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THE PERFORMANCE OF LEVERAGED AND INVERSE LEVERAGED EXCHANGE TRADED FUNDS

- Drawing on years of asset management, trading and research experience, the team conducts cutting edge research in efforts to deepen the knowledge and data that inform the portfolio management decisions we make.
- This month's commentary is a contemporary white-paper written by Dr. Brian Henderson and Dr. Jeff Buetow on the return properties of leveraged and inverse leveraged ETFs.
- Leveraged and inverse leveraged ETFs use derivative contracts to provide investment exposures that are multiples of the daily benchmark index returns. The degree to which these funds of synthetic exposures provide realized returns to investors that closely mimic the promised returns, as well as the determinants of any return deviations, is an open question.
- The main results include:
    - Daily investment returns to leveraged and inverse leveraged ETFs tend to track closely the promised return.
    - The rebalancing necessary to maintain daily leverage multiples is costly during periods of high volatility.
    - Inverse leveraged ETFs exhibit negative return deviations, consistent with the cost to borrow borne by short-sellers.
    - The costs documented are small for an innovative product offering previously unavailable tradable leveraged and leveraged short exposures.

The Performance of Leveraged and Inverse Leveraged Exchange Traded Funds *

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Abstract

We document significant abnormal daily returns to leveraged and inverse leveraged exchange traded funds (ETFs). Abnormal returns are positive for leveraged funds and negative to inverse leveraged funds, and the magnitude increases in the absolute value of the leverage multiple. We propose and test a model linking the abnormal return performance to transactions costs associated with the frequent (daily) rebalancing necessary to maintain target exposures as well as other costs including the swap financing costs and the cost to borrow in the lending market. In the full cross-section, the results suggest funding costs associated with achieving leverage impact returns negatively (positively) for leveraged (inverse leveraged) funds. Capitalizing on a key institutional feature, analysis of pairs of mirror funds reveals costly transactions costs associated with daily rebalance necessary to maintain leveraged multiples at the *daily* frequency meaningfully impact fund returns. The results are also consistent with inverse leveraged funds bearing the cost-to-borrow to the benefit of the mirror positive leveraged funds.

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1 Introduction

Leveraged exchange traded funds (ETFs) aim to produce daily returns that are multiples of the daily returns to a specific benchmark index such as the S&P 500 Index. Inverse and leveraged inverse ETFs seek to produce daily returns that are negative multiples of the daily returns to a specific benchmark index. In contrast to traditional ETFs, leveraged and inverse leveraged ETFs utilize derivatives contracts (futures contracts and over-the-counter total return swaps) to synthetically produce their respective target exposures. The extent to which these funds accomplish their stated objectives remains an open question. Our study addresses this question, proposing and testing a benchmark model of return performance and investigating the determinants of return deviations from the target benchmark return.

Our study analyzes empirically a broad cross-section of 98 leveraged, inverse, and inverse leveraged ETFs targeting U.S. equity benchmark indexes. The baseline regression model uncovers significant levels of abnormal performance across the universe of funds. The abnormal return performance is a function of the leverage multiple, ℓ, where leveraged inverse funds suffer returns below the benchmark model and leveraged funds exhibit positive excess returns. The abnormal performance results are monotonic in the leverage multiple, annualizing to -8.27%, -2.31%, -1.72%, $+1.32\%$, and $+3.24\%$ for leverage multiples of $\ell \in \{-3, -2, -1, +2, +3\}$, respectively. Extended analysis proposes and tests a model linking fund performance to transactions costs associated with daily rebalancing required to maintain the stated leverage multiples. Transactions are likely costly given the funds use of over-the-counter derivatives to provide leverage. The analysis finds that funding costs and counter-party risk also influence fund returns.

Much of the extant research on leveraged and inverse leveraged ETFs focuses on their buy-and-hold return properties over holding periods longer than a day. Given the funds' objective to provide *daily* returns that are leveraged multiples (ℓ) of the target benchmark's *daily* return, the funds must rebalance their portfolios daily to maintain constant leverage each day. Cheng and Madhavan (2009) demonstrate that fund rebalance needs may be large on a daily basis and that the direction of the rebalance trades is identical for both leveraged and inverse leveraged funds, and trade directions are identical to the direction of the daily returns. Specifically, following positive returns to the benchmark index, leveraged funds much purchase additional exposure to maintain their leverage multiple while inverse leveraged funds must reduce their short exposure. In fact, Cheng and Madhavan (2009) conclude that the daily rebalance trades are of sufficient size to likely exacerbate daily market volatility through their price impacts. Given that the daily rebalance needs may be quite large, and the trade direction and magnitudes are predictable based on publicly available information, Dobi and Avellaneda (2012) argue these funds may suffer losses due to market participants front-running fund rebalance trades. In the cross-section, our analysis produces mixed evidence linking fund underperformance to our proxy for transactions costs.

We capitalize on an important and novel institutional detail of our sample to shed further light on the nature of the abnormal performance documented through our baseline model. Specifically, we analyze returns to hypothetical portfolios equally weighted across a set of funds comprising "mirror pairs," defined as two funds providing equal but directionally opposite leveraged exposure to the same benchmark index and having an identical fund sponsor. An example of such "mirror" funds are the Direxion Daily Financial 3x Bull Shares (ticker: FAS), and the Direxion Daily Financial 3x Bear Shares (ticker: FAZ). Their exposures are directionally opposite, but both funds provide triple absolute exposure ($|\ell| = 3$) to the daily Russell 1000 Financial Services Index and share the same sponsor (Direxion). We analyze the hypothetical returns to 36 such portfolios of "mirror" funds. Returns to the "mirror pairs" portfolios average -4.07% and -1.90% annually for 3x and 2x leverage multiples, despite the fact their exposures to the baseline index should net to zero and the maximum expense ratio is 0.95% annually. Extended analysis highlights that transactions costs associated with fund rebalancing needs and proxied by index volatility, drive the underperformance. We find significant return drag for these funds at even moderate levels of index volatility.

The most closely related study to ours is Tang and Xu (2012). Their study documents abnormal return performance at the daily level, finding that the fund net asset value (NAV) tracks closely the target leverage multiple times the daily benchmark index return. Notably, Tang and Xu (2012) propose a model where wealth transfers take place such that the leveraged long funds subsidize the leveraged short funds. The source of this subsidy comes from the structure of the total return swaps used by these funds to provide their leveraged exposures. The leveraged long fund enters into swap agreements where they make payments based on LIBOR plus a spread and receive payments based on the equity index total return. Conversely, the leveraged short fund receives payments of LIBOR plus a spread but pay out based on the equity index total return. Our cross-sectional analysis is consistent with their results. Our extended analysis of mirror pairs, however, uncovers wealth transfers in the opposite direction, most likely reflective of the cost to borrow the underlying securities.

Our study presents several novel results. To our knowledge, ours is the first study to evaluate the broad cross-section, as well as the first to include funds offering triple long and short exposures. Additionally, our focus is on realized investment performance, as measured by market prices, as opposed to fund-reported net asset values which are themselves uninvestible. Utilizing the full cross section, we demonstrate broad patterns of abnormal performance concentrated among the inverse and leveraged inverse funds, which is in contrast to Tang and Xu (2012) who find the exact opposite result. The costs and frictions associated with providing leveraged and inverse leveraged returns likely result from factors specific to each index such as the availability, liquidity, and cost of derivative contracts referencing the target index, coupled with other costs that are systemic such as funding cost and counter-party risk. Through our analysis of mirror pairs, we find a negative and significant relation between the "bull" fund return deviations and those of the matching "bear" fund. These results are consistent with index-specific replication costs, most likely stemming from short funds incurring the cost of borrowing to the benefit of long investors. This result contrasts the model of Tang and Xu (2012) which focuses on the role LIBOR plays in the swap funding cost, constituting a transfer from the leveraged (long) funds to the inverse leveraged (short) funds. Finally, utilizing a model of transactions costs that links the daily portfolio rebalancing needs to the volatility of the underlying index, our analysis of "mirror" pairs uncovers significant costs born by these funds stemming from their utilization of over-the-counter derivatives for provision of their leveraged and inverse leveraged exposures.

The balance of the paper is organized as follows. Section 2 describes the sample of funds and presents sample descriptive statistics. The main empirical results are presented in Section 3 which includes the baseline performance model and an extended model linking transactions costs, funding costs, and counter-party risks to fund performance. Section 4 analyzes returns to portfolios of pairs of "mirror" funds and the determinants of return deviations, and Section 5 briefly concludes.

2 Sample Description

Our sample begins with the universe of all U.S.-listed leveraged and inverse exchange-traded products as identified by Morningstar Direct on July 1, 2012. Morningstar identifies 243 such exchange traded products. Eliminating Exchange Traded Notes (ETNs) reduces the sample to 178 funds. To marginalize the impact on our analysis of nonsynchronous measures of Fund and Index returns, we further restrict to ETFs targeting U.S. equity benchmark indexes, eliminating those tracking international equities, commodities, currencies, or bonds. The final sample consists of 98 unique ETFs.

For each sample fund, we collect the CUSIP number, ticker symbol, benchmark index name, and the index's Bloomberg ticker from each fund's website and filings with the U.S. Securities and Exchange Commission. From Datastream, we collect the historical prices, shares outstanding, distribution dates, and distribution amounts for each sample fund. Additionally, we collect daily index levels from Bloomberg.

The sample period begins in June 2006, corresponding to the introduction by ProShares of the first leveraged and inverse U.S. ETFs. Several of the first leveraged and inverse funds introduced offer investors 2x exposure to daily returns ($\ell = +2$), while another set of these funds offer short ($\ell = -1$) exposures to the major U.S. equity indexes including the S&P 500 (SSO, SH), S&P Midcap 400 (MVV, MYY), NASDAQ-100 (QLD, PSQ), and Dow Jones Industrial Average (DDM, DOG), respectively. Shortly thereafter in July of 2006, ProShares expanded their offerings to include ETFs with leveraged short exposures. These funds offer double short ($\ell = -2$) exposure to the daily returns of the S&P 500 (SDS), S&P Midcap 400 (MZZ), NASDAQ-100 (QID), and Dow Jones Industrial Average (DXD). On November 15, 2008, Direxion introduced the first triple-leveraged funds offering +3 and -3 times the daily returns to the Russell 1000 Index (BGU, BGZ), and Russell 2000 Index (TNA, TZA).

Table 1 presents sample descriptive statistics for the sample ETFs. For each sample year, beginning in 2006 and ending on June 29, 2012, the table presents the number of funds and total market capitalization across the sample.[1] The table presents these statistics for sub-samples based on the leverage multiple, $\ell \in \{-3, -2, -1, +2, +3\}$, and for the full sample in the right-most columns of the table.

By the end of 2006, the sample comprises 11 funds totaling approximately $2 billion of total assets under management. The year 2007 saw the introduction of 40 additional funds, all of which have leverage multiples of -2, -1, and +2. During 2008, the sample increases to 65 funds, the majority of which come through Direxion's introduction of the triple leveraged funds. The assets under management peak during 2009 at just over $21.2 billion. By the end of the sample period, June 29, 2012, the sample contains 98 funds totaling $16.95 billion.

3 Empirical Analysis

The analysis presented in this section evaluates empirically the return performance of leveraged and inverse ETFs. The analysis begins with a baseline model of fund returns. Subsequent analysis extends the baseline model to include proxies for various costs which may impact return performance.

[1]On June 29, 2012 Direxion modified eight of their funds to track S&P indexes instead of Russell indexes. http://www.direxionfunds.com/press-release/new-tickers-and-indexes-now-trade-the-sp-500-and-more. Truncating the sample period to June 29, 2012 avoids including potentially atypical returns stemming from benchmark index changes to eight sample ETFs.

The section concludes with analysis of the determinants of fund return deviations.

3.1 Main Results: Baseline Performance Model

Leveraged ETFs aim to provide daily returns that are integer multiples (ℓ) of the daily return to a benchmark index, where $\ell \in \{+2, +3\}$. Among the inverse and inverse leveraged ETFs, the leverage multiple (ℓ) is a negative integer such that $\ell \in \{-3, -2, -1\}$. Thus, on any day t, the return to ETF i, $r_{i,t}^{ETF}$, should equal $\ell \times r_{i,t}^{Index}$, where $r_{i,t}^{Index}$ is the return to the fund's benchmark index on day t. To evaluate the performance of the sample ETFs against their stated return objectives, the analysis begins by testing the following baseline regression model:

$$r_{i,t}^{ETF} = \alpha + \beta_1 \times (\ell_i \times r_{i,t}^{Index}) + \epsilon_{i,t}. \tag{1}$$

We estimate this regression model for each sample ETF using all available data from the fund inception date through June 29, 2012. We compute daily returns to each ETF as: $r_{i,t}^{ETF} = (P_{i,t} + D_{i,t})/P_{i,t-1} - 1$, where P_t is the daily closing price of ETF i on trading day t, $D_{i,t}$ is the distribution amount when applicable, as reported in Thomson's Datastream Database. Returns to the benchmark index are $r_{i,t}^{Index} = (INDEX_{i,t}/INDEX_{i,t-1}) - 1$, where $INDEX_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index and come from Bloomberg. Identification of the benchmark index tickers results from searching each fund's fact sheet and prospectus.

Under the null hypothesis that each fund replicates accurately the target exposure, across the sample of funds we expect the estimates to reveal: no abnormal return performance ($\alpha = 0$), unit exposure to the leverage multiple units of the benchmark index ($\beta_1 = 1$), and that the fund returns are explained by the baseline model ($R^2 = 1$). Across our sample, the annual fund expense ratio ranges from 0.90% to 0.95%, thus absent all other frictions, we reasonably expect to find approximately annual underperformance between -0.90% and -0.95%, as measured by the intercept (α).

Panel A of Table 2 presents the regression results for each ETF in our sample using all available daily return data. Although we estimate the model for each individual fund, the table presents the average coefficients and test statistics by leverage multiple based on the distribution of those estimates in the cross-section. Each column of the table presents the results grouped by sub-samples based on the fund leverage multiple (ℓ). The first row of Panel A presents the cross-sectional average under-performance measure, $\bar{\alpha}$, for each sub-sample. Scanning across the columns, the pattern emerges that inverse exposure funds ($\ell \in \{-3, -2, -1\}$) suffer negative abnormal performance while the positive leveraged funds ($\ell \in \{+2, +3\}$) demonstrate positive abnormal performance.

The magnitude appears asymmetric, as the triple short funds, $\ell = -3$, experience daily average underperformance of 4 basis points (multiplying by 252 trading days per year results in -10.45% per year), versus roughly one basis point per day for the $\ell = +3$ funds, which corresponds to roughly +3.24% annually. The t-statistics associated with the $\bar{\alpha}$s indicate that the results are statistically significant at conventional levels.

Referring to the third row of Panel A, across each subsample the average fund loadings on the target index, $\bar{\beta}_1$, appear to be close to, but noticeably less than unity, suggesting the typical sample fund has less than the stated multiple, ℓ, units of exposure to the benchmark index. The fifth row presents the test statistic for the hypothesis that the average fund β_1 in each sub-sample equals one: $H_0 : \bar{\beta}_1 = 1.0$. For each subsample, the t-statistic suggests rejection of the null hypothesis at conventional levels. Finally, referring to the sixth row of the Panel which reports the average R^2, we note that the regression model captures the overwhelming majority of the daily fund return variation since $\bar{R}^2$ ranges from 92.4% to 98.5%.

Interpreting the results presented in Panel A of Table 2 requires caution due to the use of daily returns. Measurement errors, which are more pronounced in high-frequency daily data, have the tendency to bias downward estimated slope coefficients (Scholes and Williams (1977)). These measurement errors may come from several sources including the bid-ask spread, non-synchronicity between the closing index levels and the last reported ETF trade, and the potential for stale prices to influence the closing index level.[2] To address this potential concern, Panels B and C of Table 2 repeat the analysis using weekly and monthly returns, respectively. Since the sample ETFs seek to provide *daily* returns that are multiples of the *daily* benchmark index return, all estimates performed using weekly and monthly consider returns compounded geometrically based on the daily data. Specifically, the dependent variable over any N day period τ is: $r^{ETF}_{i,\tau} = \prod_{n=1}^{N}(1 + r^{ETF}_{i,n}) - 1$. Similarly, the index return is: $r^{Index}_{i,\tau} = \prod_{n=1}^{N}(1 + \ell \times r^{Index}_{i,n}) - 1$.

Comparing the estimation results across the three observation frequencies (daily, weekly, and monthly) presented in Panels A, B, and C, reveals that estimates of $\bar{\beta}_1$ increase toward one as the observation period length increases from daily, to weekly, to monthly. For example, the $\bar{\beta}_1$ for the triple-leveraged funds ($\ell = +3$), increases from 0.9221 using daily returns, to 0.9592 for weekly, and 0.994 for monthly. Additionally, for all sub-samples except the $\ell = +2$ funds, we fail to reject the null that beta equals one at the monthly frequency. Correspondingly, the model fit, $\bar{R}^2$, increases noticeably for each leverage group as the observation period increases.

[2] Studying the daily closing prices and net-asset-values (NAVs) for a sample of Canadian Leveraged ETFs, Charupat and Miu (2011) find that nonsynchronicity influences daily returns.

Comparing the results presented in all three panels of Table 2, the robust result emerging across all panels is that the length of the observation period does not attenuate the abnormal performance, as measured by the intercept $\bar{\alpha}$. This robust pattern suggests the under-performance of inverse funds and the outperformance of long (positive leverage) funds, as measured by our statistical model, does not result from errors in variables in daily returns. To understand the source of the observed abnormal return patterns, the analysis next considers the role of the likely determinants, including the transactions costs associated with the frequent rebalancing required to maintain leveraged exposures and the funding costs associated with the funds' use of leverage.

3.2 The Determinants of Return Deviations

The analysis presented in this section investigates the determinants of fund return deviations from the stated daily benchmark. The analysis proceeds by extending the statistical model presented in Section 3.1 by linking transactions costs to under-performance. The analysis subsequently measures the influence of transactions costs and funding costs on actual return deviations.

3.2.1 Index Volatility and Rebalancing Costs

The sample leveraged and inverse leveraged ETFs seek to provide returns that are multiples of the *daily* returns to those of their respective benchmark index. As discussed by Cheng and Madhavan (2009), these funds require daily rebalancing to maintain the target leverage multiples. In fact, Cheng and Madhavan (2009) demonstrate that the daily rebalancing need of both "bull" funds ($\ell \in \{+2, +3\}$), and "bear" funds ($\ell \in \{-2, -3\}$) are of identical direction as that of the daily return to the benchmark index. Specifically, positive returns to the benchmark index require both "bull" and "bear" funds to buy exposure: the "bull" fund increases its exposure while the "bear" fund reduces its short exposure. Since the rebalance trades of leveraged funds are predictable, Dobi and Avellaneda (2012) argue other traders may have incentive to front-run the rebalance trade, exacerbating the cost of daily rebalancing near the market close that are born by investors in these funds.

The analysis in this section tests the hypothesis that transactions costs associated with frequent rebalancing impact fund performance. Rebalance costs for leveraged and inverse leveraged funds may be large, particularly during periods of heightened volatility owing to their stated objective of maintaining constant daily return multiples (Cheng and Madhavan (2009)). Given their usage primarily of over-the-counter derivatives, typically total return swaps, these funds may realistically incur significant transactions costs associated with frequent rebalancing activities. Absent direct measures of transaction costs in over-the-counter derivatives markets, we propose a model relating transactions costs to the realized volatility of the benchmark index. Under the assumption that transactions costs are proportional to the size of rebalance trades, and a fund's rebalance needs are correlated with the magnitude of the daily index movement, we propose and test the following model relating the contemporaneous index volatility to the daily return:

$$r_{i,t}^{ETF} = \alpha + \beta_1 \times (\ell_i \times r_{i,t}^{Index}) + \beta_2 \times (r_{i,t}^{Index})^2 + \varepsilon_{i,t}, \tag{2}$$

where all variables are as defined previously. The intuition behind the model is that the daily rebalancing trade size required to adjust the fund exposure to the target daily multiples is an increasing function of the magnitude of the daily index return. Such trades incur both direct costs from the bid-ask spread in the over-the-counter market, as well as indirect market-impact costs. Under the joint hypothesis that rebalance costs decrease fund returns and that index volatility is correlated with these costs, we expect estimates of β_2 to be negative. Table 3 presents the estimation results of the model in equation 2. Similar to Table 2, Panels A, B, and C present results for daily, weekly, and monthly return observations, respectively.

Scanning the columns of Table 3, across each panel the abnormal performance pattern of $\bar{\alpha}$ persists despite the inclusion of the rebalance cost proxy. The annualized abnormal performance measures in fact are slightly larger in magnitude than those reported in the previous table, suggesting rebalance costs are not the key determinant of the observed abnormal return patterns. As in the baseline model, estimates of β_1 are less than one when using daily return observations, but not significantly different than one at conventional levels when using monthly observations. In Panel A, the estimates of β_2, are positive and statistically significant for the "bear" funds and negative for the "bull" funds, a result which likely stems from the capture of non-synchronous measurement errors between the daily index and ETF returns. In fact, as the observation window lengthens, β_2 estimates for the "bear" funds become negative and significant. While estimates for the "bull" funds are positive, they do not differ significantly from zero at conventional levels. Since rebalance costs likely affect returns to both bear and bull funds, these results are not consistent with the hypothesis that rebalancing costs lead to significantly lower returns, despite these funds' reliance on over-the-counter derivatives.

3.2.2 Analysis of Fund Return Deviations

The analysis in the previous section analyzes the returns of leveraged, inverse, and inverse leveraged ETFs in the context of realized returns relative to a statistical model of performance. While that statistical model allows for returns to differ from those of the identity model, we now consider another measure of unexpected returns assuming returns adhere to the identity model such that $\alpha = 0$ and $\beta_1 = 1$. Specifically, for each fund i, on each trading day t, we define the return deviation, $RD_{i,t}^{ETF}$, as:

$$RD_{i,t}^{ETF} = r_{i,t}^{ETF} - \ell_i \times r_{i,t}^{Index}, \tag{3}$$

where all right-hand side variables are as described previously. Estimation involving the return deviation avoids the potential bias in the β_1 estimates of Equations 1 and 2 resulting from the correlation of returns and the variance of returns. In this case, the restrictions imposed under the null hypothesis remove the potentially spurious correlation arising under such constraints (French, Schwert, and Stambaugh (1987)). Our analysis involves the computation of return deviation at the daily, weekly, and monthly frequencies. For weekly and monthly frequencies, the return deviation is the difference between the geometrically compounded fund return and the leveraged index return: $RD_{i,t}^{ETF} = \prod_{n=1}^{N}(1 + r_{i,n}^{ETF}) - \prod_{n=1}^{N}(1 + \ell \times r_{i,n}^{INDEX})$.

Defining fund abnormal return performance as the return deviation from equation 3, we extend the analysis to consider three potential sources of fund return deviation: transactions costs associated with frequent rebalancing, the funding cost of leveraged total return swap portfolios, and counter-party risk. We do so by estimating the following regression model:

$$RD_{i,t}^{ETF} = \gamma_0 + \gamma_1 \sigma_{i,t}^{Index} + \gamma_2 LIBOR_t + \gamma_3 \Delta SwapSpread_t + \eta_{i,t}, \tag{4}$$

where $\sigma_{i,t}$ is the standard deviation of the benchmark index returns during period t, LIBOR$_t$ is the average three-month LIBOR rate during t, and ΔSwapSpread is the basis points change from $t-1$ to t in the five-year plain vanilla interest rate swap spread. We estimate the regression model using daily, weekly, and monthly return frequencies and report the results in Panels A, B, and C of Table 4. Table 4 reports group means and t-statistics for the coefficient estimates across leverage multiples (ℓ).

For each subgroup, the table begins by presenting results of a restricted model, referred to as Model (1) in the Table, imposing that the slope coefficients jointly equal zero: $\gamma_1 = \gamma_2 = \gamma_3 = 0$. The restricted model produces only one estimate, the intercept, γ_0, which is the average return deviation for each group. The average return deviations are consistent with estimates of abnormal returns in the baseline analysis. Across all return frequency observations, estimates of $\bar{\gamma_0}$ for the inverse leveraged funds indicate significant under-performance that is proportional to the leverage multiple. Annualizing estimates of γ_0 reported in Panels A, B, and C for triple inverse leveraged funds suggests these funds have return deviations between -6.3% and -8.9%, depending on the observation frequency. Similarly, return deviations for double inverse leveraged funds range from -1.9% to -3.3% annually. These intercepts are statistically significant at conventional levels and exceed the annual expense ratio (0.95%) by statistically significant margins. At the daily frequency (Panel A), however, the leveraged funds ($\ell = +2, +3$) exhibit slight negative return deviations, which contrasts the results of the statistical model. The weekly and monthly return deviation estimates, however, are consistent with those of the statistical model, as the double leveraged funds exhibit annualized returns of approximately +1.1% to +1.4% while triple leveraged fund annualized return deviations are +1.3% to +2.3%.

Turning to the unrestricted model in equation 4, presented as Model (2) in Table 4, the results in Panel A reveal that daily return deviations are related to contemporaneous index volatility. The average coefficient estimates for inverse funds are positive, suggesting these funds tend to outperform on volatile days. Conversely, leveraged funds exhibit negative estimates, indicating they suffer worse return deviations on volatile days. Referring to the coefficients, the economic magnitude is fairly small. Assuming 30% annual volatility, the 0.0041 average coefficient estimate for triple inverse funds corresponds to an 8 basis point daily return deviation. Over longer observation windows, the results in Panels B and C present no evidence that contemporaneous volatility is related to fund return deviations.

Given the sample funds' use of leverage, the funding costs, as proxied by LIBOR, likely influence returns. Tang and Xu (2012) present and test a model linking deviations of fund net-asset-value (NAV) from the return target to the LIBOR rate. The results in Table 4 are consistent with the view that funding costs are related to return deviations. Across the panels of Table 4, among inverse leveraged funds, $\bar{\gamma_2}$ estimates are positive and significantly greater than zero at conventional levels. Conversely, among (long) leveraged funds, $\bar{\gamma_2}$ estimates are negative and statistically less than zero. The significance increases in observation period length, which is not surprising since high-frequency data contains more noise than low frequency. Further, the patterns in the magnitudes of the coefficients are consistent with the funding cost explanation since the magnitude of the coefficient increases in the absolute value of the leverage multiple. The economic magnitudes of the funding cost's influence on return deviations indicate the impact is meaningful. Across the full sample, the average three-month LIBOR rate is 45 basis points. Referring to estimates using monthly observations, in Panel C, the results indicate LIBOR rates at the sample average contribute +70, +16, −5, and −60 basis points annually to the return deviations of the $\ell = -3, -2, +2, \text{and} +3$ funds, respectively. A one standard deviation change in the average monthly LIBOR rate (+26 basis points) corresponds to incremental influences of +40, +9, −3, and −35 basis points of annual return deviation across the respective leverage multiples.

The final variable, $\Delta SwapSpread$, proxies for innovations to counter-party risk in the swaps market. $\Delta SwapSpread$ is the change in the spread of the 5-year plain vanilla interest rate swap fixed rate over the corresponding maturity U.S. Treasury yield from time $t-1$ to t. Estimates of $\bar{\gamma}_3$ indicate inverse leveraged funds benefit from declines in the price of counter-party risk whereas long leveraged funds benefit from increases. We interpret this result in the context of marking-to-market of fund assets. Leveraged funds incur the periodic funding costs, which rates set in advance and are paid in arrears, meaning that an increase in funding costs provides short-term increases in the value of their swaps positions. The converse is true of the inverse leveraged funds. Turning to the economic magnitude of the results, however, it is clear that while statistically significant, the economic impact of this variable on fund return deviations is negligible. The average monthly change in spreads during the sample is −2 basis points, which corresponds to +0.9, +0.1, −0.1, and −0.8 basis points annually to the return deviations of the $\ell = -3, -2, +2, +3$ funds, respectively, based on the estimates in Panel C. A one standard deviation change in the average monthly spread change (−8 basis points) corresponds to incremental influences of +3.5, +0.1, −0.3, and −3 basis points of annual return deviation across the respective return multiples.

Having investigated the determinants of leveraged and inverse leveraged ETF return deviations from their stated daily target using both a statistical model and the actual return deviations, the analysis in the next section turns to returns to hypothetical portfolios of "mirror" funds which provide identical, but directionally opposing, leveraged exposures to a stated benchmark index.

4 Analysis of "Mirror" Fund Pairs

The analysis in this section capitalizes on a novel institutional feature of the ETF product space to further investigate the determinants of fund return performance. Noting that across the sample many leveraged ETFs ("Bull" Funds) coexist with a corresponding, "mirror," inverse leveraged ETF ("Bear" Funds), a hypothetical portfolio consisting of equal allocations to each of these "mirror" funds should result in a portfolio absent any investment exposure to the funds' benchmark index. In this section, we exploit this institutional detail to shed further light on the sources of abnormal return performance.

We define a pair of "mirror" funds as two funds providing equal but directionally opposite leveraged exposure to the same benchmark index and sharing a common fund sponsor. An example of such “mirror” funds are the Direxion Daily Financial 3x Bull Shares (ticker: FAS), and the Direxion Daily Financial 3x Bear Shares (ticker: FAZ). Their exposures are directionally opposite, but both funds provide triple exposures ($\ell = -3, +3$) to the daily Russell 1000 Financial Services Index and share the same sponsor (Direxion). Across our cross-sectional sample, we identify 36 pairs of such “mirror” funds comprising 25 funds providing two times exposure ($|\ell| = 2$) and 11 providing three times exposure ($|\ell| = 3$).

The costs and frictions associated with providing leveraged and inverse leveraged returns likely result from factors specific to each index such as the availability, liquidity, and cost of derivative contracts referencing the target index, coupled with other costs that are systemic such as LIBOR and counter-party risk. The cross-sectional results presented in the previous sections are influenced by both such influences. By analyzing returns to hypothetical portfolios allocated equally between pairs of “mirror” funds, the analysis in this section is better able to isolate the impact of the factors associated with index-specific replication costs.

4.1 Analysis of Returns to Portfolios of Mirror Funds

We define the daily return to each of these pair portfolios as $r_{i,t}^{pair} = \frac{1}{2} \times (r_{i,t}^{bull} + r_{i,t}^{bear})$, where $r_{i,t}^{bull}$ is the day t return to the leveraged ETF and $r_{i,t}^{bear}$ is the day t return to the inverse leveraged fund tracking the same benchmark. Under the identity model that the daily return to a leveraged ETF equals $\ell_i \times r_{i,t}^{Index}$, the expected daily return to the pairs portfolio exactly offset, equaling zero. Considering the annual expense ratio, we may expect a time-invariant constant negative return equal to the annual expense ratio. Given the sample funds' *daily* leverage, to maintain constant offsetting allocations, the pairs portfolio assumes daily rebalancing for the purpose of maintaining constant, offsetting index exposures. Admittedly, daily rebalancing likely results in significant transactions costs suppressed in our analysis. Ignoring the costs associated with daily rebalancing of the pairs portfolio does not diminish the significance of our results because our purpose is to evaluate empirically the return properties and return deviations as opposed the identification of profitable trading strategies.

As noted above, under the null hypothesis that each of the funds comprising a mirror pair achieves its stated return objective, the returns to each pairs portfolio equal zero. For this reason, the analysis begins by estimating a restricted version of the model introduced below, regressing the monthly returns to each portfolio of mirror pairs against only the intercept δ_0. Table 5 presents the regression results, labeled Model (1), presenting estimates separately for the funds offering two and three times exposures. Panels A, B, and C present the results using daily, weekly, and monthly return frequencies, respectively. The reported cross-sectional average coefficients indicate annualized average returns to the mirror pairs portfolios range from -1.6% to -1.90% annualized for $|\ell| = 2$ pairs and -4.07% to -4.12% for $|\ell| = 3$ funds. These estimates indicate portfolios of mirror pairs suffer significant under-performance in excess of their expense ratios.

The analysis next turns to the following regression model of returns to the mirror pairs portfolios to determine the sources of the underperformance, considering returns to the benchmark index, rebalance costs as proxied by the volatility of the benchmark index, the leverage funding cost, counter-party risk, and measures of fund size and flows, in the following model:

$$r_{i,t}^{pair} = \delta_0 + \delta_1 r_{i,t}^{Index} + \delta_2 \sigma_{i,t}^{Index} + \delta_3 LIBOR_t + \delta_4 \Delta SwapSpread_t + \delta_5' Size_t + \delta_6' Flows + \zeta_{i,t}. \quad (5)$$

$Size$ is a vector containing three variables measuring fund size and the asymmetry of size between the pairs; $log(Size)$ is the log of the market capitalization summed across the fund pair, $Asymmetry$ is the Herfindahl Index measuring the concentration of fund size for each pair fund, and $log(Size) \times Asymmetry$ is the interaction of $log(Size)$ and $Asymmetry$. $Flows$ is a vector containing three variables measuring the magnitude of fund flows and the symmetry across the pair of mirror funds: $log(Flows)$ is the logarithm of the sum of flows to the pair of funds, measured as the daily change in shares outstanding times the closing price, $FlowSkew$ is the ratio of the absolute value of the difference in flows across fund pairs divided by the absolute value of fund flows, and $log(Flows) \times FlowSkew$ is the interaction of the two previous variables.

Table 5 presents the regression results across six separate models, where each model adds variables incrementally, allowing for identification of the variables' incremental explanatory power. The estimation results presented in Panels A, B, and C of the table consider daily, weekly, and monthly returns respectively. Expanding on Model (1), Model (2) includes the contemporaneous monthly return to the pairs' benchmark index and the benchmark index return volatility. The estimates indicate the mirror pair portfolios have small, positive exposures to the benchmark index, although we note the coefficient magnitude and incremental explanatory power are both negligible. In the cross-section, returns to the mirror fund portfolios exhibit significant negative exposure to the underlying index volatility. In fact, we note that inclusion of index volatility has two important effects: 1) ameliorating the negative and significant estimates of δ_0 and 2) increasing meaningfully the explanatory power of the regressions ($\bar{R}^2$). The coefficient estimates imply even moderate levels of index volatility lead to significant losses across fund pairs. To illustrate, given the cross-sectional average $\bar{\delta}_3$ for the $|\ell| = 2, 3$ pairs, which are -0.1351 and -0.0708, as reported in Panel C, annual realized index volatility of 20% leads to -78 and -35 basis points per month, respectively, or roughly −9.35% and −4.16% per year. By isolating the common components through the pairs analysis, we find evidence consistent with the costly daily rebalance hypothesis, connecting even moderate levels of index volatility to meaningful levels of fund losses.

Model (3) introduces funding cost, as proxied by LIBOR, and counter-party risk, as proxied by changes in the 5-year plain vanilla swap spread over U.S. Treasuries. Based on the magnitude of the estimated coefficients and the lack of statistical significance, the results are consistent with the interpretation that funding cost and counter-party risk are not important determinants of the mirror pair portfolio returns. This result is consistent with the results presented in Section 3.2.2. Although the cross-sectional analysis supports the conclusion that funding costs and counter-party risk constitute significant determinants of individual fund tracking errors, by their nature these costs are largely wealth transfers from the long leveraged funds to the inverse leveraged funds. Thus, their explanatory power for the mirror pairs is reduced through the netting that results in portfolios comprised of the mirror pairs.

In addition to the variables mentioned above, Model (4) includes measures of fund size, measured as the market capitalization of both the leveraged and inverse leveraged funds comprising the pair, as well as a measure of balance between the two funds comprising the pair. *Asymmetry* is the sum of the squared weights of the two mirror funds, where the weights are each fund's proportion of the pair's total assets and range from 0.5 for pairs comprised of equal-sized funds to 1.0 for pairs where one fund is large and the other small. The intuition behind this variable is that the derivative counterparties have net balanced exposures when the funds are of equal size. When the pair assets are skewed in one direction, the swaps dealer takes on incremental risk which may make transacting more costly. We include the interaction term since asymmetry in fund size likely matters more for larger funds.

Referring to the results presented in Panel A, the coefficients for *Size* and *Asymmetry* tend to be positive while the interaction term, $Size \times Asymmetry$, is negative and significant. These results are strongest at the daily frequency, consistent with the interpretation that synthetic exposures gained through over-the-counter derivatives markets become increasingly expensive when those exposures are larger and less balanced. Across all Panels of Table 5, the sign of the interaction term is consistently negative.

In response to the supply and demand for shares in the secondary market, authorized participants create and redeem fund shares. Their efforts at alleviating any short-term imbalance of supply and demand prevents the market price from diverging to the value of the underlying basket of securities. It is through this process that new shares are created or existing shares redeemed.

The sample funds analyzed in this paper have cash, as opposed to in-kind, creation and redemption processes, requiring the fund itself to rebalance its exposures resulting from such flows. Proceeding with similar logic as above, when $Flows$, defined as the sum of absolute change in fund assets, are skewed in either direction the funds will likely encounter greater difficulty and likely transactions costs associated with these trades. The analysis next considers the impact of daily fund flows on return performance to the mirror pairs portfolios. Referring to the results of Model (5), presented in Table 5, coefficient estimates for $log(Flows)$, $FlowSkew$, and the interaction term $log(Flows) \times FlowSkew$ are negative and generally statistically significant at conventional levels. The results are consistent with the interpretation that fund flows result in costs born by all shareholders and that those costs are larger when the flows are not balanced between the bull and bear funds. This result is only evident in high-frequency daily data and is not evident when tested using weekly or monthly return observations.

4.2 Intra-Paired Fund Return Deviations

What is the nature of the measured abnormal performance between the funds comprising the "mirror" pairs? Are the patterns consistent with wealth transfers, and if so, in which direction? The analysis turns to this question by first plotting in Figure 1 the abnormal performance (α) from the baseline regression model in equation 1. For each pair of "mirror" funds, we plot the leveraged fund ($\ell > 1$) α on the horizontal axis and the corresponding inverse leveraged fund ($\ell < -1$) α on the vertical axis. The graphical relation between mirror fund αs speaks to the nature of the documented underperformance across subsamples of leverage multiples, but isolates factors specific to the target index. Visual inspection of the figure suggests a negative relation between the mirror fund αs suggesting transfers or subsidies from the inverse funds to the long funds.

This result is particularly interesting in light of the findings of Tang and Xu (2012). Their model posits that fund net-asset-value diverges from the return to the benchmark index due to funding cost and the expense ratio. According to their model, wealth transfers take place in the opposite direction as observed in our analysis. According to their model, the lone source of this subsidy comes from the structure of the total return swaps used by these funds to provide their leveraged exposures. The leveraged long funds make payments based on LIBOR plus a spread and receive payments based on the equity index total return. Conversely, the leveraged short funds receive payments of LIBOR plus a spread but make payments based on the equity index total return.

In the context of the "mirror" pairs, an additional implication of the Tang and Xu (2012) model is that the wealth transfers between long and short funds does not reflect index-specific factors.

According to their model, Figure 1 should present a cluster of plots such that $\alpha^{bear} < \alpha^{bull}$ by a magnitude of twice the accrued funding cost and each α is invariant to the benchmark index. Visual inspection of the realized αs, however, reveals a negative relation between the pairs' αs which suggests the presence of other, meaningful index-specific determinants.

To quantify the relation between the underperformance across the pairs of "mirror" funds, we test the following regression model:

$$\alpha_i^{bear} = a + b \times \alpha_i^{bull} + \upsilon_i, \tag{6}$$

where α_i refers to the estimated coefficient from Equation 1 resulting from analysis of weekly returns. Weekly results are chosen to avoid the bias induced by measurement errors at the daily frequency, and to permit sufficient observations for estimation across each sample year individually. Table 6 presents the regression results. The results are estimated separately for two subsets based on fund leverage multiple ($|\ell| = 2, 3$), and the table reports the cross-sectional average coefficients and the associated test statistics.

The average intercept, $\bar{a}$, is negative and significant for all years 2009 through 2011 for both sets of leverage multiple (2 and 3), consistent with lower average abnormal performance of the leveraged short funds compared to the corresponding long funds. Interestingly, the estimates are positive and significant during the years 2007 and 2008 among the two times leverage funds ($|\ell| = 2$). Note that the triple leverage funds ($|\ell| = 3$) did not exist prior to December 2008.

The cross-sectional average slope, $\bar{b}$, is negative and significant across all years and leverage multiples, indicating that among pairs of "mirror" funds, the underperformance of the fund targeting short exposure is proportional to the outperformance of the fund targeting long exposure. These results are consistent with transfers of wealth from the short fund to the long fund, likely determined by the cost of borrowing the assets comprising the benchmark index. A swap dealer must build their cost of hedging into the spread at which they offer total return swaps. Since they incur cost to borrow when their hedging needs require shorting exposure to the index, they reasonably pass this cost through to the swaps investors. Our results are entirely consistent with the cost of borrowing being born by the short investors and the corresponding rebate rate being earned by the long investors. Our results suggest the model of Tang and Xu (2012) is a partial explanation for observed return deviations from the target multiples of daily returns to the benchmark index. In fact, the negative relation is indicative of subsidies in the opposite direction as that predicted by their model.

5 Summary and Conclusion

ETFs providing investors leveraged, short, and leveraged short exposures to benchmark indexes have become an important part of the investment landscape. Utilizing a large cross-sectional sample, our study investigates the extent to which these funds achieve their stated return objective. We employ a progression of empirical models to benchmark performance. We document meaningful underperformance among leveraged short funds and positive excess returns to leveraged funds. This finding is robust to the inclusion of a proxy for rebalancing costs.

Capitalizing on an important institutional detail, we analyze returns to hypothetical portfolios consisting of long positions in "mirror pairs," which by design have zero exposure to the benchmark index. We document statistically and economically meaningful negative returns to holding these mirror funds, indicating that when common replication costs are isolated, the true replication costs born by fund investors become evident.

An important insight of our results is that we consider a broad array of likely determinants of return deviations including transactions costs associated with frequent reblancing necessary to maintain daily leverage multiples, funding costs for portfolio leverage, counter-party risk, and the cost to borrow. We find mixed evidence linking transactions costs to fund performance. The primary insight gained from the mirror funds analysis comes from the ability to utilize these funds to isolate shared, index-specific replication costs which we argue stem from the cost-to-borrow the benchmark securities. We document economically meaningful wealth transfers from the inverse leveraged funds to the leveraged funds, patterns which are consistent with the borrowing cost hypothesis.

Although our analysis focuses on determinants of costs incurred by the sample of synthetic ETFs, our results must be viewed in light of the fact that these innovative products provide tradable, leveraged exposure to investors previously unable to access such exposures. While we focus on the determinants of return deviations, we acknowledge that the magnitude of the documented return deviations seems small compared to the costs involved with transacting in more traditional products such as exchange-traded options or borrowing from a broker on margin.

Our results are of interest to a wide array of investors, ranging from individual investors to institutional investors. Short-term investors seeking to hedge other portfolio holdings, or speculators seeking the use of leverage to profit from their views, potentially have uses for leveraged and inverse leverage ETFs. Understanding their performance at providing the target exposure and the determinants of return deviations are critical for such investors.

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Table 1: Sample Descriptive Statistics

Descriptive statistics for the sample leverage, inverse, and inverse leverage ETFs. The sample comprises all leveraged, inverse, and inverse leveraged exchange traded funds listed in the U.S. and tracking U.S. equity benchmark indexes as identified by Morningstar Direct. The sample begins in June, 2006 and ends June 29, 2012. The table presents the number of funds and year-end market capitalizations. The table presents these statistics for sub-samples formed by grouping funds according to their stated leverage multiple exposure (ℓ) to the benchmark index, where $\ell \in \{-3, -2, -1, +2, +3\}$. Market capitalization for each subsample is the sum of year-end market capitalization for each sample fund, where each fund's market capitalization is the product of shares outstanding and the closing share price on the last trading day of each calendar year, and come from Thomson's Datastream database.

Leverage Multiple	$\ell = -3$		$\ell = -2$		$\ell = -1$		$\ell = +2$		$\ell = +3$		*All*	
Year	N	Market Cap ($ millions)	N	Market Cap ($ millions)	N	Market Cap ($ millions)	N	Market Cap ($ millions)	N	Market Cap ($ millions)	N	Market Cap ($ millions)
2006	0	-	4	1,231.92	3	287.83	4	531.97	0	-	11	2,051.72
2007	0	-	23	6,302.93	5	382.46	23	2,455.40	0	-	51	9,140.78
2008	5	350.56	24	6,670.63	7	560.59	24	10,345.72	5	700.32	65	18,627.82
2009	8	2,181.81	25	6,877.83	7	2,097.96	25	7,569.62	8	2,482.46	73	21,209.68
2010	15	2,438.77	26	4,979.62	10	2,190.96	27	6,357.43	15	3,988.98	93	19,955.77
2011	17	2,623.15	26	3,999.71	11	3,402.03	27	4,864.44	17	4,272.31	98	19,161.64
2012*	17	2,418.71	26	3,582.40	11	2,771.81	27	4,296.91	17	3,883.88	98	16,953.71

* As of June 29, 2012.

Table 2: Leverage and Inverse ETF Return Benchmark Model

This table presents regression results for the sample ETFs. The table presents results of the following baseline regression model:

$$r_{i,t}^{ETF} = \alpha + \beta_1 \times (\ell_i \times r_{i,t}^{Index}) + \epsilon_{i,t},$$

where $r_{i,t}^{ETF}$ is the day t return to leveraged or inverse ETF i, computed as $r_{i,t}^{ETF} = (P_{i,t} + D_{i,t})/P_{i,t-1} - 1$, where P_t is the daily closing price of ETF i on trading day t, $D_{i,t}$ is the distribution amount when applicable, as reported in Thomson's Datastream Database, ℓ_i is the fund leverage multiple where $\ell \in \{-3, -2, -1, +2, +3\}$, and $r_{i,t}^{Index}$ is the return to the fund's benchmark index on day i. Computation of the benchmark index returns are based on daily closing index levels, where $r_{i,t}^{Index} = (INDEX_{i,t}/INDEX_{i,t-1}) - 1$ and $INDEX_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index from Bloomberg. The table presents results for subsamples formed based on the fund leverage multiple (ℓ). For each subsample, the reported parameter estimates $\bar{\alpha}$ and $\bar{\beta}_1$ are cross-sectional averages of the regression estimates for each individual fund. Corresponding to each parameter estimate, the table reports corresponding t-statistics, computed for each parameter as: $t_{\bar{\alpha}} = \frac{\bar{\alpha}}{se(\hat{\alpha})/\sqrt{N}}$, where $se(\hat{\alpha})$ is the cross-sectional standard deviation of $\hat{\alpha}$. The table reports in separate panels A, B, and C, results of estimation across daily, weekly, and monthly return observation frequencies. The table reports average explanatory power for the regression model, $\bar{R}^2$. The bottom row of each panel reports the number of funds, N, comprising each leverage multiple subsample.

Panel A: Regression Results, Daily Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0004	−0.0002	−0.0001	0.0000	0.0001
$t_{\bar{\alpha}}$	(−6.516)	(−5.927)	(−2.972)	(1.667)	(2.641)
$\bar{\beta}_1$	0.9550	0.9401	0.9352	0.9274	0.9221
$t_{\bar{\beta}_1}$	(50.569)	(144.831)	(55.850)	(102.867)	(33.946)
$t_{\bar{\beta}_1=1}$	(−2.382)	(−9.225)	(−3.870)	(−8.054)	(−2.866)
$\bar{R}^2$	0.985	0.945	0.924	0.932	0.948
Number Funds	14	26	11	26	16

Panel B: Regression Results, Weekly Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0016	−0.0004	−0.0003	0.0003	0.0006
$t_{\bar{\alpha}}$	(−7.029)	(−4.994)	(−2.621)	(3.193)	(3.377)
$\bar{\beta}_1$	0.9743	0.9876	0.9832	0.9814	0.9592
$t_{\bar{\beta}_1}$	(49.274)	(235.865)	(144.019)	(309.883)	(40.725)
$t_{\bar{\beta}_1=1}$	(−1.301)	(−2.956)	(−2.467)	(−5.867)	(−1.733)
$\bar{R}^2$	0.992	0.988	0.984	0.987	0.988
Number Funds	14	26	11	26	16

Panel C: Regression Results, Monthly Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0072	−0.0015	−0.0003	0.0012	0.0036
$t_{\bar{\alpha}}$	(−6.810)	(−3.376)	(−0.608)	(3.477)	(5.308)
$\bar{\beta}_1$	0.9911	0.9998	0.9925	0.9964	1.0046
$t_{\bar{\beta}_1}$	(66.946)	(264.672)	(156.755)	(634.295)	(64.283)
$t_{\bar{\beta}_1=1}$	(−0.601)	(−0.058)	(−1.183)	(−2.264)	(0.296)
$\bar{R}^2$	0.993	0.991	0.992	0.994	0.994
Number Funds	8	25	7	25	8

Table 3: Leverage and Inverse ETF Return, Extended Model

This table presents regression results for the sample ETFs. The table presents results of the following regression model:

$$r_{i,t}^{ETF} = \alpha + \beta_1 \times (\ell_i \times r_{i,t}^{Index}) + \beta_2 \times (r_{i,t}^{Index})^2 + \varepsilon_{i,t},$$

where $r_{i,t}^{ETF}$ is the day t return to leveraged or inverse ETF i, computed as $r_{i,t}^{ETF} = (P_{i,t} + D_{i,t})/P_{i,t-1} - 1$, where P_t is the daily closing price of ETF i on trading day t, $D_{i,t}$ is the distribution amount when applicable, as reported in Thomson's Datastream Database, ℓ_i is the fund leverage multiple where $\ell \in \{-3, -2, -1, +2, +3\}$, and $r_{i,t}^{Index}$ is the return to the fund's benchmark index on day i. Computation of the benchmark index returns are based on daily closing index levels, where $r_{i,t}^{Index} = (INDEX_{i,t}/INDEX_{i,t-1}) - 1$ and $INDEX_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index from Bloomberg. The table presents results for subsamples formed based on the fund leverage multiple (ℓ). For each subsample, the reported parameter estimates $\bar{\alpha}$, $\bar{\beta}_1$, and $\bar{\beta}_2$ are cross-sectional averages of the regression estimates for each individual fund. The table reports t-statistics corresponding to each parameter estimate, computed as: $t_{\bar{\alpha}} = \frac{\bar{\alpha}}{se(\hat{\alpha})/\sqrt{N}}$, where $se(\hat{\alpha})$ is the cross-sectional standard deviation of $\hat{\alpha}$. The table reports in separate panels A, B, and C, results of estimation across daily, weekly, and monthly return observation frequencies. The table reports group average explanatory power for the regression model, $\bar{R}^2$. The bottom row of each panel reports the number of funds, N, comprising each leverage multiple subsample.

Panel A: Regression Results, Daily Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0005	−0.0002	−0.0002	0.0002	0.0003
$t_{\bar{\alpha}}$	(−7.723)	(−4.809)	(−3.825)	(3.244)	(4.245)
$\bar{\beta}_1$	0.9549	0.9398	0.9345	0.9276	0.9222
$t_{\bar{\beta}_1}$	(50.410)	(142.289)	(54.254)	(102.449)	(34.009)
$t_{\bar{\beta}_1=1}$	(−2.380)	(−9.121)	(−3.801)	(−7.990)	(−2.870)
$\bar{\beta}_2$	0.0238	0.0654	0.3253	−0.0940	−0.0390
$t_{\bar{\beta}_2}$	(2.677)	(1.974)	(2.901)	(−3.414)	(−1.238)
$\bar{R}^2$	0.985	0.945	0.925	0.933	0.948
Number Funds	14	26	11	26	16

Panel B: Regression Results, Weekly Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0015	−0.0005	−0.0005	0.0004	0.0009
$t_{\bar{\alpha}}$	(−3.518)	(−4.256)	(−2.268)	(3.688)	(5.705)
$\bar{\beta}_1$	0.9763	0.9870	0.9815	0.9813	0.9607
$t_{\bar{\beta}_1}$	(51.757)	(252.888)	(133.990)	(309.119)	(40.941)
$t_{\bar{\beta}_1=1}$	(−1.259)	(−3.327)	(−2.522)	(−5.894)	(−1.674)
$\bar{\beta}_2$	0.0167	0.0217	0.0756	−0.0331	−0.0358
$t_{\bar{\beta}_2}$	(0.676)	(0.968)	(1.020)	(−1.736)	(−2.032)
$\bar{R}^2$	0.993	0.988	0.984	0.987	0.989
Number Funds	14	26	11	26	16

Panel C: Regression Results, Monthly Returns

Leverage Multiple (ℓ)	**−3**	**−2**	**−1**	**+2**	**+3**
$\bar{\alpha}$	−0.0063	−0.0012	−0.0000	0.0009	0.0034
$t_{\bar{\alpha}}$	(−6.282)	(−2.494)	(−0.039)	(2.661)	(2.882)
$\bar{\beta}_1$	0.9893	1.0013	0.9937	0.9985	1.0046
$t_{\bar{\beta}_1}$	(65.545)	(302.418)	(145.532)	(629.459)	(70.562)
$t_{\bar{\beta}_1=1}$	(−0.711)	(0.389)	(−0.922)	(−0.942)	(0.320)
$\bar{\beta}_2$	−0.0314	−0.0360	−0.0863	0.0221	0.0077
$t_{\bar{\beta}_2}$	(−2.859)	(−1.332)	(−1.571)	(1.591)	(0.380)
$\bar{R}^2$	0.993	0.991	0.992	0.994	0.994
Number Funds	8	25	7	25	8

Table 4: Regression Analysis of Fund Return Deviations

This table presents results of the following regression model: $RD_{i,t}^{ETF} = \gamma_0 + \gamma_1 \sigma_{i,t}^{Index} + \gamma_2 LIBOR_t + \gamma_3 \Delta SwapSpread + \eta_{i,t}$, where $RD_{i,t}^{ETF}$ is the return deviation for ETF i on trading day t, computed as: $RD_{i,t}^{ETF} = r_{i,t}^{ETF} - \ell \times r_{i,t}^{Index}$, where $r_{i,t}^{ETF}$ is the day t return to ETF i, and $\ell \times r_{i,t}^{Index}$ is the product of the fund leverage multiple (ℓ) and the concurrent return to the fund benchmark index. $\sigma_{i,t}$ is the standard deviation of the benchmark index returns during t for weekly and monthly observations and the squared index return for daily observations. LIBOR$_t$ is the average three-month LIBOR rate during month t, and ΔSwapSpread is the basis points change in the five-year plain vanilla interest rate swap spread from $t-1$ to t. The table presents results for subsamples formed based on the fund leverage multiple. For each subsample, the reported parameter estimates $\bar{\gamma_0}$, $\bar{\gamma_1}$, $\bar{\gamma_2}$, $\bar{\gamma_3}$ are cross-sectional averages of the regression estimates for each individual fund. The table reports t-statistics, computed for each parameter as: $t_{\bar{\gamma}} = \frac{\bar{\gamma}}{se(\hat{\gamma})/\sqrt{N}}$, where $se(\hat{\gamma})$ is the cross-sectional standard deviation of $\hat{\gamma}$. The table reports in separate panels A, B, and C, results of estimation across daily, weekly, and monthly return observation frequencies. The table reports average explanatory power for the regression model, $\bar{R}^2$. The bottom row of each panel reports the number of funds, N, comprising each leverage multiple subsample.

Panel A: Daily Regression Results

Leverage Multiple	$\ell = -3$		$\ell = -2$		$\ell = -1$		$\ell = +2$		$\ell = +3$	
Model:	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
$\bar{\gamma_0}$	−0.0004	−0.0001	−0.0001	−0.0002	−0.0001	−0.0001	−0.0001	0.0002	−0.0001	−0.0002
$t_{\bar{\gamma_0}}$	(−5.181)	(−0.395)	(−5.066)	(−4.710)	(−2.428)	(−0.586)	(−0.032)	(4.178)	(−0.169)	(−0.896)
$\bar{\gamma_1}$		0.0041		0.0046		0.0144		−0.0099		−0.0030
$t_{\bar{\gamma_1}}$		(2.108)		(1.772)		(2.582)		(−2.693)		(−0.587)
$\bar{\gamma_2}$		0.0002		0.0002		0.0001		−0.0001		0.0002
$t_{\bar{\gamma_2}}$		(0.718)		(5.538)		(0.698)		(−2.684)		(0.586)
$\bar{\gamma_3}$		−0.0001		−0.0001		−0.0001		0.0004		0.0013
$t_{\bar{\gamma_3}}$		(−4.277)		(−3.492)		(−3.305)		(2.512)		(0.848)
$\bar{R}^2$	0.000	0.010	0.000	0.011	0.000	0.012	0.000	0.015	0.000	0.008
N	14	14	26	26	11	11	26	26	16	16

Panel B: Weekly Regression Results

Leverage Multiple	$\ell = -3$		$\ell = -2$		$\ell = -1$		$\ell = +2$		$\ell = +3$	
Model:	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
$\bar{\gamma_0}$	−0.0014	−0.0001	−0.0004	−0.0014	−0.0003	−0.0003	0.0002	0.0005	0.0003	−0.0010
$t_{\bar{\gamma_0}}$	(−4.937)	(−0.026)	(−4.750)	(−4.265)	(−2.454)	(−1.317)	(2.833)	(3.387)	(0.898)	(−1.437)
$\bar{\gamma_1}$		0.0081		0.0162		0.0186		−0.0115		0.0223
$t_{\bar{\gamma_1}}$		(1.071)		(2.620)		(1.129)		(−1.231)		(1.291)
$\bar{\gamma_2}$		0.0017		0.0005		0.0007		−0.0006		−0.0025
$t_{\bar{\gamma_2}}$		(1.723)		(1.273)		(1.319)		(−2.379)		(−2.042)
$\bar{\gamma_3}$		−0.0001		−0.0001		−0.0001		0.0006		−0.0034
$t_{\bar{\gamma_3}}$		(−2.268)		(−0.515)		(−1.477)		(2.811)		(−0.018)
$\bar{R}^2$	0.000	0.092	0.000	0.093	0.000	0.128	0.000	0.104	0.000	0.096
N	14	14	26	26	11	11	26	26	16	16

Table 4 Continued: Regression Analysis of Fund Return Deviations

Panel C: Monthly Regression Results

Leverage Multiple	$\ell = -3$		$\ell = -2$		$\ell = -1$		$\ell = +2$		$\ell = +3$	
Model:	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
$\bar{\gamma}_0$	-0.0052	0.0017	-0.0016	-0.0055	-0.0011	-0.0011	0.0012	0.0021	0.0019	-0.0069
$t_{\bar{\gamma}_0}$	(-4.212)	(0.430)	(-3.899)	(-10.569)	(-1.916)	(-1.567)	(3.672)	(5.453)	(1.538)	(-1.431)
$\bar{\gamma}_1$		-0.0104		0.0042		0.0458		-0.0196		0.0555
$t_{\bar{\gamma}_1}$		(-0.171)		(0.279)		(0.804)		(-1.554)		(0.531)
$\bar{\gamma}_2$		0.1296		0.0304		0.0318		-0.0084		-0.1120
$t_{\bar{\gamma}_2}$		(4.174)		(16.784)		(1.346)		(-2.019)		(-2.100)
$\bar{\gamma}_3$		-0.0359		-0.0017		-0.0115		0.0028		0.0309
$t_{\bar{\gamma}_3}$		(-3.261)		(-1.457)		(-1.515)		(1.424)		(2.129)
$\bar{R}^2$	0.000	0.173	0.000	0.254	0.000	0.265	0.000	0.182	0.000	0.148
N	14	14	26	26	10	10	26	26	15	15

Table 5: Determinants of Abnormal Returns to Portfolios of Mirror Funds

This table presents results of the following regression model: $r_{i,t}^{pair} = \delta_0 + \delta_1 r_{i,t}^{Index} + \delta_2 \sigma_{i,t}^{Index} + \delta_3 LIBOR_t + \delta_4 \Delta SwapSpread_t + \delta_5' Size_t + \delta_6' Flows + \zeta_{i,t}$, where $r_{i,t}^{pair}$ is the return to a portfolio allocated equally to across a pair of two "mirror" funds. We define mirror funds as two funds providing equal but directionally opposite leveraged exposure to the same benchmark index and sharing a common fund sponsor. An example comes from the Direxion Daily Financial 3x Bull Shares (ticker: FAS), and the Direxion Daily Financial 3x Bear Shares (ticker: FAZ). Thus, the dependent variable is $r_{i,t}^{pair} = \frac{1}{2} \times (r_{i,t}^{bull} + r_{i,t}^{bear})$, where $r_{i,t}^{bull}$ is the day t return to the leveraged ETF, $r_{i,t}^{bear}$ is the day t return to the inverse leveraged fund tracking the same benchmark. $r_{i,t}^{Index}$ is the return to the fund's benchmark index on day i. Computation of the benchmark index returns are based on daily closing index levels, where $r_{i,t}^{Index} = (INDEX_{i,t}/INDEX_{i,t-1}) - 1$ and $INDEX_{i,t}$ is the closing index level on trading day t for ETF i's benchmark index obtained from Bloomberg. The regressions use monthly return estimates, where monthly returns are computed as geometrically compounded daily returns. $\sigma_{i,t}$ is the standard deviation of the benchmark index returns during month t, LIBOR$_t$ is the average three-month LIBOR rate during month t, and ΔSwapSpread is the basis points change in the five-year plain vanilla interest rate swap rate spread from $t-1$ to t. $Size$ is a vector containing three variables measuring fund size and the asymmetry of size between the pairs; $log(Size)$ is the log of the market capitalization summed across the fund pair, $Asymmetry$ is the Herfindahl Index measuring the concentration of fund size for each pair fund, and $log(Size) \times Asymmetry$ is the interaction of $log(Size)$ and $Asymmetry$. $Flows$ is a vector containing three variables measuring the magnitude of fund flows and the symmetry across the pair of mirror funds: $log(Flows)$ is the logarithm of the sum of flows to the pair of funds, measured as the daily change in shares outstanding times the closig price, $FlowSkew$ is the ratio of the absolute value of the difference in flows across fund pairs divided by hte absolute value of fund flows, and $log(Flows) \times FlowSkew$ is the interaction of the two previous variables. The table presents results for subsamples formed based on the fund leverage multiple. For each subsample, the reported parameter estimates $\bar{\delta}_0$, $\bar{\delta}_1$, $\bar{\delta}_2$, $\bar{\delta}_3$, and $\bar{\delta}_4$ are cross-sectional averages of the regression estimates for each individual fund. Corresponding to each parameter estimate, the table reports t-statistics, computed for each parameter as: $t_{\bar{\delta}} = \frac{\bar{\delta}}{se(\hat{\delta})/\sqrt{N}}$, where $se(\hat{\delta})$ is the cross-sectional standard deviation of $\hat{\delta}$. Finally, the table reports average explanatory power for the regression model, $\bar{R}^2$ and the number of mirror fund pairs, N.

Panel A: Monthly Regression Results

Leverage Multiple:	$\lvert\ell\rvert = 2$						$\lvert\ell\rvert = 3$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
$Intercept$	−0.0001	−0.0001	−0.0001	−0.0086	0.0011	−0.0068	−0.0002	−0.0001	−0.0001	−0.0005	−0.0020	−0.0013
	(−5.445)	(−0.890)	(−0.783)	(−2.411)	(1.600)	(−1.781)	(−4.007)	(−4.692)	(−1.146)	(−0.039)	(−1.859)	(−0.101)
r^{Index}		−0.0051	−0.0051	−0.0052	−0.0050	−0.0051		0.0005	0.0004	0.0004	0.0004	0.0003
		(−1.821)	(−1.821)	(−1.836)	(−1.792)	(−1.803)		(0.296)	(0.276)	(0.237)	(0.246)	(0.207)
σ^{Index}		−0.0179	−0.0146	−0.0127	−0.0184	−0.0149		−0.0088	−0.0082	−0.0072	−0.0064	−0.0042
		(−1.049)	(−0.814)	(−0.677)	(−0.915)	(−0.687)		(−1.063)	(−0.990)	(−0.790)	(−0.718)	(−0.426)
$LIBOR$			0.0001	0.0001	0.0001	0.0001			0.0001	0.0002	0.0001	0.0001
			(2.958)	(1.740)	(2.515)	(1.933)			(0.426)	(1.519)	(−0.079)	(1.275)
$SwapSpread$			−0.0000	−0.0000	−0.0000	−0.0000			−0.0000	−0.0000	−0.0000	−0.0000
			(−1.783)	(−2.385)	(−1.319)	(−2.452)			(−1.982)	(−1.421)	(−0.978)	(−1.367)
$log(Size)$				0.0009		0.0008				0.0002		0.0001
				(2.313)		(2.008)				(0.134)		(0.060)
$Asymmetry$				0.0095		0.0090				0.0024		0.0039
				(1.990)		(1.745)				(0.172)		(0.290)
$log(Size) \times Asymmetry$				−0.0009		−0.0009				−0.0001		−0.0002
				(−1.864)		(−1.632)				(−0.056)		(−0.169)
$log(Flows)$					−0.0004	−0.0004					−0.0002	−0.0002
					(−1.901)	(−1.908)					(−1.506)	(−1.405)
$FlowSkew$					−0.0014	−0.0014					−0.0021	−0.0021
					(−1.897)	(−1.900)					(−1.442)	(−1.408)
$log(Flows) \times FlowSkew$					−0.0004	−0.0004					−0.0002	−0.0002
					(−1.278)	(−1.267)					(−1.677)	(−1.639)
$\bar{R}^2$	0.000	0.013	0.013	0.011	0.013	0.012	0.000	0.021	0.019	0.019	0.022	0.022
N	25	25	25	25	25	25	11	11	11	11	11	11

Table 5 Continued: Determinants of Abnormal Returns to Portfoilios of Mirror Funds

Panel B: Weekly Regression Results												
Leverage Multiple:	$\lvert\ell\rvert = 2$						$\lvert\ell\rvert = 3$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.0004	0.0005	0.0002	−0.0134	−0.0002	−0.0105	−0.0008	0.0001	−0.0001	0.0132	−0.0001	0.0186
	(−5.865)	(3.013)	(1.102)	(−2.042)	(−0.024)	(−0.913)	(−4.072)	(0.307)	(−0.227)	(0.394)	(−0.009)	(0.453)
r^{Index}		−0.0064	−0.0058	−0.0062	−0.0058	−0.0060		−0.0016	−0.0014	−0.0015	−0.0016	−0.0012
		(−1.567)	(−1.428)	(−1.477)	(−1.424)	(−1.442)		(−0.711)	(−0.648)	(−0.601)	(−0.730)	(−0.519)
σ^{Index}		−0.0251	−0.0243	−0.0236	−0.0286	−0.0294		−0.0175	−0.0155	−0.0160	−0.0156	−0.0182
		(−4.537)	(−3.654)	(−3.477)	(−3.920)	(−3.485)		(−2.343)	(−2.418)	(−2.206)	(−2.369)	(−2.332)
$LIBOR$			−0.0001	−0.0001	−0.0001	−0.0001			−0.0005	0.0004	−0.0004	0.0005
			(−0.326)	(−0.347)	(−0.173)	(−0.279)			(−0.683)	(0.560)	(−0.728)	(0.662)
$SwapSpread$			0.0000	0.0000	0.0000	0.0000			0.0000	0.0000	0.0000	0.0000
			(0.4561)	(0.538)	(0.166)	(0.419)			(1.054)	(0.623)	(0.862)	(−0.072)
$log(Size)$				0.0014		0.0011				0.0009		0.0014
				(2.100)		(1.505)				(0.279)		(0.427)
$Asymmetry$				0.0180		0.0179				0.0195		0.0190
				(2.206)		(2.134)				(0.553)		(0.524)
$log(Size) \times Asymmetry$				−0.0018		−0.0018				−0.0014		−0.0013
				(−2.163)		(−2.073)				(−0.419)		(−0.390)
$log(Flows)$					0.0001	0.0002					0.0004	0.0004
					(0.053)	(0.112)					(0.303)	(0.250)
$FlowSkew$					−0.0007	−0.0012					−0.0001	−0.0019
					(−0.084)	(−0.144)					(−0.008)	(−0.174)
$log(Flows) \times FlowSkew$					0.0001	0.0002					−0.0004	−0.0001
					(0.076)	(0.113)					(−0.291)	(−0.090)
$\bar{R}^2$	0.0000	0.052	0.063	0.056	0.066	0.061	0.0000	0.099	0.099	0.107	0.093	0.106
N	25	25	25	25	25	25	11	11	11	11	11	11

Table 5 Continued: Determinants of Abnormal Returns to Portfoilios of Mirror Funds

Panel C: Monthly Regression Results												
Leverage Multiple:	$\lvert\ell\rvert = 2$						$\lvert\ell\rvert = 3$					
Model:	(1)	(2)	(3)	(4)	(5)	(6)	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	−0.0016	0.0030	0.0014	0.0496	−0.0204	0.0342	−0.0034	0.0003	−0.0001	−0.1377	−0.0962	−0.2475
	(−5.974)	(6.636)	(2.913)	(1.765)	(−0.424)	(0.877)	(−4.016)	(0.242)	(−0.074)	(−0.565)	(−0.893)	(−0.905)
r^{Index}		−0.0109	−0.0069	−0.0066	−0.0073	−0.0071		−0.0006	0.0002	−0.0015	0.0024	0.0010
		(−3.598)	(−2.276)	(−2.138)	(−2.338)	(−2.169)		(−0.172)	(0.076)	(−0.332)	(0.544)	(0.179)
σ^{Index}		−0.1351	−0.1313	−0.1269	−0.1378	−0.1706		−0.0708	−0.0614	−0.0568	−0.0604	−0.0851
		(−9.517)	(−8.878)	(−8.115)	(−7.489)	(−6.283)		(−2.436)	(−2.397)	(−2.408)	(−1.868)	(−2.498)
$LIBOR$			0.0007	0.0006	0.0010	0.0011			−0.0009	0.0007	0.0008	0.0013
			(3.130)	(1.394)	(2.378)	(1.235)			(−0.322)	(0.310)	(0.326)	(0.541)
$SwapSpread$			0.0000	0.0000	0.0000	0.0000			0.0000	0.0000	0.0000	0.0000
			(1.0046)	(1.757)	(0.931)	(1.163)			(1.167)	(0.675)	(0.096)	(−0.077)
$log(Size)$				0.0047		0.0058				0.0146		0.0107
				(1.654)		(1.640)				(0.634)		(0.457)
$Asymmetry$				−0.0560		−0.0426				0.1162		0.0947
				(−1.629)		(−1.062)				(0.462)		(0.360)
$log(Size) \times Asymmetry$				−0.0055		−0.0041				−0.0132		−0.0111
				(−1.606)		(−1.012)				(−0.564)		(−0.462)
$log(Flows)$					0.0004	0.0013					0.0108	0.0187
					(0.041)	(0.129)					(0.879)	(1.263)
$FlowSkew$					0.0193	0.0144					0.0929	0.1405
					(0.382)	(0.263)					(0.831)	(1.080)
$log(Flows) \times FlowSkew$					−0.0001	0.0011					−0.0106	−0.0169
					(−0.001)	(0.104)					(−0.823)	(−1.101)
$\bar{R}^2$	0.0000	0.219	0.293	0.272	0.302	0.293	0.0000	0.297	0.296	0.330	0.318	0.323
N	25	25	25	25	25	25	11	11	11	11	11	11

Table 6: Regression Analysis of Mirror Bull and Bear Leveraged Fund Return Deviations

This table presents results of the following regression model:

$$\alpha_i^{bear} = a + b \times \alpha_i^{bull} + \upsilon_i,$$

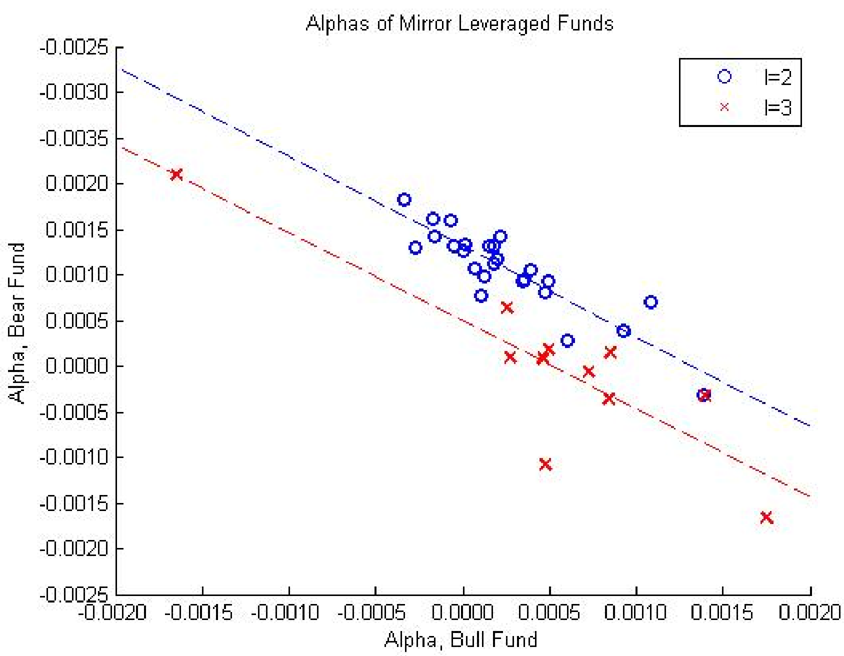
where α_i^{bear} and α_i^{bull} refer to the estimated coefficients from Equation 1 where estimation uses weekly return observations. The pair of "mirror" funds i comprise two funds providing equal but directionally opposite leveraged exposure to the same benchmark index and sharing a common fund sponsor. An example of such "mirror" funds are the Direxion Daily Financial 3x Bull Shares (ticker: FAS), and the Direxion Daily Financial 3x Bear Shares (ticker: FAZ). The cross-sectional sample contains 36 pairs of such "mirror" funds, consisting of 25 funds providing leverage multiples of 2 ($|\ell| = 2$) and 11 having leverage multiples of 3 ($|\ell| = 3$). Estimates of α come from estimation of the baseline regression model in equation 1 using weekly return observations. The table presents the average coefficient estimates, the corresponding test statistic, the regression R^2, and the number of pairs for each sample year, and across the full sample period.

Regression Results

Leverage Multiple	**Period**	$\bar{a}$	$t_{\bar{a}}$	$\bar{b}$	$t_{\bar{b}}$	R^2	Nobs
	2007	0.0015	(9.740)	−0.8441	(−3.873)	0.389	23
	2008	0.0003	(2.850)	−0.2370	(−1.866)	0.097	24
	2009	−0.0008	(−6.305)	−1.0643	(−6.931)	0.672	24
$\ell = 2$	2010	−0.0006	(−7.431)	−0.9575	(−8.474)	0.747	25
	2011	−0.0008	(−12.896)	−0.8683	(−7.361)	0.689	25
	All Years	−0.0002	(−3.657)	−0.9895	(−9.077)	0.772	25
	2009	−0.0013	(−5.080)	−1.0536	(−10.906)	0.983	3
	2010	−0.0007	(−2.841)	−1.1338	(−4.778)	0.708	10
$\ell = 3$	2011	−0.0009	(−8.941)	−1.0490	(−8.411)	0.875	11
	All Years	−0.0010	(−5.653)	−0.9653	(−5.289)	0.730	11

Figure 1: Weekly Return Deviations of Mirror Bull and Bear Funds

This figure displays cross-sectional average estimates of weekly return deviations for the mirror Funds. We define pairs of "mirror" funds as those seeking to provide returns of equal, but directionally opposing, multiples of the daily return to a specific benchmark model, and are offered by the same sponsor. The sample comprises 25 pairs of funds targeting 2x exposure ($|\ell| = 2$) and 11 pairs of funds targeting 3x exposure ($|\ell| = 3$) to the benchmark index. Fund return deviations are parameter estimates of α from the baseline model, equation 1, estimated using weekly return observations.



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