible to market timing strategies. Such strategies, which are similar to those considered by Goetzmann, Ivkovic, and Rouwenhorst (2001), imply at best marginal timing abilities.

We propose and test a statistical model linking benchmark-adjusted ETF performance to proxies for potentially costly flows. We find that ETF return deviations to international *cash* exchange

[4] The pass back fee also serves as a deterrent to opportunistic behavior such as market timing trading rules.

funds are correlated positively and significantly with our measure. To our knowledge, ours is the first research to quantitatively evaluate the potential influence of the ETF creation and redemption process on fund return performance. Since ETF flows do not predict returns and we do not find evidence these funds are particularly susceptible to market timing strategies, these costs most likely stem from costs associated with portfolio transactions necessary to accommodate the cash liquidity.

The balance of the paper is organized as follows: Section 2 describes the sample ETFs and sources for the data used in this study, Section 3 describes the empirical approach and presents and summarizes the results, and Section 4 briefly concludes.

2 Sample Description

The sample begins with all publicly traded ETFs listed on U.S. Exchanges, as identified in Morningstar Direct on July 1, 2012. Since our empirical analysis relies on high-frequency data, to eliminate the potential impact of funds that trade infrequently, we restrict the analysis to include ETFs having assets of at least $25 million and average daily turnover of at least one-tenth of one percent of outstanding shares. These data filters remove noisy data and we have no a priori reason to believe the filters influence the quantitative results. We further restrict the analysis to funds having at least six months of daily data available. From the fund prospectus and fact sheet, which are available through the sponsor website, we identify for each sample fund the ticker symbol, benchmark index name and Bloomberg ticker symbol, and whether primary market transactions involve *cash* or *in-kind* exchanges.

We categorize sample funds according to the asset class (equity or fixed income) of the securities comprising the benchmark index, their geography (domestic U.S. or international), and whether the fund creation and redemption process consists of *cash* or *in-kind* exchanges. We exclude from the final sample any ETFs tracking commodity, leveraged, or currency indexes. Although many of those funds feature *cash* exchanges, a natural control sample of *in-kind* funds does not exist for this sample of ETFs. We collect historical daily closing share prices, the number of shares outstanding, distribution dates, and distribution amounts for each sample ETF from Thomson's Datastream database. Daily closing index levels come from Bloomberg. The sample period covers the years 2006 through and including June 2012. The sample begins in 2006 to coincide with the entrance to our sample of the first *cash* creation and redemption fund.

Table 1 presents descriptive statistics for the sample ETFs. The sample comprises 379 unique ETFs, 333 of which track equity benchmarks while the balance (46) track fixed income indexes. Of the 333 equity ETFs, 203 track domestic U.S. indexes, 130 track international indexes, 33 have *cash* creations and redemptions, and 300 have *in-kind* exchanges. Of the 46 fixed income ETFs, 40 track domestic indexes, 6 track international indexes, 16 feature *cash* creations and redemptions, and 30 feature *in-kind* exchanges. *Cash* creations and redemptions are most common among international (33 of 136) and fixed income funds (16 of 46). The average sample fund has an approximately $1.03 billion market capitalization, defined as the product of shares outstanding and daily closing price. The largest sample funds on average come from the domestic fixed income sector having in-kind exchanges. Notably, the domestic equity and fixed income funds featuring *cash* creations and redemptions are the smallest funds, with average market capitalizations of $131 and $160 million, respectively. The average sample ETF has daily turnover, defined as the number of shares traded per shares outstanding, of 3.6%. Turnover is, on average, higher among equity ETFs than fixed income ETFs. For example, average daily turnover among equity funds ranges from 3.2% among domestic *cash* exchange funds to 4.6% among domestic *in-kind* funds, compared to 1.6% for international *in-kind* funds to 2.7% for domestic *in-kind* fixed income funds.

Admittedly, our data do not allow for direct observation of fund creation and redemption activity for the sample ETFs. Our analysis uses the daily changes in the number of shares outstanding, through which we are able to measure the daily *net* creation and redemption activity, collectively referred to as $flows$. We measure daily share creation activity as the percentage change in shares outstanding from the previous trading day when the change is greater than zero. Conversely, we measure daily redemption activity as the percentage change in shares outstanding from the previous day when that change is less than zero (i.e. shares outstanding decrease). Referring to Table 1, the average creation size is 0.8% of the fund assets. As a fraction of fund assets, creations are largest for domestic and international equity funds having *cash* creations and redemptions. At −0.2% of assets, the average redemption size tends to be smaller in magnitude compared to creations, which is not surprising since the sample period coincides with a large secular rise in ETF assets under management. The final two columns in Table 1 present the frequencies of creations and redemptions. The average sample fund has daily net creations on 10% of the sample days, or on one out of every ten trading days. Redemptions tend to occur less frequently, averaging 6.3% of the sample days, or once every 16 trading days. Among fixed income funds, creations and redemptions occur more frequently during the sample for funds having *in-kind*, as opposed to cash, exchanges. Among equity funds, creations and redemptions occur slightly more frequently during the sample for funds featuring *cash* exchanges.

3 Empirical Analysis

This section presents the results of our empirical analyses. The analysis begins with an investigation of the relation between ETF flows and returns to determine whether there is evidence of flows' timing ability at the fund level. Next, the analysis considers the potential profitability to a simple day-trading strategy to ascertain whether the sample funds are vulnerable to timing strategies. The analysis then turns to the cross-section of ETFs and considers whether there is an empirical link between ETF return performance and fund flows.

3.1 ETF Flows and Returns

We begin the empirical analysis by examining patterns in the benchmark index returns around ETF flows to understand the relation between fund flows and returns. Specifically, we are interested in whether there is evidence at the fund level of timing ability in fund flows. We proceed by classifying each ETF-Date observation according to whether on that date the fund experienced net outflows (share redemptions), zero net flows (no change in shares outstanding from previous day), or net inflows (share creations). Table 2 presents average benchmark index returns during the three-day period centered on the event date for the three daily flow categories.

Referring to Table 2, the left-hand columns highlight that redemptions generally follow negative returns to the benchmark index. In fact, across all but one sub-sample, the average index return on the day immediately prior to a redemption is negative. Redemptions do not appear to coincide with or predict index returns, as evidenced by the average index returns on the redemption date or the next subsequent trading day. Referring to the center columns, which correspond to days on which there are no fund flows, the averages appear to be generally small, ranging from -4 to $+4$ basis points. The final three columns present returns around net-creations, or inflows. Interestingly, creations tend to follow positive returns to ETF benchmark indexes. In fact, several estimates are statistically significant at conventional levels and, with the exception of only one estimate, all are positive. Further, there is no evidence that creations coincide with or precede index returns that differ significantly from zero. These patterns hold across asset class, geography, and creation type.

The return patterns presented in Table 2 are consistent with return-chasing behavior among ETF investors, where flows respond to recent returns. This pattern is also consistent with the possibility that both ETF flows and index returns share a common response to another, unobserved, driver such as information flow. Similar patterns exist in open-end mutual fund shares (Edelen and Warner, 2001; Goetzmann and Massa, 2003). Further, there is no evidence of a contemporaneous link between index returns and fund flows, as well as no evidence flows predict or cause subsequent returns.

Our purpose in this section is to provide descriptive evidence as to whether or not evidence exists of flows' timing ability at the ETF-level. We interpret the results in Table 2 as evidence of no timing ability in ETF flows since creations do not precede or coincide with positive returns and redemptions to not precede or coincide with negative returns. Were flows "smart," at daily frequency, flows should predict next-day or same-day returns. It is noteworthy that these patterns hold across all sub-groups, implying that *cash* exchange funds do not appear more exposed to opportunistic flows than *in-kind* funds.

The sample period coincides with a large secular rise in ETF assets under management, during which ETFs have claimed market share from open-end mutual funds (Salisbury, 2011). By definition, these inflows may plausibly dampen our ability to detect a "smart money" flow effect by masking such flows. This is the unavoidable reality for any sample of successful funds, which by definition increase their assets under management.

3.2 A Simple Timing Rule

The analysis in this section considers a simple market-timing strategy regarding ETFs. In order for the ETF exchange mechanism to affect return performance, we have hypothesized the influence carries through two possible channels: transactions costs or opportunistic timing of flows. The analysis in the previous section highlights that, at the fund level, flows do not appear to predict returns. This section considers more generally whether the sample funds are susceptible to timing strategies that take advantage of potentially stale prices or predictable changes in the value of the portfolio before the fund transacts in the portfolio securities to accommodate the flows. In the context of ETFs featuring *cash* exchanges, stale prices may arise when APs create and redeem shares at the NAV, but the fund faces a lag time before transacting in the portfolio securities. If the NAVs are stale or future returns are predictable, the fund may be exposed to such opportunistic behavior.

We consider a strategy that purchases ETFs shares at the close of trading on day t if the return to the S&P 500 Index is positive on that day. Otherwise, the strategy invests at the risk-free rate. Other studies have used a similar strategy to find evidence of profitable timing strategies among open-end mutual funds (Goetzmann, Ivkovic, and Rouwenhorst, 2001; Greene and Hodges, 2002). Table 3 presents the results by groups formed based on the fund asset class (equity or fixed income), geography (domestic U.S. or international), and creation type (*cash* or *in-kind*) and the first three columns identify the subsample. The fourth column of the table presents the sample sizes. The fifth column presents the return correlation between the S&P 500 Index and the next day ETF return. The correlations are negative among equity ETFs, both domestic and international, and positive among fixed-income ETFs. The table also presents the mean daily return and standard deviations to equal-weighted portfolios of the sample ETFs on the "bullish" days, those following S&P 500 advances, "bearish" days defined as the days following S&P 500 declines, followed by difference in means tests across the two groups. The average daily return difference is positive among fixed income funds, but the t-statistics do not indicate statistical significance. Return volatility is on average lower during the "bullish" subsample, compared to the "bearish" subsample of days following S&P 500 Index declines.

Overall, the simple trading strategy does not present strong evidence that any sub-sample of ETFs is particularly exposed to opportunistic trading, even though funds featuring *cash* creations are the most likely candidates. The analysis next turns to the cross-sectional return performance of the sample funds relative to their benchmark indexes.

3.3 Cross-sectional Analysis of ETF Flows and Fund Returns

Do exchange-traded fund flows affect investor returns? This question forms the basis for the main empirical hypothesis proposed and tested in this study. While many ETFs feature *in-kind* creation and redemption processes, a growing number of funds feature *cash* exchanges. The purpose of *cash*, as opposed to *in-kind*, exchanges relates to the relative ease with which the APs transact in the underlying portfolio securities. In certain cases, such as international ETFs, barriers may exist such as legal restrictions on foreign (non-domestic) ownership. *Cash* creations transfer responsibility for the trade execution to the fund and existing investors. Although the funds charge fees, providing cash liquidity at times when the portfolio transactions likely lag the NAV computation, may expose shareholders to costs associated with flows.

Funds receiving *cash* in primary market exchanges likely experience lags between the share creation and redemption activity and when the fund transacts in the underlying securities. In contrast to *in-kind* exchanges, where the APs transact in the underlying, the *cash* process passes on this trading requirement, requiring the fund to transact the portfolio securities. Given non-synchronicities that arise from time zones and even across domestic markets (the U.S. bond market closes at 2pm EST), the fund transacts in the underlying with a lag. This lag, and the delegation of costly trading activities to the fund may impact returns.

We next present an empirical framework for modeling ETF returns, allowing for direct tests of the hypotheses linking ETF flows and returns. The analysis begins with a statistical model of ETF returns, based on the funds' stated return objective to provide daily returns that replicate those of the stated benchmark index. Thus, on any day t, returns to sample ETF i, $r_{i,t}^{ETF}$ should equal the return to the underlying index, $r_{i,t}^{Index}$. To evaluate the performance of the sample ETFs against their stated return objectives, the analysis begins with the following baseline regression model:

$$r_{i,t}^{ETF} = \beta_0 + \beta_1 \times r_{i,t}^{Index} + \epsilon_{i,t}, \tag{1}$$

where $r_{i,t}^{ETF}$ is the day t return on ETF i, and $r_{i,t}^{Index}$ is the return on ETF i's benchmark index. The model includes an intercept capturing any time-invariant component of fund returns. We compute the daily ETF returns as $R_{i,t}^{ETF} = (P_{i,t} + D_{i,t})/P_{i,t-1}$, where $P_{i,t}$ is the closing price of ETF i on trading day t, and $D_{i,t}$ is the distribution amount received by the seller on the ex-dividend date, where all values come from Thomson's Datastream database. We compute returns to the benchmark index as $r_{i,t}^{Index} = (Index_{i,t}/Index_{i,t-1})$, where $Index_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index as reported by Bloomberg. For each sample ETF, we estimate the regression model for all available data starting on January 1, 2006 through the end of June, 2012.

Under the null hypothesis that sample ETFs replicate exactly the returns to the benchmark index, we expect the estimates to reveal no abnormal performance ($\beta_0 = 0$), that each fund provides the promised "beta" exposure to the benchmark index ($\beta_1 = 1$), and that the model captures a large portion of the fund return variation ($\bar{R}^2 \approx 1$). Although we estimate the regression separately for each sample fund, we report the cross-sectional averages of those estimates. Doing so allows for comparisons across groups of funds, where groups are formed based on the type of primary market transactions (*cash* or *in-kind*) for each sample fund.

Panel A of Table 4 presents the regression results of estimating equation 1 across the sample. The table presents the cross-sectional mean estimates for subsamples formed based on fund exchange type. The first group of results reported include all ETFs (domestic and international) for those funds having *cash* creations and redemptions and those having *in-kind* exchanges. The mean estimates are statistically indistinguishable across the two groups, where both exhibit small, positive intercepts that are indistinguishable from zero, and loadings on the benchmark return which are less than unity.

The statistical model explains only 60% of the daily return variation for *cash* funds compared to nearly 75% for funds having *in-kind* exchanges. The following two rows present subsets consisting of sample funds tracking indexes comprised primarily of domestic and international securities. The model fit is noticeably higher among domestic as opposed to international funds. Otherwise, the estimates are similar to those of the full sample. It is noteworthy that estimates of β_1 are less than unity. In fact, at conventional levels, we reject the null hypothesis $H_0 : \bar{\beta}_1 = 1$ for each subsample in Panel A. Measurement errors are most pronounced in high-frequency data and have the tendency to bias downward the slope coefficient estimates (Scholes and Williams, 1977). Measurement errors are particularly relevant to non-domestic U.S. asset classes due to time-zone differences, but are also relevant to all ETF investors due to the potential for stale prices to influence daily index computation and microstructure effects such as the bid-ask spread.

We address the potential influence of measurement errors by also considering the restricted form in which the ETF return is assumed to follow the identity model, which is to say in equation 1 that $\beta_0 = 0$, and $\beta_1 = 1$.[5] By subtracting the index return from each side, the dependent variable becomes the return deviation, RD, defined as $RD_{i,t}^{ETF} = r_{i,t}^{ETF} - r_{i,t}^{Index}$. The right hand side in this baseline specification contains only the intercept term (δ_0) measuring the average return deviation for each sample ETF i. This leads to the following regression model:

$$RD_{i,t}^{ETF} = \delta_0 + \varepsilon_{i,t}. \tag{2}$$

Regression estimates of equation 2 appear in Panel B of Table 4. Across all subsamples, we do not reject the null hypothesis of no abnormal performance, which is to say the regression intercepts do not differ significantly from zero. Additionally, we do not reject the null hypothesis that *cash* exchange funds underperform *in-kind* funds since the intercepts do not differ significantly.

Alternatively, we replicate the analysis using lower frequency data, considering weekly and monthly frequencies. In unreported results, the slope estimates increased, becoming statistically indistinguishable from unity at the monthly frequency, and the R^2s increased meaningfully. Since our analysis focuses on flows, and we expect their impact on returns to be concentrated in short time intervals around when those flows take place, our focus remains on high-frequency daily data.

Since the sample ETF shares trade on U.S. stock exchanges, non-synchronicity between the ETF prices at the close of trading and the daily index marking likely influence the estimation results, particularly among sample funds tracking international indexes. Non-synchronicity arises among domestic fixed-income ETFs since the U.S. fixed income markets close at 2pm EST, two hour before ETF trading ceases. In a contemporary study, Tucker and Laipply (2013) find that fixed income ETF prices lead bond market composits, implying an additional source of non-synchronicity

[5] "Fixing" the slope coefficient under the null hypothesis removes the potentially spurious correlation (French, Schwert, and Stambaugh, 1987).

between daily ETF and index returns among fixed income ETFs. In response, we include the contemporaneous return to the S&P 500 index to control for any value-relevant information revealed during the U.S. stock market trading day that is not reflected in the benchmark index returns due to non-synchronicity.[6] We extend the models in equations 1 and 2 by including the contemporaneous S&P 500 return, so that:

$$r_{i,t}^{ETF} = \beta_0 + \beta_1 r_{i,t}^{Index} + \beta_2 r_t^{SP500} + \eta_{i,t}, \quad (3)$$

$$RD_{i,t}^{ETF} = \delta_0 + \delta_1 r_t^{SP500} + \zeta_{i,t}, \quad (4)$$

where r_t^{SP500} is the day t return to the S&P 500 total return index.

Panels A and B of Table 5 present the regression results for equations 3 and 4. Referring to the first rows of Panel A, which present the estimates for all *cash* and *in-kind* funds, funds featuring *cash* exchanges have negative average intercepts which annualize to approximately −76 basis points, compared to an average +51 basis points for in-kind funds. The difference in means across the two groups of −1.26% annually is statistically significant. Comparing the estimation results in Panel A of Table 5 to those in Panel A of Table 4, the significant loadings on the S&P 500 return and increased $\bar{R}^2$s indicate controlling for non-synchronicity in this sample is important. Referring to the sub-samples of ETFs tracking domestic and international ETFs, it is clear the improved fit and positive loading is concentrated primarily among funds tracking international indexes. We also note the positive, significant loading on the S&P 500 return among domestic *cash* exchange funds. Since many of those funds track fixed-income benchmark indexes, this loading picks up the information revelation between the close of the fixed income markets at 2pm and the close of ETF trading.

The relative underperformance of *cash* versus *in-kind* exchange funds manifests in the subsample of international funds, where the average performance differential of −1.1 basis points daily annualizes to approximately −2.7% relative performance. The regression results of equation 4 in Panel B are consistent with those in Panel A, implying ETFs with *cash* creations and redemptions under-perform funds having in-kind exchanges by statistically significant −1.76% annually among international funds. Similarly, controlling for non-synchronicities appear important for international funds, as evidenced by the positive loadings on the included S&P 500 return.

The preceding analysis implies that, for U.S. ETFs tracking international benchmark indexes,

[6] We favor the S&P 500 instead of broader indexes to minimize the impact of stale prices on index return computation. Empirical studies have shown the S&P 500 to lead other major indexes comprised of less-frequently traded securities (Lo and MacKinlay, 1988).

cash creations and redemptions may be costly to ETF shareholders. This cost likely stems from the delegation of trading from APs to the fund, and lag times between *cash* exchanges and the fund's actual transactions due to time-zone or cross-market differences. The above analysis implicitly assumes these costs are arise as time-invariant returns across the two groups of funds. The analysis next turns to connecting ETF performance to time-varying creation and redemption activities.

To connect ETF performance to fund flows, we propose a proxy we expect to be highly correlated with the potential impact of fund flows on returns. The measure takes account of the magnitude of flows relative to fund size since all shareholders participate in proportion to their relative stake, and the volatility of the benchmark index. For each sample ETF, on each day, we construct the measure $Dilution_{i,t} = -r_{i,t}^{Index} \times \%\Delta SharesOut_{i,t-1}$, where $\Delta SharesOut_{i,t-1}$ is the one-day lag percentage change in shares outstanding. This measure is similar to the dilution measure proposed by Greene and Hodges (2002). Including the dilution measure in the regression models results in the following equations:

$$R_{i,t}^{ETF} = \beta_0 + \beta_1 R_{i,t}^{Index} + \beta_2 R_{i,t}^{SP500} + \beta_3 Dilution_{i,t-1} + \nu_{i,t}, \quad (5)$$

$$RD_{i,t}^{ETF} = \delta_0 + \delta_1 R_{i,t}^{SP500} + \delta_2 Dilution_{i,t-1} + \upsilon_{i,t}, \quad (6)$$

where all variables have been defined previously. Under the null hypothesis that flows are not costly, $H_0 : \beta_3 = 0$ in equation 5, and $H_0 : \delta_2 = 0$ in equation 6. Additionally, we test for differences between funds having *cash* versus *in-kind* creations: $H_0 : \beta_3^{cash} = \beta_3^{in-kind}$, and $H_0 : \delta_2^{cash} = \delta_3^{in-kind}$.

Panels A and B of Table 6 presents the regression results of equations 5 and 6. We first refer to the column in Panel A presenting estimates of β_3. Across all sample ETFs having *cash* exchange processes, the cross sectional mean estimate is positive, indicating that fund returns are lower among funds with higher potential dilution stemming from fund flows. Analyzing subsamples of domestic and international funds reveals the dilutive impact is concentrated among ETFs having *cash* creation processes and tracking international indexes. That is, among *in-kind* funds and domestic *cash* exchange funds, we fail to reject the null hypothesis that $\beta_3 = 0$. Additionally, we reject this null for international *cash* exchange funds. Further, it is important to note that the intercepts β_0 are statistically indistinguishable from zero after inclusion of the dilution measure, implying the source of underperformance among *cash* exchange funds in Table 5 likely stems from creation and redemption activity as opposed to differential expense ratios or other time-invariant sources.

The results in Panel B, where the dependent variable is the ETF return deviation, are consistent with the results of Panel A. Across the full sample of funds, we reject the null hypothesis that ETF returns are unrelated to fund flows ($\delta_2 = 0$), for funds that have *cash* creations and redemptions, but not for funds having *in-kind* exchanges. Analysis of subgroups consisting of ETFs tracking indexes of domestic securities and international securities reveals that this result is concentrated among the international *cash* exchange funds. Further, we reject the hypothesis that *cash* and *in-kind* funds have identical loadings on the dilution proxy (δ_2) for the full sample and the subsample comprising international funds. Additionally, the intercepts no longer differ significantly from zero, consistent with the interpretation that our proxy for costly flows subsumes a significant portion of the underperformance captured with the intercepts in Table 5. Overall, the results are consistent with the interpretation that *in-kind* ETF flows are not costly to shareholders, but that flows to ETFs tracking international indexes and having *cash* creations and redemptions do expose investors to average annual costs of approximately 1.76%.

3.4 Analysis of ETF Spreads

Unlike open-end mutual funds which provide daily liquidity at the fund NAV, ETF shares trade in the secondary market and incur direct and indirect costs associated with the transactions. One such cost is the bid-ask spread, defined as the cost of an instantaneous round-trip transaction. Since APs create and redeem shares in response to imbalances of supply and demand, the secondary market price tracks closely the fund NAV. Under the reasonable assumption that ETF spreads are proportional to the costs and risks associated with APs' share creation and redemption activities, when transacting in the underlying basket of securities is more difficult or costly, we anticipate spreads will be greater. We expect spreads to be higher among *cash* exchange ETFs. The underlying securities tend to be more difficult to transact and the process involves additional steps associated with the delegation of trading activities from the APs to the ETF provider. We conjecture that these costs should manifest in the spread investors pay when transacting in the ETF shares.

We use the spread estimator of Corwin and Schultz (2012) to measure bid-ask spreads of ETF shares in the secondary market. This spread measure is advantageous given its reliance on readily available data (daily high and low prices), and its superior performance, as measured by standard error, relative to the popular spread estimate of Roll (1984). Table 7 presents average estimates for each sub-sample of ETFs formed based on asset class, geography, and exchange type. For each category, the table presents annual averages of the Corwin and Schultz (2012) spread estimate, as well as the average across all years.

Among domestic equity funds, *cash* funds typically have larger bid-ask spreads than *in-kind* funds. The mean differences are large during 2009 and 2010, and decline during the later portion of the sample. Over the full sample, domestic equity ETF investors incur on average 4.3 basis points greater spreads than investors in in-kind funds, and that the sample average spreads are approximately 43 basis points for *in-kind* exchange funds.

Spread estimates for international equity ETFs are not noticeably greater than estimates for domestic equity funds. In general, spread estimates are greater for *cash* funds than for *in-kind* funds, with the largest and statistically significant differences taking place during 2008 and 2009. Over the full sample period, international equity *cash* exchange funds have only 1.1 basis points higher spread estimates than *in-kind* funds.

Spread estimates for fixed income ETFs are smaller than those for equity ETFs. Among ETFs tracking domestic bond indexes, average spread estimates for *cash* and *in-kind* funds are 12.9 and 15.1 basis points, respectively, but not statistically different. These estimates are approximately 30 basis points smaller than those for domestic equity. Spread estimates for international fixed income ETFs are greater than those of domestic ETFs, but still noticeably smaller than domestic or international equity.

Overall, the spread estimates indicate significant marginally higher spreads for ETFs having *cash* versus *in-kind* exchanges. The meaningful differences come primarily during the first part of the sample, and differences since 2010 are neither economically large or statistically significant. We also note the large magnitude of spread estimates during the financial crisis of 2008 and 2009, implying that although estimates are large during that time, they are almost definitely influenced by capital market decouplings that took place during the crisis.

4 Conclusions

We analyze the impact of the share creation and redemption process on ETF return performance, focusing on the impact of ETFs featuring *cash* exchanges as opposed to the more traditional *in-kind* exchanges. We find no evidence that fund-level flows predict returns, but find evidence of fund flows "chasing" returns. We find no evidence that ETFs are particularly susceptible to opportunistic trading behavior based on market-timing strategies. Our cross-sectional performance analysis, however, implies that among ETFs tracking international benchmarks, funds featuring *cash* creations and redemptions underperform their benchmark indexes by an average 1.76% more than *in-kind* funds, annually.Our empirical analysis presents evidence that fund flows can be costly to ETF investors. These results are concentrated among U.S. traded ETFs tracking international indexes and allowing *cash*, as opposed to *in-kind*, creations and redemptions.

Our findings are of interest to the many practitioners utilizing ETFs for the purpose of targeted portfolio exposures. These investors will benefit from awareness of the conditions under which return deviations may occur. Additionally, regulators and fund sponsors will be interested in the results, as well as academics. In light of our results, it may be reasonable to place short-term gates on exchange activity for the most vulnerable funds during extreme market movements.

While our finding that flows to international ETFs having *cash* creations and exchanges can be costly to fund investors may appear on the surface to be an indictment of such funds, it is important to consider our results in a broader context. First, our results highlight that for the vast majority of ETFs, including those featuring *in-kind* exchange processes and domestic funds featuring *cash* exchange processes, fund flows take place efficiently with apparently little or no impact on fund investors. These ETFs seem to deliver the targeted exposures promised. Additionally, although investors in international funds having *cash* exchanges appear to bear costs associated with the provision of primary market liquidity, this result must be considered in the context of "what is the alternative?" In fact, researchers have found open-end mutual funds to suffer larger costs associated with such flows. In light of investment frictions which lead these funds to depart from the traditional in-kind exchanges in favor of cash, there may not be a better alternative for such targeted exposures offering intra-day liquidity.

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Table 1: Sample Descriptive Statistics

Descriptive statistics for the sample ETFs. The sample comprises all publicly traded ETFs listed on U.S. exchanges, as identified by Morningstar Direct, and having at least $25 million of assets and average daily turnover of at least one-tenth of one percent. The sample begins in January 2006 and extends through June, 2012. We classify each sample ETF according to the assets comprising the benchmark index (equity or debt), and further subdivide the sample based on geography (domestic or international), and exchange type (cash or in-kind). The table presents summary statistics for each of the eight sub-samples. After the sample sizes, the table presents average market capitalizations, where market capitalization is the product of shares outstanding and the share price as reported in Thomson's Datastream database. The column labeled "Average Daily T.O." reports turnover, which is the number of shares traded divided by shares outstanding. The columns labeled "Average Create (redeem)" reports the average percentage change in shares outstanding when shares outstanding increase (decrease). Average flows reports the unconditional daily average change in shares outstanding. The final columns report the frequency of daily net creations and redemptions, defined as the fraction of sample observation on which the average ETF has net daily creations and redemptions, respectively.

Asset Class	Domestic or International	Create / Redeem Type	Sample Size	Average Market Cap	Average Daily T.O.	Average Create	Average Redemption	Average Flows	Average |Flows|	Create Frequency	Redeem Frequency
Equity	Domestic	Cash	5	130.935	3.2%	1.5%	−0.1%	1.3%	1.6%	17.9%	3.5%
		In-Kind	198	971,136	4.6%	0.8%	−0.3%	0.5%	1.1%	11.3%	8.4%
	International	Cash	28	1,004,200	3.6%	1.2%	−0.1%	1.1%	1.2%	11.8%	3.4%
		In-Kind	102	964,520	3.6%	0.5%	−0.1%	0.4%	0.7%	6.5%	4.1%
Fixed Income	Domestic	Cash	11	159,090	2.3%	0.9%	−0.1%	0.8%	1.0%	7.0%	1.3%
		In-Kind	29	2,245,079	2.7%	0.7%	−0.1%	0.6%	0.9%	15.1%	5.7%
	International	Cash	5	504,401	1.7%	0.8%	−0.0%	0.8%	0.9%	10.3%	1.8%
		In-Kind	1	621,225	1.6%	0.5%	−0.1%	0.5%	0.6%	25.8%	5.5%

Table 2: Benchmark Index Returns and Fund Flows

Benchmark index returns and fund flows. This table reports average benchmark index returns during three-day windows around fund flows. Observations are classified as net redemptions (creations) when fund shares outstanding decline (increase) relative to the previous day. All other observations are classified as "No Flows." For the full cross-section, the table reports the mean benchmark index returns. Sample funds are classified according to asset class of the benchmark constituents (equities or fixed income), geography (domestic or international), and by primary market exchange type (cash or in-kind). $*$, $**$, and $***$ indicate significance at the 10, 5, and 1% levels, respectively.

Asset	Domestic or	Create /	**Net Redemptions**			**No Flows**			**Net Creations**		
Class	International	Redeem Type	r_{t-1}^{Index}	r_{t}^{Index}	r_{t+1}^{Index}	r_{t-1}^{Index}	r_{t}^{Index}	r_{t+1}^{Index}	r_{t-1}^{Index}	r_{t}^{Index}	r_{t+1}^{Index}
Equity	Domestic	Cash	−0.07%	0.12%	0.38%*	0.00%	0.04%	0.00%	0.35%**	−0.14%	−0.11%
		In-Kind	−0.01%	0.04%**	0.04%*	0.03%**	0.04%**	0.03%**	−0.01%	0.00%	0.01%
	International	Cash	−0.31%**	0.01%	0.13%	−0.03%*	−0.02%	−0.01%	0.21%**	−0.06%	−0.07%
		In-Kind	−0.17%***	0.04%	0.04%	0.02%**	0.02%**	0.02%**	0.04%	−0.01%	−0.04%*
Fixed Income	Domestic	Cash	−0.08%	0.02%	−0.11%	0.04%**	0.04%**	0.04%**	0.07%	−0.11%	0.00%
		In-Kind	−0.01%	0.07%**	−0.04%	0.03%**	0.03%**	0.03%**	0.04%**	0.03%**	0.06%**
	International	Cash	0.10%	0.09%	0.24%	0.02%**	0.03%**	0.03%**	0.03%	0.00%	0.01%
		In-Kind	−0.16%	−0.05%	−0.04%	0.04%	0.03%	0.04%	0.08%	0.08%	0.06%
ALL	ALL	Cash	−0.19%	0.03%	0.12%	−0.01%	0.00%	0.00%	0.18%	−0.07%	−0.05%
	ALL	In-Kind	−0.06%	0.04%	0.03%	0.03%	0.03%	0.03%	0.01%	0.00%	0.00%
		Difference	−0.13%	−0.01%	0.09%	−0.04%**	−0.03%**	−0.02%**	0.17%**	−0.07%	−0.05%
ALL	Domestic	Cash	−0.07%	0.05%	0.07%	0.02%	0.04%	0.02%	0.17%	−0.12%	−0.04%
	Domestic	In-Kind	−0.01%	0.05%	0.03%	0.03%	0.04%	0.03%	0.00%	0.00%	0.02%
		Difference	−0.06%	0.01%	0.04%	−0.01%	0.00%	−0.01%	0.17%**	−0.12%	−0.06%
ALL	International	Cash	−0.24%	0.02%	0.15%	−0.02%	−0.01%	−0.01%	0.18%	−0.05%	−0.06%
	International	In-Kind	−0.17%	0.04%	0.04%	0.02%	0.02%	0.02%	0.05%	−0.01%	−0.04%
		Difference	−0.07%	−0.02%	0.10%	−0.04%**	−0.03%**	−0.02%	0.14%	−0.04%	−0.02%

Table 3: ETF Returns and Prior Day S&P 500 Return

The table presents return correlations between the S&P 500 Index return and next day ETF returns for all sample funds, labelled $\rho_{r_{t-1}^{SP}, r_t^{ETF}}$, as well as returns of equally-weighted ETF porfolios classified by asset class, geography, and exchange type, conditional on the previous day S&P 500 Index return. The columns labelled $r_{t-1}^{SP} > 0$ present the average daily equally-weighted return for sample funds on days when the previous day return the S&P 500 index return is positive. The balance of dates are presented in the columns labelled $r_{t-1}^{SP} \leq 0$. The final two columns present mean return differences and the t-statistic associated with the mean difference. The table reports return values as daily percentage returns.

Asset Class	Domestic or International	Create / Redeem Type	Sample Size	$\rho_{r_{t-1}^{SP}, r_t^{ETF}}$	$r_{t-1}^{SP} > 0$		$r_{t-1}^{SP} \leq 0$		Difference in Means	t-statistic
					Mean Return	Stdev	Mean Return	Stdev		
Equity	Domestic	Cash	5	−0.021	0.10	1.58	−0.06	1.88	0.16	0.98
		In-Kind	198	−0.038	0.01	1.68	0.05	2.01	−0.04	−0.37
	International	Cash	28	−0.096	−0.08	1.91	0.10	2.21	−0.18	−1.22
		In-Kind	102	−0.084	−0.07	1.86	0.13	2.48	−0.20	−1.65
Fixed Income	Domestic	Cash	11	0.076	0.03	0.45	0.03	0.48	0.00	−0.10
		In-Kind	29	0.094	0.04	0.49	0.00	0.58	0.04	1.21
	International	Cash	5	0.087	0.05	0.68	−0.01	0.70	0.06	1.25
		In-Kind	1	0.214	0.17	1.48	−0.12	1.61	0.29	1.58

Table 4: ETF Return Performance

This table presents regression results for the sample ETFs. In Panel A, the table presents results of the following baseline regression model: $r^{ETF}_{i,t} = \beta_0 + \beta_1 \times r^{Index}_{i,t} + \epsilon_{i,t}$, where $r^{ETF}_{i,t}$ is the day t return on ETF i and $r^{Index}_{i,t}$ is the return to ETF i's benchmark index. We compute ETF returns as $R^{ETF}_{i,t} = (P_{i,t} + D_{i,t})/P_{i,t-1}$, where $P_{i,t}$ is the closing price of ETF i on trading day t, and $D_{i,t}$ is the distribution amount received by the seller on the ex-dividend date, and all values come from Thomson's Datastream database. We compute returns to the benchmark index as $r^{Index}_{i,t} = (Index_{i,t}/Index_{i,t-1})$, where $Index_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index as reported by Bloomberg. Panel B presents results of the following regression model: $RD^{ETF}_{i,t} = \delta_0 + \varepsilon_{i,t}$, where $RD^{ETF}_{i,t} = r^{ETF}_{i,t} - r^{Index}_{i,t}$. For each sample ETF, we estimate the regression model for all available data starting on January 1, 2006 through the end of June, 2012. The table presents results for subsamples formed based on the geography (Domestic or International) of the securities comprising the benchmark index, and type of creations and redemptions (cash or in-kind). For each subsample, the table reports cross-sectional means of the regression estimates and goodness of fit for the individual funds, labeled μ. $*$, $**$, and $***$ indicate significance at the 10, 5, and 1% levels, respectively. Below the group means, the tables present the difference in means, computed as $\mu_{Cash} - \mu_{In-Kind}$, and the corresponding t-statistic.

Panel A: Regression Results, Baseline Model

Domestic or International	Create / Redeem Type		$\bar{\beta_0}$	$\bar{\beta_1}$	$\bar{R^2}$
ALL	Cash	μ_{Cash}	0.00009	0.89756***	0.5913
	In-Kind	μ_{InKind}	0.00007	0.89541***	0.7443
		Difference	0.00002	0.00215	
		t-statistic	(0.7742)	(0.0789)	
Domestic	Cash	μ_{Cash}	0.00005	0.88214***	0.7063
	In-Kind	μ_{InKind}	0.00002	0.93132***	0.8500
		Difference	0.00002	−0.04919	
		t-statistic	(1.3531)	(−0.9058)	
International	Cash	μ_{Cash}	0.00011	0.90503***	0.5356
	In-Kind	μ_{InKind}	0.00017	0.81625***	0.5114
		Difference	−0.00005	0.08878**	
		t-statistic	(−0.8385)	(2.0061)	

Panel B: Regression Results, Return Deviation Model

Domestic or International	Create / Redeem Type		$\bar{\delta_0}$	$\bar{R^2}$
ALL	Cash	μ_{Cash}	0.00007	0.0000
	In-Kind	μ_{InKind}	0.00004	0.0000
		Difference	0.00002	
		t-statistic	(0.9142)	
Domestic	Cash	μ_{Cash}	−0.00001	0.0000
	In-Kind	μ_{InKind}	0.00000	0.0000
		Difference	−0.00004	
		t-statistic	(−0.2333)	
International	Cash	μ_{Cash}	0.00010	0.0000
	In-Kind	μ_{InKind}	0.00014	0.0000
		Difference	−0.00004	
		t-statistic	(−0.6058)	

Table 5: ETF Return Performance, Augmented Model

This table presents regression results for the sample ETFs. In Panel A, the table presents results of the following augmented regression model: $r_{i,t}^{ETF} = \beta_0 + \beta_1 \times r_{i,t}^{Index} + \beta_2 \times r_{i,t}^{SP500} + \eta_{i,t}$, where $r_{i,t}^{ETF}$ is the day t return on ETF i, $r_{i,t}^{Index}$ is the return to ETF i's benchmark index, and $r_{i,t}^{SP500}$ is the return to the S&P 500 Index. We define further all variables in Table 4. Panel B presents results of the following regression model: $RD_{i,t}^{ETF} = \delta_0 + \delta_1 \times r_{i,t}^{SP500} + \zeta_{i,t}$, where $RD_{i,t}^{ETF} = r_{i,t}^{ETF} - r_{i,t}^{Index}$. For each sample ETF, we estimate the regression model for all available data starting on January 1, 2006 through the end of June, 2012. The table presents results for subsamples formed based on the geography (Domestic or International) of the securities comprising the benchmark index, and type of creations and redemptions (cash or in-kind). For each subsample, the table reports cross-sectional means of the regression estimates and goodness of fit for the individual funds, labeled μ. $*$, $**$, and $***$ indicate significance at the 10, 5, and 1% levels, respectively. Below the group means, the tables present the difference in means, computed as $\mu_{Cash} - \mu_{In-Kind}$, and the corresponding t-statistic.

Panel A: Regression Results, Augmented Baseline Model

Domestic or International	Create / Redeem Type		$\bar{\beta_0}$	$\bar{\beta_1}$	$\bar{\beta_2}$	$\bar{R}^2$
ALL	Cash	μ_{Cash}	−0.00003	0.65898***	0.45752***	0.7264
	In-Kind	μ_{InKind}	0.00002	0.80580***	0.23611**	0.8402
		Difference	−0.00005*	−0.14681**	0.2214**	
		t-statistic	(−1.6830)	(−2.4256)	(2.8754)	
Domestic	Cash	μ_{Cash}	0.00003	0.73324***	0.14974*	0.7202
	In-Kind	μ_{InKind}	0.00001	0.96699***	−0.02133	0.8622
		Difference	0.00002	−0.23375*	0.17107	
		t-statistic	(0.8348)	(−1.6754)	(1.5543)	
International	Cash	μ_{Cash}	−0.00006	0.62298**	0.60675**	0.7294
	In-Kind	μ_{InKind}	0.00006	0.45054**	0.80347**	0.7918
		Difference	−0.00011*	0.17244**	−0.19671**	
		t-statistic	(−1.8418)	(2.4864)	(−2.7481)	

Panel B: Regression Results, Augmented Return Deviation

Domestic or International	Create / Redeem Type		$\bar{\delta_0}$	$\bar{\delta_1}$	$\bar{R}^2$
ALL	Cash	μ_{Cash}	−0.00001	0.29331**	0.1973
	In-Kind	μ_{InKind}	0.00002	0.13883	0.1456
		Difference	−0.00003	0.15448**	
		t-statistic	(−1.2144)	(2.6487)	
Domestic	Cash	μ_{Cash}	−0.00000	0.00659	0.0715
	In-Kind	μ_{InKind}	0.00001	−0.02713	0.0731
		Difference	−0.00001	0.03372	
		t-statistic	(−0.1843)	(1.3365)	
International	Cash	μ_{Cash}	−0.00002	0.43232**	0.2582
	In-Kind	μ_{InKind}	0.00005	0.50457**	0.3054
		Difference	−0.00007**	−0.07225	
		t-statistic	(−1.9472)	(−1.1345)	

Table 6: ETF Return Performance and Fund Flows

This table presents regression results for the sample ETFs. In Panel A, the table presents results of the following augmented regression model: $r_{i,t}^{ETF} = \beta_0 + \beta_1 \times r_{i,t}^{Index} + \beta_2 \times r_{i,t}^{SP500} + \beta_3 Dilution_{i,t-1} + \nu_{i,t}$, where $r_{i,t}^{ETF}$ is the day t return on ETF i, $r_{i,t}^{Index}$ is the return to ETF i's benchmark index, and $r_{i,t}^{SP500}$ is the return to the S&P 500 Index. For each sample ETF, the dilution measure is: $Dilution_{i,t} = -r_{i,t}^{Index} \times \%\Delta SharesOut_{i,t-1}$, where $\Delta SharesOut_{i,t-1}$ is the one-day lag percentage change in shares outstanding. For definitions of other variables, refer to Table 4. Panel B presents results of the following regression model: $RD_{i,t}^{ETF} = \delta_0 + \delta_1 \times r_{i,t}^{SP500} + \delta_2 Dilution_{i,t-1} + \upsilon_{i,t}$, where $RD_{i,t}^{ETF} = r_{i,t}^{ETF} - r_{i,t}^{Index}$. For each sample ETF, we estimate the regression model for all available data starting on January 1, 2006 through the end of June, 2012. The table presents results for subsamples formed based on the geography (Domestic or International) of the securities comprising the benchmark index, and type of creations and redemptions (cash or in-kind). For each subsample, the table reports cross-sectional means of the regression estimates and goodness of fit for the individual funds, labeled μ. $*$, $**$, and $***$ indicate significance at the 10, 5, and 1% levels, respectively. Below the group means, the tables present the difference in means, computed as $\mu_{Cash} - \mu_{In-Kind}$, and the corresponding t-statistic.

Panel A: Regression Results, Baseline Model with Dilution Measure

Domestic or International	Create / Redeem Type		$\bar{\beta_0}$	$\bar{\beta_1}$	$\bar{\beta_2}$	$\bar{\beta_3}$	$\bar{R}^2$
ALL	Cash	μ_{Cash}	−0.00002	0.66056***	0.45687**	0.50348*	0.7271
	In-Kind	μ_{InKind}	0.00001	0.80887***	0.23279**	−0.16565	0.8413
		Difference	−0.00003	−0.14831**	0.22408***	0.66913*	
		t-statistic	(−1.0280)	(−2.6675)	(3.0562)	(1.6515)	
Domestic	Cash	μ_{Cash}	0.00004	0.73588***	0.14867*	0.12018	0.7210
	In-Kind	μ_{InKind}	0.00001	0.96819***	−0.02284	−0.15545	0.8624
		Difference	0.00002	−0.23231*	0.17151	0.27563	
		t-statistic	(0.7125)	(−1.8524)	(1.4384)	(1.4461)	
International	Cash	μ_{Cash}	−0.00005	0.62403***	0.60630**	0.68932	0.7300
	In-Kind	μ_{InKind}	0.00002	0.45773***	0.79618***	−0.18813	0.7947
		Difference	−0.0008	0.16630**	−0.18988**	0.87745*	
		t-statistic	(−1.2921)	(2.5220)	(−2.3802)	(1.8265)	

Panel B: Regression Results, Return Deviation Model with Dilution Measure

Domestic or International	Create / Redeem Type		$\bar{\delta_0}$	$\bar{\delta_1}$	$\bar{\delta_2}$	$\bar{R}^2$
ALL	Cash	μ_{Cash}	−0.00001	0.29389***	0.94420**	0.2007
	In-Kind	μ_{InKind}	0.00001	0.13906*	0.11785	0.1481
		Difference	−0.00001	0.15483***	0.82635*	
		t-statistic	(−0.5010)	(3.1138)	(1.8119)	
Domestic	Cash	μ_{Cash}	0.00002	0.00557	−0.00690	0.0760
	In-Kind	μ_{InKind}	0.00001	−0.02696	−0.07213	0.0762
		Difference	0.00001	0.03254	0.06524	
		t-statistic	(1.0456)	(1.0913)	(0.1080)	
International	Cash	μ_{Cash}	−0.00002	0.43368***	1.40533*	0.2612
	In-Kind	μ_{InKind}	0.00001	0.50496***	0.53654	0.3072
		Difference	−0.00003**	−0.07128	0.86879*	
		t-statistic	(−0.5462)	(−1.2095)	(1.7329)	

Table 7: Bid-Ask Spread Estimates

Estimates of bid-ask spreads for sample ETFs. Estimates of bid-ask spreads come from daily high and low prices following the methodology of Corwin and Schultz (2012). The table reports equal-weighted average spread estimates for the sample ETFs, categorized based on asset class (equity or fixed income), geography (domestic U.S. or international), and exchange type (cash or in-kind). $*$ and $**$ indicate significance at the 10 and 5% levels, respectively.

Equity ETF Spread Estimates

	Domestic Equity			International Equity		
	Cash	In-Kind	Difference	Cash	In-Kind	Difference
2006	-	0.431%	-	0.258%	0.367%	−0.109%
2007	-	0.316%	-	0.403%	0.322%	0.081%
2008	0.712%	0.713%	−0.002%	0.791%	0.684%	0.107%*
2009	1.292%	0.574%	0.718%**	0.622%	0.539%	0.083%*
2010	0.414%	0.355%	0.059%*	0.377%	0.354%	0.023%
2011	0.405%	0.386%	0.019%	0.378%	0.368%	0.010%
2012	0.412%	0.373%	0.039%*	0.394%	0.372%	0.022%
All	0.473%	0.430%	0.043%	0.448%	0.437%	0.011%

Fixed Income ETF Spread Estimates

	Domestic Fixed Income			International Fixed Income		
	Cash	In-Kind	Difference	Cash	In-Kind	Difference
2006	0.086%	-	-	-	-	-
2007	0.218%	0.144%	0.073%	0.122%	0.156%	−0.034%
2008	0.260%	0.223%	0.037%	0.375%	0.908%	−0.533%**
2009	0.103%	0.206%	−0.103%	0.203%	0.603%	−0.400%**
2010	0.104%	0.110%	−0.006%	0.172%	0.113%	0.058%
2011	0.139%	0.130%	0.010%	0.204%	0.102%	0.102%
* [2pt] 2012	0.125%	0.128%	−0.003%	0.231%	0.134%	0.097%*
All	0.129%	0.151%	−0.021%	0.202%	0.415%	−0.213%*

PORTFOLIO UPDATE

Recent decisions in regard to the use of the extra collateral have included two separate round-trip investments in a leveraged inverse (short) Europe exposure and another investment in a long exposure to expectations for short-term market volatility.

On January 31, we added a two-times (2x) inverse European market exposure (via the ProShares UltraShort MSCI Europe ETF, ticker: EPV) to the Risk-Based Opportunity portfolios, using funds freed up by reducing the exposure to U.S. high yield corporate (SPDR Barclays Capital High Yield Bond ETF, ticker: JNK). The weights in the Conservative, Moderate and Growth portfolios were 3%, 4% and 5%, in that order. We sold the position on February 21, returning the proceeds to JNK. The total return, using end-of-day prices, for the position was 6.5%, 195% annualized, as the respective index (MSCI Europe) fell 3.7%. We initiated a similar trade in EPV on March 11 that we exited on March 27; the total return over that period using end-of-day prices was 5.3%, 220% annualized, as the relevant index fell 2.7%. In addition, on March 15, we initiated a position in the ProShares VIX Short-Term Futures ETF (VIXY), which seeks to reflect changes in expectations for short-term equity market volatility.

IMPORTANT INFORMATION

The information provided comes from independent sources believed reliable, but accuracy is not guaranteed and has not been independently verified. The security information, portfolio management and tactical decision process are opinions of Innealta Capital (Innealta), a division of AFAM Capital, Inc. and the performance results of such recommendations are subject to risks and uncertainties. For more information about AFAM Capital, Inc. please visit afamcapital.com. Past performance is not a guarantee of future results.

Any investment is subject to risk. Exchange traded funds (ETFs) are subject to risks similar to those of stocks, such as market risk, and investors that have their funds invested in accordance with the portfolios may experience losses. Additionally, fixed income (bond) ETFs are subject to interest rate risk which is the risk that debt securities in a portfolio will decline in value because of increases in market interest rates. The value of an investment and the return on invested capital will fluctuate over time and, when sold or redeemed, may be worth less than its original cost. This material is not intended as and should not be used to provide investment advice and is not an offer to sell a security or a solicitation or an offer, or a recommendation, to buy a security. Investors should consult with an investment advisor to determine the appropriate investment vehicle. Investment decisions should be made based on the investor's specific financial needs and objectives, goals, time horizon and risk tolerance. All opinions and views constitute our judgments as of the date of writing and are subject to change at any time without notice.

Sector ETFs, such as Real Estate Investment Trusts ("REITs") are subject to industry concentration risk, which is the chance that stocks comprising the sector ETF will decline due to adverse developments in the respective industry.

The use of leverage (borrowed capital) by an exchange-traded fund increases the risk to the fund. The more a fund invests in leveraged instruments, the more the leverage will magnify gains or losses on those investments.

Country/Regional risk is the chance that world events such as political upheaval or natural disaster will adversely affect the value of securities issued by companies in foreign countries or regions. Country/Regional risk is especially high in emerging markets.

Emerging markets risk is that chance that stocks of companies located in emerging markets will be substantially more volatile, and substantially less liquid, than the stocks of companies located in more developed foreign markets.

Securities rated below investment grade, commonly referred to as "junk bonds", may involve greater risks than securities in higher rating categories. Junk bonds are regarded as speculative in nature, involve greater risk of default by the issuing entity, and may be subject to greater market fluctuations than higher rated fixed income securities.

Diversification does not protect against loss in declining markets.

Registration of an investment adviser does not imply any certain level of skill or training.

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Innealta's competitive advantage is its quantitative investment strategy driven by a proprietary econometric model created by Dr. Gerald Buetow, Innealta's Chief Investment Officer. The firm's products include Tactical ETF Portfolios, a U.S. Sector Rotation Portfolio and a Country Rotation Portfolio. Innealta aims to beat appropriate benchmark performance by tactically managing portfolios utilizing a proprietary econometric model. By harnessing the benefits of ETFs, Innealta is able to provide investors with exposure to multiple asset classes and investment styles in highly liquid, low cost portfolios.

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