Of Seesaws and Swings: The Market-wide Impact of Levered ETF Rebalancing during Stressful Times*

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Abstract

We show theoretically that the interplay between investor behavior (LETF fund flows) and index return autocorrelation ("see-saw effect") plays a central role in either moderating or amplifying the portfolio rebalancing demand of levered and inverse-levered ETFs (LETFs). Rebalancing, in turn, affects the underlying ETF and market-wide volatility. Disagreement between LETF investors and other market participants surprisingly leads to moderation of volatility at the onset of COVID-19 pandemic. However, after the announcement, there was agreement and an amplification of volatility. Furthermore, we observe the amplification in volatility has an informational component and illustrates that LETFs can provide a price discovery channel.

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We show theoretically that the interplay between investor behavior (LETF fund flows) and index return autocorrelation ("see-saw effect") plays a central role in either moderating or amplifying the portfolio rebalancing demand of levered and inverse-levered ETFs (LETFs). Rebalancing, in turn, affects the underlying ETF and market-wide volatility. Disagreement between LETF investors and other market participants surprisingly leads to moderation of volatility at the onset of COVID-19 pandemic. However, after the announcement, there was agreement and an amplification of volatility. Furthermore, we observe the amplification in volatility has an informational component and illustrates that LETFs can provide a price discovery channel.

1. Introduction

Exchange traded funds (ETFs) have become one of the most successful innovations over the last 30 years with more than $4 trillion of assets under management in the U.S.[1] The spectrum of funds range from those passively tracking an underlying index to those utilizing derivative securities offering investors unique return profiles. This rapid innovation has helped make leveraged investments more accessible to investors, particularly retail traders. In addition, leveraged and inverse-leveraged ETFs (referred to generally as LETFs here) – i.e., funds that promise investors some positive or negative multiple of the underlying index return – have grown in importance over the past decade. The LETF frenzy has now even spread to single stock positions.[2] However, its benefits have not come without cost.

Researchers have increasingly documented potential adverse effects of structured product innovations on macroeconomic (market-wide) risk, liquidity, and volatility due to ETF "frictions" such as creation and redemption block unit sizes, possible asynchronous trading, and illiquidity of the underlying securities held by the ETF.[3] Regulators have also raised concerns about the increasing complexity of ETFs and their possible impact on counterparty risk and market-wide risk. However, ETFs have also been shown to improve price discovery (Ahn & Patatoukas, 2022) and LETFs are especially useful in measuring speculative sentiment (Davies, 2022) and investor expectations (Egan et al., 2022) because of their use by extrapolative-type investors (momentum versus contrarian trading).

Accordingly, we formulate a theoretical model that builds upon earlier research on the rebalancing requirements of LETFs and find that the interplay between investor behavior

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[1] See the 2020 Investment Company Institute Fact Book, Chapter 4: https://www.ici.org/pdf/2020_factbook.pdf.

[2] https://on.ft.com/3ppwTJ7

[3] For example, see research on the potential adverse impact of ETFs and LETFs on retail investors (Pessina and Whaley, 2020), systemic risk (Bhattacharya & O'Hara, 2018; O'Hara, 2020), liquidity (Saglam, Tuzun, & Wermers, 2019), and volatility (Shum, Hejazi, Haryanto, & Rodier, 2016). In a 2011 report by the Financial Stability Board, regulators have also raised concerns about the complexity of ETFs and their possible impact on counterparty risk and systemic risk. Also, see Evans, et al. (2017) for more details on the creation/redemption process and its implications for liquidity provision by ETF market makers as well as the underlying securities held by ETFs. A summary of these concerns can be found in Bhattacharya and O'Hara (2020): "These frictions suggest that ETFs are unlikely to be 'innocent bystanders' in markets. Instead, the mechanics of ETF creation and redemption, as well as the very role ETFs play in enabling new types of investment activity, mean that ETFs will actively influence markets."

and return autocorrelation (referred to here as the "see-saw effect") plays a central role in either moderating or amplifying the rebalancing demand. We then empirically analyze the see-saw effect to understand whether it adds noise to the market.

LETFs have been under the microscope because they must actively re-leverage and rebalance their holdings daily to achieve their promised returns to investors over each 1-day horizon, which can lead to market destabilization.[4] For example, Sorkin (2011) documents that rebalancing demand from LETFs led to a 1% run-up (unrelated and incremental to fundamental news) in the last 18 minutes of trading in the S&P 500 on October 10, 2011. More recent studies confirm this end-of-day effect of LETFs on volatility (Shum, Hejazi, Haryanto, and Rodier, 2016; Ivanov and Lenkey, 2018). In an even more dramatic example, Augustin, Cheng, and Van den Bergen (2021) explore the impact of rebalancing demand on concentrated and highly levered "inverse volatility" LETFs such as XIV that were forced to liquidate after a sudden surge in the VIX volatility index on February 5, 2018 (dubbed "Volmageddon").

Although it was not a LETF, the 2021 meltdown of Bill Hwang's concentrated and levered bet on Viacom CBS stock using total return swaps is another recent example of how leveraged derivatives positions similar to the swap positions typically employed by LETFs can magnify volatility in the underlying securities held by a fund.[5] Despite these extreme events involving LETFs and highly leveraged portfolios, the assets under management for LETFs have more than doubled to over $120 billion in the U.S. since the beginning of 2020, as more retail traders entered the market.[6] The consensus of the literature is that an LETF rebalancing typically exacerbates volatility in not only the prices of LETFs but also the underlying securities held by those funds.[7] Therefore, to understand

[4] See Tang and Xu (2013) for details on how LETF returns deviate from their underlying securities' returns and Pessina and Whaley (2021) for the impact on investor returns if the LETF is held for more than day. In contrast to this view, it should also be noted that LETFs can provide benefits by offering a relatively low-cost, liquid vehicle for gaining access to financial leverage for financially constrained investors (Frazzini & Pedersen, 2022) and creating ways to gauge speculative sentiment in financial markets (Davies, 2022; Egan et al., 2022).

[5] See "Inside Archegos's Epic Meltdown," *Wall Street Journal*, April 1, 2021, accessed at: https://www.wsj.com/articles/inside-archegoss-epic-meltdown-11617323530?mod=series_archegos.

[6] See "Global passive assets hit $15 trillion as ETF boom heats up." https://www.ft.com/content/7d5c2468-619c-4c4b-b3e7-b0da015e939d?shareType=nongift

[7] For example, see Shum, Hejazi, Haryanto, and Rodier (2016) which finds that end-of-day volatility is higher when rebalancing trades are a larger percentage of LETF trading volume, especially during more volatile days.

the effect that LETFs have on the market, we must understand the determinants of rebalancing demand.

Cheng and Madhavan (2009) show theoretically that rebalancing is typically in the same direction as the underlying return tracked by the LETF. That is, when the benchmark index returns are high, both positive- and inverse-leveraged ETFs (LETFs) will induce buying pressure on the underlying index. When the index returns are negative, LETFs will induce selling pressure on the underlying index.[8] In contrast, Ivanov and Lenkey (2018) build upon Cheng and Madhavan's model to show that flows in and out of LETFs can also have a mitigating effect on rebalancing demand and, ultimately, on their market impact. These theoretical results, along with the empirical findings of Shum et al. (2016), provide a foundation upon which we develop additional theoretical and empirical insights.

As we describe below, our study contributes to the existing LETF literature in three ways. First, we formulate a theoretical model that builds upon these seminal papers by extending Ivanov and Lenkey (2018) to include a potentially important additional variable related to the *interaction* between index returns and fund flows that can impact rebalancing demand, especially during stressful market conditions such as those caused by the COVID-19 pandemic in 2020 and the Great Financial Crisis of 2008. This theoretical contribution also provides empiricists with a simple expression of rebalancing demand that will help avoid possible misspecification errors. Second, we use this model to understand its empirical implications for how different types of investor behavior, such as "momentum" and "contrarian" fund flows in these LETFs, might affect index-level risk as well as market-wide volatility. Third, we use our framework to see if investor behavior adds volatility and noise to financial markets.[9]

We extend the theoretical understanding of LETFs by showing that the conventional view of rebalancing does not fully consider the complexity of the inter-relationships

[8] This potential impact has garnered the attention of policymakers who are trying to understand and regulate the market due to concerns for retail investors and possible market fragility. An example of the uncertainty that policymakers identify is the case of ForceShares' +4 times levered exchange traded products. On the second of May 2017, the SEC legally approved the creation of the fund. However, on the twelfth of May 2017, the approval was stayed citing the fund's potential systemic impact.

[9] We define noise in the classic sense as non-informational component of price fluctuations. As noted by Black (1986), "Anything that changes the amount or character of noise trading will change the volatility of price."

between index and LETF fund returns. These inter-relationships are driven by leverage (e.g., in opposite ways for positively versus inversely levered funds), fund flows, and rebalancing demand. We develop a theoretical model which suggests that researchers cannot ignore these higher-order, interactive relationships. The model illustrates that a LETF's rebalancing demand is proportional to the "excess" growth in fund assets, which we define as an increase in LETF assets under management over and above the underlying index return. This excess growth is affected in a non-linear and asymmetric manner by: a) the underlying asset's returns, b) the LETF's momentum versus contrarian flow of funds due to the creation/redemption process, c) the interest rates on swap collateral that cannot be ignored in a rising interest rate environment, and d) the interaction amongst these variables. The practical implication of our model is that the impact of LETFs on market-wide volatility is nuanced and can lead to some counter-intuitive effects.

The influence of the interaction of returns and fund flows is separate and distinct from the direct effect of fund flows identified by Ivanov and Lenkey (2018). In this way, our model re-focuses the analysis to synthesize the effects of both Ivanov and Lenkey's (2018) emphasis on fund flows and Cheng and Madhavan's (2009) earlier consideration of index returns. In effect, our model suggests that the expected net impact of returns and fund flows on rebalancing demand presents a middle ground between Cheng and Madhavan's predictions based solely on returns and Ivanov and Lenkey's estimates that are based on returns and flows (but not the return-flow interaction).

In addition, our approach facilitates an empirical analysis of trading behavior (e.g., momentum versus contrarian strategies of LETF investors), where the interactions between fund flows and fund returns determine the net impact of LETFs on volatility. The importance of trading behavior in leveraged ETFs has been noted by recent literature.[10] For example, Davies (2022) uses LETFs to build a sentiment index showing that investors behave in a bullish fashion during down markets and negatively predict returns. Egan et al. (2022) use LETFs to recover the distribution of expected future returns, showing an

[10] This is true not only for LETFs but also for ETFs. Broman (2022) shows that institutional ETF investors trade on style momentum over a one-quarter horizon.

increase in disagreement amongst investors during downturns. Our paper shows that disagreement across markets plays a role in moderating rebalancing demand and can help the underlying price reflect fundamentals more accurately.

In comparison to the theoretical models noted above, our model shows that investor behavior can either "amplify" return volatility in the LETF's underlying index or "moderate" this index volatility depending on the direction of the trading (momentum/contrarian) *relative to* the direction of the underlying index's return auto-correlation. Conceptually, we can think of this as "agreement" or "disagreement" between LETF investors and those investing directly in the underlying index. Our contribution to the theoretical literature identifies the potential stabilizing and destabilizing market impact of the indirect effects of flows, returns, and rebalancing demand on the volatility of the underlying individual indexes tracked by LETFs, as well as their impact on market-wide risk. The implications of our theoretical model of LETFs can help researchers and policy makers better understand the net impact of flows into these funds on market conditions during stressful periods, such as the 2008 Great Financial Crisis and the 2020 COVID-19 pandemic.[11]

As noted earlier, our model also yields insights into how momentum and contrarian investor behavior in these funds can influence volatility. This relationship is consistent with "contrarian" or "buy the dip" investor behavior, as observed in Kelley and Tetlock (2013) and Pagano, Sedunov, and Velthuis (2021), among others. We perform empirical tests and confirm our model's predicted parameters at the cross-sectional level using data on 97 LETFs during the 2006-2020 period. Our estimates provide statistically and economically significant incremental explanatory power in describing market-wide volatility. We also show that this increase in market volatility, however, was not due to increases in noise-related trading behavior.

[11] The intuition for the above insight is based on the idea that fund flows and fund returns that move in the same direction due to momentum trading strategies can reinforce each other for positive LETFs. This occurs because momentum-related flows and fund returns put increased pressure in the same direction to adjust the dollar amount of underlying securities and the leveraged derivatives position that must be held by these funds. Conversely, when investors engage in contrarian strategies such as "buying the dip" in *fund* returns, the effect on rebalancing demand from an increase in a positively levered fund's flow is at least partially offset by these negative LETF returns.

Thus, LETF investor behavior can have an important moderating effect on noise by helping increase the sensitivity of prices to fundamentals. In other words, LETF rebalancing provides a possible channel through which information from LETF trading can be efficiently incorporated into prices, increasing the transmission of news into prices. Changes in LETF trading activity related to rebalancing demand, particularly during volatile market conditions, strengthen price discovery in the overall market.

2. Understanding Exchange Traded Funds

In this section, we briefly discuss the institutional features of ETFs and LETFs that set them apart from other assets.[12] We then build a theoretical model that captures these institutional features to understand more fully why funds rebalance.

ETFs are funds which hold a portfolio of assets and issue funds' own shares or units to investors. ETF shares are traded on exchanges but may also be created or redeemed upon request by large institutional investors through *authorized participants*. In general, ETFs are created to track an index, such as SPY which tracks the S&P 500 index, or an asset class, like GLD, which tracks physical gold bullion. Investors have embraced the unique structure behind ETFs since it gives them greater access to markets which they would otherwise not trade in (Ben-David et al., 2021), relatively lower fees (Box et al., 2020), greater tax efficiency (Moussawi et al., 2020), and better intra-day liquidity when compared to other investment vehicles. Structurally, what sets exchange traded funds apart from other financial products is the share creation-redemption mechanism.

The creation mechanism of shares in an ETF is straightforward. Shares of an ETF are created when *authorized participants* enter a contract with the ETF sponsor to allow it to create or redeem shares directly with the fund. The contract states exactly what mix of assets (*creation basket*) can be exchanged for large blocks of shares (*creation unit*) in the

[12] Interested readers are directed to Lettau and Madhavan (2018) for more institutional details.

ETF. The authorized participant can then turn around and sell these shares or redeem the shares at a later point in exchange for a redemption basket (or cash settlement).

The creation and redemption process allows the secondary market price of shares to remain close to the underlying value of the ETF.[13] This is accomplished by authorized participants taking advantage of arbitrage opportunities between the ETF's market price and the underlying value of the basket of securities held in the fund, which balances the supply and demand and causes the market price of shares in the ETF to closely follow the basket's underlying value. This arbitrage mechanism keeps supply and demand in equilibrium for the end users of the ETFs.

2.1. Institutional Features of LETFs

LETFs also employ the arbitrage mechanism described above. The only difference between ETFs and LETFs is the promise to pay shareholders a multiple of the daily change in the underlying asset's value. Leveraged funds promise a positive multiple (2 or 3 times) while inverse funds promise a negative leverage multiple (-1, -2, or -3 times).

The fund fulfills this promise primarily through rolling derivative contracts. Rolling positions allow the LETF to avoid delivering (or taking delivery of) the underlying basket of securities while maintaining exposure to the underlying index. The derivatives that LETFs employ include total return swaps, futures, and options. A portion of each LETFs net assets is used to meet its collateral requirements.

To maintain the promised leverage, LETFs need to rebalance their positions daily. For example, if the price of the underlying asset has risen on a given day, the NAV of a positively (negatively) levered ETF should rise (fall). As a result, the positively levered ETF will require additional leveraged investment exposure to the underlying asset to account for its relative increase in net assets. Conversely, the negatively levered ETF's

[13] This underlying value of the ETF is the net asset value (NAV), which is defined as the current market value of a fund's total assets after subtracting any liabilities divided by the number of outstanding shares. The NAV is calculated by the administrator once a day at the close of the market and is disseminated daily to all market participants at the same time.

exposure would need to be decreased because its investment holdings provide more exposure than required, relative to its NAV.

Our paper investigates the role that the fund flows from share creation/redemption mechanism has on rebalancing demand. To do this, we build a model in the next sub-section that captures the institutional features of LETFs.

2.2. Modeling Rebalancing Demand

2.2.1. A Decomposition of Rebalancing Demand

LETFs that promise to expose their assets to leveraged and inverse returns of their underlying asset's returns generally rely on total return swaps (Shum et al., 2016).[14] This means that the LETF will enter into a swap agreement with a counterparty that will give the LETF m times the daily change in the underlying index in exchange for a fee.[15] The dollar amount on which the returns and fee are based is called the notional principal, which never exchanges hands. Nonetheless, arbitrage relations ensure that the valuation of the underlying securities and the swap contracts are strictly connected to each other.

We define the assets of the LETF at the end of day t as the product of the number of shares outstanding and the share price of the fund,

$$A_t = N_t^s P_t. \tag{1}$$

The variable L_t represents the notional dollar amount of total return swaps the LETF requires at the end of day t before the market opening the next trading day to generate the promised leveraged return multiple (m) of the underlying return and can be expressed as

$$L_t = mA_t. \tag{2}$$

[14] In addition to swaps, LETFs could use futures or other derivative securities. In general, however, futures contracts do not give LETF's enough customization and do not exist for a gamut of underlying assets. There is also more basis risk associated with imperfect hedging due to differences in pricing or misaligned sale and expiration dates. Leveraged returns can also be produced by trading on margin, however, the costs of this strategy are usually prohibitive. The model's implications are orthogonal to the actual mechanics employed to generate the leveraged returns. See §2.1 of Cheng and Madhavan (2009) for a thorough discussion of the market strategies employed by LETFs.

[15] In practice, the counterparty is often the parent company of the ETF issuer and the fee depends on an interest rate (e.g., the LIBOR or some other short-term reference rate).

To create the desired swap contract the LETF trust will pay an amount to the swap counterparty at the end of the following trading day that is equal to

$$M_{t+1} = (m-1)A_t i_{t+1}, \tag{3}$$

where i_t is the risk-free interest rate over the trading day.

The net return, r_s, that this swap will generate at the end of day $t+1$ is equal to

$$r_s = mr_{t+1} - (m-1)i_{t+1} \tag{4}$$

where r_{t+1} is the unlevered return of the underlying index over the trading day. Like all derivative securities, the value of the swap is equivalent to a market strategy that goes long the underlying and shorts the risk-free rate.[16] In other words, the terms of the swap are equivalent to the LETF trust borrowing M_{t+1} from the money markets to finance buying L_{t+1} of the underlying index. In the LETF literature, Cheng and Madhavan (2009) assume that the transactions are carried out by swaps and ignore any fees paid to the counterparty while Jarrow (2010) more accurately assumes the LETFs borrow from the money markets to buy the underlying index.

This implies that the growth of assets under management over the trading day is composed of two parts. First, the flows in and out of the fund for a specific number of units – the value of which depends on the timing of the creation and redemption process of the fund's AP[17] – and the net return (i.e., the change in price) during the day

$$A_{t+1}/A_t \equiv (1+g_{t+1}) = (1+f_{t+1})[1+mr_{t+1} - (m-1)i_{t+1}]. \tag{5}$$

At the end of trading on t, the LETF will need an updated notional swap (L_{t+1}) amount to continue generating a constant m-times levered return on the following day of trading

$$L_{t+1} = mA_{t+1} \tag{6}$$

The actual notional value, X_{t+1}, of the continuing swap contract from yesterday *before* the update, will evolve over the course of the trading day based on the returns of the underlying benchmark index (r) and the previous day's notional value of the swaps (L_t), as follows:

[16] This equivalency between plain-vanilla swap payoffs and these market transactions was shown by Chance and Rich (1998).

[17] Note that the assumption is that traders are using the beginning day information set to influence their demand for the fund. The stronger the role that the beginning day price plays in their demand-formation, the larger the influence of the interaction effects we will be deriving later in this section.

$$X_{t+1} = L_t(1 + r_{t+1}) \tag{7}$$

The dollar rebalancing demand of the fund is going to equal the difference between the actual notional value of the existing swap contracts at the end of the trading day (determined by historical exposure and realized returns) and the new required notional amount for the following day of trading including the effects of fund flows and return interactions,

$$Rebalancing = \quad L_{t+1} - X_{t+1}. \tag{8}$$

The sign of the deviation between the notional amount and the actual exposure captures whether the fund needs to buy (positive sign) or sell (negative sign) a portion of the underlying index to generate the promised m-times levered return.

Finally, we define the rebalancing demand as a percentage of assets (Δ) and decompose it into the fundamental factors:

$$\begin{aligned}
\Delta_{t+1} &= \frac{L_{t+1} - X_{t+1}}{A_t} \\
&= \underbrace{m(g_{t+1} - r_{t+1})}_{\text{"Excess" Growth}} \\
&= \underbrace{(m^2 - m)(r_{t+1} - i_{t+1})}_{\text{Return Component}} + \underbrace{mf_{t+1}}_{\text{Flow Component}} \\
&\quad + \underbrace{\boldsymbol{m^2(f_{t+1} \times r_{t+1})}}_{\textbf{Return-Flow Interaction}} - \underbrace{\boldsymbol{(m^2 - m)(i_{t+1} \times f_{t+1})}}_{\textbf{Interest Rate-Flow Interaction}}
\end{aligned} \tag{9}$$

The model shows that rebalancing demand is proportional to the "excess" growth of assets under management over the underlying index return and that this excess growth is affected in a non-linear and asymmetric way by the underlying asset's returns, fund flows via the creation-redemption process, and interest rates. These factors are also moderated by the complex interactions between them. The "excess growth" expression of rebalancing demand shown in equation (9) provides empiricists with a simple formula that captures the entirety of rebalancing demand rather than having to rely on the less detailed return approximation used in prior research.

2.2.1.1. Numerical Example

The following numerical example explains the dynamics of rebalancing demand. Suppose that a 3-times positively levered LETF has 100 shares outstanding and the underlying benchmark index price is at \$1, thus implying an initial value of assets, A_t, equal to \$100; initially assuming that investor demand equals supply such that there are no net share creations or redemptions, and that the LETF faces zero costs to enter in the total return swap (TRS) following Cheng and Madhavan (2009). The required notional amount, L_t, for the total return swap to generate the levered return is \$300 (or 3 times \$100). Suppose further that the benchmark index falls to 90¢ by the end of the trading day. This will cause the assets to fall in value to \$70, reflecting a 30% drop in its value (3 times r_t of 10% underlying price drop), whereas the exposure of the TRS, X_{t+1}, falls to \$270, reflecting a 10% drop in its value. Meanwhile, the required notional amount for the TRS swap for the next day, L_{t+1}, is \$210 (or 3 times A_{t+1} of \$70), which means the LETF will need to reduce its exposure of TRS by \$60 (\$270 minus \$210) at the end of the trading day.

Now let us relax the equilibrium assumption and look at what would happen if investor demand at the beginning of day t+1 for the LETF caused an additional 5 shares to be created. Although the 5 new shares will be associated with an investment of \$5 initially, the dollar value of the 5 new shares has dropped to \$3.50 by the end of the trading day. In this case, the net asset value of the fund A_{t+1} falls to \$73.50, reflecting the per share asset value of 70¢ times the 105 shares actual shares outstanding at the end of the day. In other words, the fall in the LETF's asset value due to the decrease in price of the underlying benchmark index is offset by only a \$3.50 increase in investor demand (\$0.70 times 5) instead of \$5 due to the impact of intra-day returns. The required notional amount for the TRS swap for the next day, L_{t+1}, is now \$220.50 (\$73.50 times 3), which means the LETF will need to reduce its exposure of the TRS by \$49.50 rather than the \$60 if there was no creation/redemption activity due to funds flow and its interaction with returns.

If we were to use Ivanov and Lenkey's model, the dollar rebalancing would be \$45. Why does their model differ from ours? The reason the models differ is due to the way flows are defined. Ivanov and Lenkey define capital flows as the dollar flow as a fraction of assets. This is akin to assuming that the additional shares that are created are bought at the price at the *beginning* of the day. However, this assumption is problematic. Firstly, creation and redemption take place at the *end* of the trading day, and the "investment gap" of \$4.50 between our model and Ivanov and Lenkey's arises because the shares are executed at the price at the end of the day.[18] Secondly, share creation/redemption is done in fixed discrete blocks (Evans, Moussawi, Pagano, and Sedunov, 2020). Although more than 70% of the ETFs traded in the United States have creation units with blocks of 50,000 ETF shares, a few ETFs have larger creation units, equivalent to more than 100,000 shares (Ben-David et al. 2017). The more natural way to think about capital flows in this setting is therefore in terms of *shares outstanding* rather than *dollar flows*. This can even be seen in Ivanov and Lenkey's empirical definition of flows which is based on the growth of shares and apparently inconsistent with its theoretical counterpart (see fn. 10 on p. 39 and Section 4.3 on p. 41 of their paper).

This does not mean that Ivanov and Lenkey's model is incorrect. What it suggests is that their model is an approximation, in the same way Fisher's interest rate relation is approximated in practice when analysts drop the interaction term between inflation and the real interest rate. However, it does mean that the interaction term is necessary to avoid model misspecification, especially for larger leverage multipliers, by using share and dollar investments interchangeably for creation and redemption. Our paper shows that the multiplicative effect is an important determinant of rebalancing demand that can have economically significant effects on the volatility of underlying indexes and market-wide measures. And these effects are dependent on investor behavior during stressful times which can amplify or dampen market volatility.

[18] Investment gap is defined as the difference between the expected investment in a fixed number of LETF units with 0 returns versus the actual investment incorporating the effect of non-zero returns on a per share LETF price.

2.2.2. Investor Behavior and the Dynamics of Rebalancing Demand

In order to investigate how investor behavior impacts rebalancing demand in a simple setting, we impose the following structure which is common in the literature. Let the return of index i be an $AR(1)$ process

$$r_{i,t+1} = \phi_i r_{i,t} + w_{i,t+1}, \tag{10}$$

where ϕ_i is the daily autocorrelation of index i and $w_{i,t+1}$ is a normally distributed mean-zero return innovation with a standard deviation of σ_w. The return of the $m \in \{-3,-2,-1,2,3\}$ multiple fund j is defined as

$$r_{j,t+1} = m_i r_{i,t+1}. \tag{11}$$

Investor flows into the m multiple fund j is assumed to be an affine function of yesterday's return on the fund,

$$f_{j,t+1} = \theta_j r_{j,t+1} + u_{j,t+1} \tag{12}$$

and substituting equation (11) into the definition of the return on the fund, we get the following

$$f_{j,t+1} = \theta_j m r_{i,t} + u_{j,t+1} \tag{13}$$

where $\theta_j$is the investor behavior of fund j denoting momentum behavior ($\theta_j > 0$) i.e., fund inflows with positive returns (and outflows with negative returns) or contrarian behavior ($\theta_j < 0$) i.e., fund outflows with positive returns (and inflows with negative returns) and $u_{j,t+1}$ is a normally distributed mean-zero flow innovation with a standard deviation of σ_w. As derived earlier in equation (9), fund j has the following rebalancing demand in order to meet the promised return if we set the swap's interest rate to zero: [19]

$$\Delta_{j,t+1} = \left(m_j^2 - m_j\right) r_{i,t+1} + m_j f_{j,t+1} + m_j^2 r_{i,t+1} f_{j,t+1}, \tag{14}$$

[19] The rationale for this is presented in Table A2 of the Internet Appendix, which presents results from estimating the empirical counterpart of the rebalancing demand decomposition described by equation (9). As expected, the coefficients are the deterministic functions of the leverage multiples we have identified. Furthermore, the interaction term does matter in explaining rebalancing demand. Only the interest rate-to-fund flow interaction is not statistically significant. This result is expected because risk-free interest rates have been at historical lows during most of our sample period. Due to this finding, we ignore the effect of interest rates in the subsequent analyses. However, during times of high interest rates these terms may play a larger role as the theoretical model predicts.

Our goal is to understand the dynamics of this system. The system described above captures the intuition that prior day returns impact rebalancing demand directly through its effect on contemporaneous returns (*return channel*) and indirectly through its effect on flows (*flow channel*). Therefore, we are interested in analyzing:

$$\frac{d\Delta_{jt+1}}{dr_{it}} = \frac{\partial\Delta_{j,t+1}}{\partial r_{i,t+1}}\frac{dr_{i,t+1}}{dr_{it}} + \frac{\partial\Delta_{j,t+1}}{\partial f_{j,t+1}}\frac{df_{j,t+1}}{dr_{it}} \tag{15}$$

Proposition 1 (The Expected Dynamic Reaction of Rebalancing Demand). *The effect that returns have on rebalancing demand depends on the autocorrelation of returns ϕ, and investor behavior θ, the multiple of the fund m, and on the level of returns r_{it}*

$$\frac{d\Delta_{jt+1}}{dr_{it}} = (m^2 - m)\phi + \theta m^2 + 2m^3\phi\theta r_t \tag{16}$$

Remarks. According to Proposition 1, the main *return* channel can amplify or moderate rebalancing demand depending on the autocorrelation of returns. This result sheds an important, and different light, on recent LETF literature. We show that the dynamic effect hinges on the sign of the autocorrelation of returns (ϕ). Positively autocorrelated indexes will amplify rebalancing demand while negatively autocorrelated indexes will be moderated, regardless of the sign of the multiple m. Similarly, the main *flow* channel can amplify or moderate depending on the sign of the correlation between current and past fund flows, θ. Momentum behavior in terms of fund flows ($\theta > 0$) will amplify rebalancing demand while contrarian behavior ($\theta < 0$) will moderate.

The *interaction* effects depend on the sign of the leverage multiple as well as the sign of the product of the autocorrelation of the index (ϕ) and the fund's investor behavior (θ). When there is disagreement between the signs, there will be a reduction (increase) in the impact for positively (negatively) levered funds. Furthermore, the sign and magnitude of returns (r_{it}) also impact the interaction effect. While the interaction effect will be relatively unimportant during normal times, it will grow in economic importance on highly volatile days that coincide with a large magnitude of positive or negative returns.

Our analyses show that this framework is an important theoretical contribution to the literature. The model is more than a simple extension of prior work and represents a deepening of the prior models that allow us to tease out more subtle, nuanced effects between a fund's returns, flows, and volatility. Next, we turn to analyzing the total contemporaneous impact of price fluctuations on rebalancing demand. This will allow us to link the fund dynamics to the static return effect.

Proposition 2 (The Amplification Ratio ζ). *The change in rebalancing demand when the underlying index experiences a price fluctuation is a function of the leverage multiple and a term that measures the amplifying or moderating effect that return and flow dynamics have on rebalancing demand, denoted as the "amplification ratio," ζ. This term depends on the product between a ratio composed of the leverage multiple and a ratio between the dynamic autocorrelations:*

$$\frac{d\Delta_{t+1}}{dr_{t+1}} \equiv \Gamma_{t+1} = \left(1+\zeta_{t+1}\right)(m^2-m) \qquad \text{where, } \zeta_{t+1} = \left(\frac{m}{m-1}\right)\frac{\theta}{\phi} + \left(\frac{2m^2}{m-1}\right)\theta r_t \tag{17}$$

Proof. Se Appendix A

Remarks. The amplification ratio ζ equals -1 when the return and flow dynamics perfectly offset the effect from the leverage ratio, *m*, and +1 when the dynamics amplify the leverage ratio. When the ratio is negative (positive), there is a moderating (amplifying) effect between the return-flow dynamics and leverage. Therefore, to understand when LETFs are adding noise to markets, we will be using this amplification ratio.

Fundamentally, what is driving the amplification ratio are expectations of future returns for the LETF and its underlying index. If index returns are positive following a trading day with positive returns, the first-order effect is an increase in demand from traders inducing momentum and therefore will lead to a positive numerator. If LETF investors see a positive return in the underlying index and their demand is such that new shares are created, it means that they are following a momentum strategy. In this case, the amplification ratio will be positive, causing increased buying or selling pressure (depending on the direction of the daily returns). If expectations between traders in these two markets are of the *opposite* sign, e.g., momentum in the underlying index and contrarian in the LETF market, then this will actually lead to a *moderation* of buying and selling pressure.[20]

It should also be noted that under the null of no predictability of returns, ($\phi = 0$), the first term of the ratio is undefined, meaning that there is no impact from yesterday's return on today's rebalancing demand while investor behavior still plays a role. In a more extreme version of exactly zero predictability, the ratio can explode if $\phi \approx 0$ and $\theta \gg 0$ and the ratio can lose economic meaning. However, we argue that in an efficient market, investors will know that predictability is weak (but non-zero) and therefore adjust their behavioral parameter to match the degree of predictability. In that case, this corresponding movement will keep the ratio from exploding and rendering it uninformative.[21]

Recent research has shown that information signals can play a vital role in generating momentum and contrarian behavior. For example, Kyle, Obizhaeva, and Wang (2022) propose a model in which investors trade on not only long-term fundamentals but also speculate in the short-term based on their expectations of future disagreement. This setup induces momentum/contrarian behavior in asset prices. Our framework shows that these informational bets can either exacerbate or dampen rebalancing fluctuations.

Overall, the relationship between a derivative's Γ and volatility has been theoretically shown to be positive via a feedback effect.[22] In our context, this means that the sensitivity of rebalancing demand (Γ) to return shocks will be positively related to volatility. Since the

[20] The second order effects will have a differing impact depending on the sign of the leverage multiple. For negatively levered LETFs, momentum after an up day leads to a moderating effect. For positively leveraged LETFs, contrarian behavior after an up-day or momentum behavior after a down day lead to moderating effects. Note however that the magnitudes of the second order effects are relatively small. Hence, we will ignore these effects for the empirical work that follows.

[21] While we believe it is a fruitful area of future research, this is beyond the scope of our current paper.

[22] The options literature has shown that options can feedback into underlying volatility and underlying liquidity and that the feedback effect depends on the derivative's Gamma (see, e.g., Ni et al., 2021; Huang et al., 2023).

amplification ratio ζ is positively related to Γ, we would also expect a positive relation between volatility and the amplification ratio.

3. Data Description and Summary Statistics

Our study uses two main sources of data: Bloomberg and CRSP. The first data set is used to identify the fund universe of interest and contains the bulk of information about the funds. The second data set was used to complement the data from Bloomberg with additional variables of interest. We supplement these two main sources with additional data from Compustat, OptionMetrics, FRED, and the Fama-French data available on Dr. French's website.[23] Our sample period is from June 2006 (inception month of the first leveraged ETF) until December 2020.

3.1. Data

We first obtain a list of all U.S. equity ETFs from Bloomberg and identify 963 ETFs. We remove 134 ETFs without benchmark index identifiers. From this sample of 829 ETFs, we remove 5 ETFs with insufficient data because they have an inception date of 12/30/2020 or 12/31/2020. Our final LETF universe contains a total of 97 LETFs, of which 48 are positively levered ETFs and 49 are inverse LETFs. For each fund and underlying index, we obtain shares outstanding, NAV, and market capitalization from Bloomberg. From CRSP, we get daily share price, return, volume, shares outstanding, and split-adjustment factors to adjust the series from CRSP. Because of possible data errors, we remove data with a two-day trading window around share splits.

We use total shares outstanding at day-end to measure the fund flows (share creations/redemptions) of each ETF at the daily level. Bloomberg is more accurate and timelier in updating ETF shares outstanding when newly created or redeemed shares are cleared with the Depository Trust & Clearing Corporation (DTCC). Therefore, Bloomberg

[23] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

is our primary source for shares outstanding and NAVs. We use Compustat and OptionMetrics to complement the ETF series when there are gaps in the Bloomberg data.[24]

3.2. Control Variable Data

As a proxy for interest rates, we use the one-month LIBOR rates available from FRED. To proxy for expected volatility, we use the daily VIX series available from FRED. We calculate Amihud's illiquidity metric using data from CRSP. We use market returns from the Fama-French daily data set.

3.3. Summary Statistics

To understand the importance of LETFs, Panel A of Figure 1 plots the assets under management of leveraged and inverse funds. Assets under management have experienced tremendous growth since the first LETF was introduced in the middle of 2006. Assets have shown an annual compounded growth rate of 54% from June 2006 to December 2020, growing from $0.21 billion to $113 billion. We can also see that inverse LETFs dominated the landscape during the 2008 financial crisis, while positively levered ETFs became more important during the subsequent bull market. Both leveraged and inverse ETFs are growing in importance since 2018. To understand our first research question, Figure 1 Panel B plots the aggregate dollar flows for positively levered and inverse ETFs. We can see that the flows are consistent with contrarian strategies for the former and momentum trading for the latter during recessions. The correlations between these two sets of aggregate fund flows flips to +77% during the Covid pandemic from its usually negative value (-31%) for the period prior to 2020 and is negative and closer to zero for the full sample period (-6%). In contrast, the correlation between these two sets during the 2008 financial crisis is -10%.

Table 1 presents the descriptive statistics for the LETF funds both for our full sample and the recession subsample. Positively leveraged ETF became smaller in asset size while inverse leveraged ETFs became larger in terms of market capitalization during recessions.

[24] A special thanks to Rabih Moussawi for providing us with this data.

However, fund flows into both positively leveraged and inverse ETFs became larger during recessions. Additionally, we can see that flows became more volatile as the standard deviations for both types of LETFs increased dramatically during the crisis periods. The negative relationship between fund flows and benchmark returns for positive LETFs is consistent with contrarian trading while this same negative fund-return relation for inverse LETFs suggests momentum behavior from investors (because lower index returns translate into higher inverse LETF returns). Finally, we can also see that there was an increase in swap selling (buying) pressure as the rebalancing demand for inverse (positively) leveraged ETFs was negative (positive) due to large negative returns during recessions despite contrarian flows.

4. Main Results

In this section, we investigate whether LETFs increase noise in markets by first examining whether the theoretical decomposition we derived in Section 2 is supported by our LETF data set. We then turn to exploring how the see-saw effect impacts market volatility and market efficiency.

4.1. The Moderating Effects of Flows on Rebalancing Demand

To empirically investigate amplification and moderation of rebalancing demand, we use the amplification ratio of equation (17), as defined earlier, assuming a baseline effect of prior-day return of zero, to examine the overall net impact on volatility :[25]

$$\zeta = \frac{m}{m-1}\frac{\theta}{\phi} \tag{18}$$

[25] Even though the evidence presented in Internet Appendix Table A2 shows that the interaction term between returns and flows matters in explaining rebalancing demand, given its relatively small magnitude, the analysis going forward presumes a baseline prior day return of zero.

For each fund, we run the following regressions to estimate investors' momentum versus contrarian behavior parameter θ and the underlying index return autocorrelation parameter ϕ,

$$\begin{aligned} f_t &= \alpha + \theta m r_{t-1} + u_t \\ r_t &= \kappa + \phi r_{t-1} + e_t \end{aligned} \tag{19}$$

using a 90-day rolling window. This allows us to extract a time-series of both parameters based on equation (19). We also create an aggregate variable for positively levered and inverse funds by taking the asset-weighted sum for each day, giving us a daily time-series for each respective market.

Table 2 presents the summary statistics of this procedure. We can clearly see that all the underlying indices exhibit negative daily return autocorrelation, on average. In contrast, investor behavior does not have a strong discernable pattern, with different segments of the market showing momentum and contrarian behavior. When we look at the aggregate estimates of θ and ϕ, we find that there seems to be more contrarian investment behavior in fund flows from LETF investors as well as negative autocorrelation in the returns for the underlying index. For investors in the aggregate LETF market, there tends to be an increase in fund flows following days with price decreases and returns tend to mean-revert over our sample period. This means that there is, on average, an increase in the amplification ratio and therefore an increase in volatility. However, increases in volatility might not necessarily increase noise because they could be helping prices impound new information signals. A good example to understand this relationship dynamic can be seen by examining the time-series.

Table 3 presents two-stage regressions to test for the statistical significance of the estimate parameters with flows and returns as the dependent variables. In the first stage, we run the time-series regressions for each fund to get their estimated sensitivity to investor behavior θ and return autocorrelation ϕ. . We then aggregate the estimates of θ and ϕ to get market and leverage-multiple parameters for each day using a Fama-MacBeth cross-sectional approach. We then find the average parameter value over time. We can see that the estimated parameters are statistically significant, with an average estimate of about -1 percent for both parameters.[26] Given that, on average, investors behave in a contrarian fashion and index returns are negatively autocorrelated with similar magnitudes, we see that the amplification ratio is not statistically significant. However, there is substantial time series variation, meaning that although it might not be important on a daily basis, there are times where the amplification ratio plays an important role.

To show this, Figure 2 plots the time series of the amplification ratio in addition to θ and ϕ individually for the full sample (panel a) and the 2020 subsample (panel b). We can see that investors seem to oscillate periodically from momentum to contrarian behavior in terms of fund flows while the daily return autocorrelation is typically negative. The interplay between both variables, which we term the see-saw effect, determines whether there is an amplification effect or moderating effect. Focusing on the 2020 subsample in Panel c, we see a big spike downwards in the ratio, which dipped about 1.5 standard deviations to around -10% and then sky-rocketed 5 standard deviations upwards to around +15%. This occurred because indexes exhibited positive return autocorrelation while investors continued a pattern of contrarian trading following the market declines during the post-February 19, 2020 period. That is, it appears that many investors engaged in "buy the dip" behavior at that time. However, by March 13, 2020, we see large swings towards negative return autocorrelations, as uncertainty about the pandemic and lockdowns increased. It took until August 2020 for the ratio to return to more normal levels of around zero.

4.2. The Effects of Investor Behavior on Noise in Markets

To understand what kind of effect that investor behavior in LETFs has on noise in financial markets, we study the impact on volatility and price discovery. In the first case, we regress index return volatility on the amplification ratio using the LETF panel data set in two ways. First, we regress index-specific returns on *fund*-level amplification ratios and, second, market-wide aggregate volatility is regressed on the aggregate amplification ratio. In

[26] In Table B15 we include additional flow lags to control for strategic share redemptions (Evans et al., 2021), and additional return lags when estimating the investor behavior parameter (Broman, 2022). The results are statistically and qualitatively similar.

addition, to explore the impact on the market's informational efficiency, we regress the five-day variance ratio on the amplification ratio both in a fund-level panel setting and the aggregate setting. We expect to find a *positive* relationship between our ratio and volatility. The evidence of increased volatility, however, does not necessarily mean increased noise. For example, we would expect to find a positive relationship between the variance ratio and the amplification ratio if there was an increase in noise. In contrast, we expect a negative relationship between these two ratios if informational efficiency was improved.

In Table 4, we present the results of regressing index volatility measured over the prior 5 days on the amplification ratio, interacted with various crisis dummies, and controlling for other factors influencing volatility. Column (1) shows that over our entire sample, the weekly volatility measure is positively related to the amplification ratio. We can also see that the amplification ratio is positively related during non-crisis periods when we include a dummy equal to one whenever the underlying index experiences a return that is more than 2 standard deviations away from its average in column (2). We also control for the Great Financial Crisis of 2008 in column (4). Columns (3) and (5), however, suggest that when we include a dummy for both the Great Financial Crisis of 2008 and for the COVID recession in 2020, there is no relationship between weekly volatility and the amplification ratio. The coefficient in the second row of Table 4 captures the change in the relationship during crisis periods. We can see in columns (2) and (5) that during the COVID crisis period, the positive volatility-amplification relationship strengthened. This finding suggests that the impact of rebalancing demand on volatility is episodic in nature and has a greater effect during stressful market conditions like those during the COVID period. The results also show that volatility is positively related to the amplification ratio we derived in Proposition 2, which is consistent with the options literature predictions of Ni et al. (2021), among others.

In Table 5, we break down the sample by looking at important subperiods to understand if there are any periods where this volatility-amplification relationship is strengthened. We are interested in distinguishing between days with large positive standard deviation movements and large negative standard deviation days. We are also interested in studying the COVID period by dividing it into three distinct blocks: (1) the pre-COVID period running from February 19 to March 13, 2020; (2) the "in-COVID" crisis period running from March 14 to March 30, 2020; and (3) the post-COVID period from April 1 to December 31, 2020. We find evidence that throughout these subperiods, there is a positive relationship between weekly volatility and the amplification ratio. Positive return days see more increases and so does the pre-COVID period.

Since the relationship between the amplification ratio and daily rebalancing demand is dynamic, we would expect to see stronger results by looking at a *longer* horizon to calculate volatility. Table 6 presents the estimates from regressing *monthly* index volatility on the amplification ratio. We can still see a significant and positive relationship across all specifications except for column (5). Table 7 shows that during the most intense moments of the COVID market reaction, the volatility-amplification relationship turned negative, which suggests contrarian trading behavior. It then became positive and significant once again during the post-COVID period. This shows that rebalancing demand impacts not just weekly volatility but also has effects on longer-term volatility as well, consistent with the predicted relationship between the amplification ratio and volatility derived in Proposition 2.

Taking all these results into account, there appears to be conclusive evidence that, in general, LETF markets do increase volatility and this volatility becomes elevated during crises. Additionally, there are some time periods (e.g., COVID) where LETF markets can actually *decrease* volatility, possibly due to contrarian "buy the dip" behavior. The predominant evidence of elevated volatility, however, does not necessarily indicate the presence of increased noise in the markets. It could be the case that higher volatility is induced because prices are reacting more strongly to fundamental news.

Therefore, in order to understand whether LETFs increase noise in the overall market, we use variance ratios to study the impact of amplification on price discovery. On day t, index i's variance ratio is defined as

$$VR_{it} = \left| \frac{Var(r_{it}^5)}{5 \cdot Var(r_{it})} - 1 \right| \tag{13}$$

where the numerator is the variance of the 5-day return and the denominator is 5-times the variance of the one-day return. In a perfectly efficient market, the numerator and denominator should be the same and thus equal to 1.0. Therefore, we can use absolute deviations of this ratio from 1.0 as a simple measure of the impact of LETF amplification on non-fundamental volatility. If LETFs add noise to prices, the absolute value of the deviation in the variance ratio should be *positively* related to amplification.

The evidence presented from running this test is displayed in Table 8. We can see that during normal times, there is no relationship between amplification and variance ratios. However, when we look at the crisis periods, we can see that the amplification ratio is *negatively* related to our variance ratio metric under all definitions, except for the Great Financial Crisis of 2008, where the relationship was positive. Table 9 shows that this negative relation holds for almost all the crisis sub-periods. The only time when there was no effect (i.e., no improvement or deterioration in market efficiency) was during the pre-COVID and in-COVID subsamples.

Taken together, the evidence from the panel regressions allows us to conclude that amplification, driven by the difference in the autocorrelation parameters between index returns and LETF flows, does *not* increase noise, but helps improve the informational efficiency of financial markets during crisis periods by increasing the sensitivity of prices to fundamental news.

Next, we are interested in seeing if an aggregate measure of amplification impacts market-wide expected volatility and if it increases market efficiency in general, and not just for the underlying index.

Table 10 presents the estimates of regressing VIX on the aggregate amplification ratio. Column (1) shows an unconditional positive effect. Looking at the other columns, we see that during non-crisis periods, increases in the aggregate amplification ratio are associated with jumps in expected market volatility. This effect rises during NBER-defined recessions and the Great Financial Crisis of 2008. However, in general, high volatility days are associated with moderating effects from LETFs. Finally, there is no discernable transmission of volatility from LETFs to a broader measure of market volatility during COVID.

Table 11 shows similar patterns for other sub-samples of our analysis. During the pre-COVID period, there is a negative and significant relationship while the post-COVID period shows a positive relationship. Therefore, we can see, at the aggregate level, that the relationship between expected volatility and LETF markets is moderated during times of crisis. Table 12 confirms that this moderation at the aggregate level is due to increases in price discovery during times of crisis. In contrast, the amplifying effect dominates during normal times, and, in these situations, this amplification effect adds noise to the markets. Table 13 shows that the aggregate market efficiency was improved for all subsamples except for the in-COVID period. However, there is no evidence of a deterioration in overall informational efficiency. These results confirm the findings of our prior tables, showing that the differences in behavior between index investors and those who invest in LETFs can reduce noise in the market, especially during crisis periods. This is an important finding as it suggests that increases in LETF trading activity, especially during stressful market conditions, can improve price discovery in the overall market. Thus, LETFs can provide useful benefits to financial markets despite possible increases in volatility due to heightened buying/selling pressure associated with changes in rebalancing demand.

5. Robustness and Additional Analysis

We present additional results and robustness tests in our internet appendix. Appendix A contains additional summary statistics for different subsamples of our data. Appendix B contains robustness tests comparing our models to the extant models; looking at the impact that rebalancing demand has on volatility; and controlling for a host of variables such as the presence of option markets (e.g., Barbon, Beckmeyer, Buraschi, and Moerke, 2021), expected volatility (e.g., Shum et al., 2016), strategic share redemptions (Evans et al., 2021), and additional return lags when estimating the investor behavior parameter (Broman, 2022). The results of these additional battery of tests are supportive of the main findings reported here.

6. Conclusion

In this study, we develop a novel theoretical model which highlights the importance of taking into account non-linear interactions between fund flows and returns for levered ETFs (LETFs). Furthermore, we show that momentum/contrarian trading at the fund level and the autocorrelation of underlying index returns can moderate rebalancing demand and reduce noise in asset prices. Using this framework, we analyze the effects of LETF rebalancing empirically. We find that these moderating effects are strong before the COVID-related turmoil of 2020, as investors exhibited both momentum and contrarian behavior during this stressful period.

Overall, the results, both for the full sample and crisis periods, are consistent with our theoretical model and demonstrate the importance of incorporating non-linear, interactive effects. Thus, from a policy perspective, both regulators and investors should consider taking into account the relationship between investor behavior and return autocorrelations when estimating the effects of daily LETF rebalancing on market-wide volatility. Agreement between both markets will amplify volatility while disagreement will moderate volatility, suggesting a differential approach towards containment. Furthermore, our results show evidence that LETF's can provide a channel through which news can be efficiently incorporated into prices. This could be due to traders using LETFs to make leveraged bets based on their private information signals. The dynamics induced by this trading could then be channeled and fed back into prices through rebalancing demand.

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Appendix A. Proofs

Proof of Proposition 2. We want to re-express the sensitivity of rebalancing demand to a contemporaneous return shock so as to incorporate return and flow dynamics. To do this, we first start off with the original expression multiply through by one in some opportune places

$$\begin{aligned}\Gamma_{t+1} &\equiv \frac{d\Delta_{t+1}}{dr_{t+1}} \\ &= \frac{d\Delta_{t+1}}{dr_{t+1}} \cdot \frac{\frac{d\Delta_{t+1}}{dr_t}}{\frac{d\Delta_{t+1}}{dr_t}} \\ &= \frac{d\Delta_{t+1}}{dr_{t+1}} \cdot \frac{\frac{d\Delta_{t+1}}{dr_t}\cdot}{\frac{d\Delta_{t+1}}{dr_t} \cdot \frac{dr_{t+1}}{dr_{t+1}}}\end{aligned}$$

We then substitute in the derivatives to get

$$(m^2 - m)\left[\frac{(m^2 - m)\phi + \theta m^2 + 2m^3\phi\theta r_{it}}{(m^2 - m)\phi}\right]$$

Simplifying gives the final expression. ■

Table 1
Summary Statistics

This table reports summary statistics for ETF-level size, returns, fund flows, and rebalancing demand. Panel A shows the number of funds in our entire sample, which includes inverse ($m < 1$), positively levered ($m > 1$), and unlevered ($m = 1$) ETFs, as well as the total number of fund-day observations. Panel B shows the summary statistics for the inverse LETF subsample ($m \in \{-3, -2, -1\}$). Panel C focuses on ETFs that have positive leverage multiples ($m \in \{+2, +3\}$). The mean, standard deviation, 1st percentile, 50th percentile, and 99th percentile are presented for our entire sample period beginning in June 2006 until December 2020 and for the crisis subsample. The crisis subsample includes the Great Financial Crisis of 2008 starting July 1, 2007 and ends August 30, 2009 and the COVID-19 crisis starting February 19,2020 to April 30, 2020.

Panel A. Sample Size							
	Leveraged	$m = -3$	m	m	-	$m = 2$	$m = 3$
ETFs	97	18	18	13	-	20	28
Obs. (Fund-	260,584	39,774	62,486	37,722	-	67,448	53,154
Panel B. Inverse LETFs ($m < 1$)							
Full Sample		Obs.	Mean	St. Dev.	$P_{1\%}$	$P_{50\%}$	$P_{99\%}$
Rebalancing Demand (%)		139,982	-0.09	16.36	-50.67	0.36	43.65
Flow (%)		139,982	0.18	4.36	-5.40	0.00	10.58
Benchmark Return (%)		139,982	0.04	1.58	-4.53	0.08	4.52
Fund Return (%)		139,982	-0.10	3.42	-10.02	-0.15	10.16
Shares Outstanding (m)		139,982	3.48	11.29	0.00	0.34	57.63
log(Market Cap. [$m])		139,982	3.99	1.83	0.83	3.90	7.73
Crisis Subsample							
Rebalancing Demand (%)		13,239	-1.06	27.65	-95.47	-0.02	78.51
Flow (%)		13,239	0.39	6.55	-8.72	0.00	25.45
Benchmark Return (%)		13,239	-0.08	3.36	-10.11	-0.01	9.40
Fund Return (%)		13,239	0.11	6.62	-19.38	0.00	19.74
Shares Outstanding (m)		13,239	2.12	9.10	0.00	0.19	46.65
log(Market Cap. [$m])		13,239	4.50	1.74	1.08	4.34	8.06
Panel C. Positively Levered ETFs ($m > 1$)							
Full Sample		Obs.	Mean	St. Dev.	$P_{1\%}$	$P_{50\%}$	$P_{99\%}$
Rebalancing Demand (%)		120,602	0.32	12.12	-29.65	0.23	31.28
Flow (%)		120,602	0.05	3.74	-7.10	0.00	5.68
Benchmark Return (%)		120,602	0.05	1.59	-4.53	0.08	4.51
Fund Return (%)		120,602	0.11	3.92	-11.33	0.20	11.21
Shares Outstanding (m)		120,602	17.84	48.51	0.01	3.02	213.98
log(Market Cap. [$m])		120,597	4.68	1.69	1.23	4.76	7.92
Crisis Subsample							
Rebalancing Demand (%)		10,684	0.93	19.47	-49.74	0.06	68.1
Flow (%)		10,684	0.54	5.87	-1.95	0.00	27.60
Benchmark Return (%)		10,684	-0.08	3.41	-10.29	-0.01	9.66
Fund Return (%)		10,684	-0.24	7.78	-23.81	-0.01	21.92
Shares Outstanding (m)		10,684	43.45	121.72	0.04	3.51	691.20
log(Market Cap. [$m])		10,679	4.35	1.72	1.25	4.22	8.09

Table 2
Investor Behavior and Autocorrelation Parameters: Fund Level Summary Statistics

This table reports the summary statistics from the fund level rolling estimation of the investors' momentum versus contrarian behavior parameter θ and the underlying index return autocorrelation parameter φ. For each fund, we run the following regressions

$$f_t = \alpha + \theta m r_{t-1} + u_{t+1},$$

$$r_t = \kappa + \varphi r_{t-1} + e_{t+1},$$

using a 90-day rolling window. This allows use to extract a time-series of both parameters. We linearly interpolate all zero flow days and include lagged flows in the regression to correct for any autocorrelation induced by the procedure. To create the aggregate parameter values, we take the asset weighted sum for each day,

$$\Theta_t = \sum_j \frac{a_{j,t}}{A_t} \Theta_{j,t}$$

where a_{jt} is the assets under management of fund j, the sum $A_t = \sum_j a_{j,t}$ is the total assets under management in the leveraged ETF space, $\Theta_{j,t}$ is the estimated parameter for fund j on day t, and Θ_t is the aggregate parameter value on day t. We use the $\log(1+\Theta)$ transformation to scale the parameter values.

Leverage (m)	Obs. (Fund- days)	Parameter	Mean	St. Dev.	$P_{1\%}$	$P_{50\%}$	$P_{99\%}$
-3	40,427	θ	0.08	0.18	-0.24	0.04	0.82
		ϕ	-0.04	0.09	-0.38	-0.03	0.14
-2	60,902	θ	0.00	0.12	-0.35	0.00	0.23
		ϕ	-0.05	0.09	-0.35	-0.04	0.14
-1	36,578	θ	-0.03	0.09	-0.40	0.00	0.20
		ϕ	-0.05	0.09	-0.36	-0.04	0.14
2	65,688	θ	-0.01	0.09	-0.32	0.00	0.22
		ϕ	-0.05	0.09	-0.35	-0.04	0.14
3	53,309	θ	-0.07	0.25	-1.05	-0.02	0.23
		ϕ	-0.05	0.10	-0.39	-0.03	0.14
Daily Aggregate	3,566	θ	-0.01	0.01	-0.02	-0.01	0.02
		ϕ	-0.01	0.02	-0.04	-0.01	0.03
		Amplification	0.00	0.03	-0.04	0.00	0.09

Table 3

Investor Behavior and Autocorrelation Parameters: Fama-Macbeth Estimation

This table reports the estimated parameters from a Fama-Macbeth two-stage estimation of the investors' momentum versus contrarian behavior parameter θ and the underlying index return autocorrelation parameter ϕ. In the first stage, we run the following regressions on a fund-by-bund basis,

$$f_t = \alpha + \theta m r_{t-1} + \delta_j f_{t-j} + u_{t+1},$$
$$r_t = \kappa + \phi r_{t-1} + e_{t+1},$$

using a 90-day rolling window. This allows use to extract a time-series of both parameters. We linearly interpolate all zero flow days. We then aggregate the investor behavior θ and return auto-correlation ϕ parameter values by taking the asset weighted sum for each day,

$$\Theta_t = \sum_j \frac{a_{j,t}}{A_t} \Theta_{j,t}$$

where a_{jt} is the assets under management of fund j, the sum $A_t = \sum_j a_{j,t}$ is the total assets under management in the leveraged ETF space, $\Theta_{j,t}$ is the estimated parameter for fund j on day t, and Θ_t is the aggregate parameter value on day t. In the second stage, we estimate the average of our time-series and use the $\log(1+\Theta)$ transformation to scale the parameter values. We use pre-whitened Newey-West (1987) standard errors with the optimal bandwidth selection procedure from Newey-West (1994). We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

		Leverage (m)				
	Aggregate	-3	-2	-1	2	3
θ	-1.014***	0.457***	0.399**	-0.414***	-0.758***	-5.274***
	(0.183)	(0.063)	(0.17)	(0.105)	(0.229)	(1.171)
ϕ	-1.152***	-0.165***	-0.734**	-0.381***	-1.864***	-1.828**
	(0.319)	(0.048)	(0.295)	(0.124)	(0.588)	(0.72)
ζ	-0.008	0.466***	0.765**	-0.015	2.333**	-5.373**
	(0.572)	(0.062)	(0.316)	(0.09)	(1.031)	(2.11)
N	3,566	2,967	3,550	3,566	3,566	2,967

Table 4
The Impact of Amplification on Weekly Volatility: Panel Regression

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: Five Day $SD(\text{Ret})_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =		SD (2)	NBER	GRec2008	COVID
Amplification	0.018**	0.009*	0.0005	0.018**	0.008
	(0.007)	(0.005)	(0.007)	(0.008)	(0.007)
× Crisis		0.147***	0.153***	0.081***	0.130**
		(0.055)	(0.046)	(0.028)	(0.063)
Crisis		0.710***	-0.049	-0.272***	0.304**
		(0.051)	(0.059)	(0.043)	(0.125)
Libor	0.231***	0.193***	0.224***	0.235***	0.194***
	(0.046)	(0.043)	(0.047)	(0.046)	(0.047)
Amihud	1.259***	0.689***	1.223***	1.263***	1.194***
	(0.147)	(0.129)	(0.145)	(0.147)	(0.14)
VIX_{t-1}	0.070***	0.066***	0.068***	0.071***	0.067***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Ret^2_{t-1}	3.157***	3.013***	3.080***	3.107***	2.979***
	(0.365)	(0.348)	(0.357)	(0.363)	(0.357)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Obs.	256,272	256,272	256,272	256,272	256,272
Adj. R^2	0.677	0.697	0.679	0.678	0.68

Table 5
The Impact of Amplification on Weekly Volatility: Crisis Subsamples

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: Five Day $SD(\text{Ret})_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =	SD (2)	+SD (2)	-SD (2)	COVID	
Amplification	0.009*	0.017**	0.013**	0.008	0.008
	(0.005)	(0.007)	(0.006)	(0.007)	(0.006)
× Crisis	0.710***	0.607***	0.553***	0.304**	
	(0.051)	(0.053)	(0.069)	(0.125)	
× preCOVID					0.606***
					(0.119)
× inCOVID					0.615
					(0.552)
× postCOVID					-0.143*
					(0.081)
Crisis	0.147***	0.002	0.169**	0.130**	
	(0.055)	(0.059)	(0.067)	(0.063)	
preCOVID					0.279***
					(0.087)
inCOVID					0.267**
					(0.132)
postCOVID					0.035*
					(0.019)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	256,272	256,272	256,272	256,272	256,272
Adj. R^2	0.697	0.683	0.687	0.68	0.685

Table 6
The Impact of Amplification on Monthly Volatility: Panel Regression

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: 30 Day *SD(Ret)* $_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =		SD (2)	NBER	GRec2008	COVID
Amplification	0.070***	0.054***	0.013***	0.071***	0.034***
	(0.006)	(0.005)	(0.003)	(0.006)	(0.003)
× Crisis		0.217***	0.434***	0.013	0.472***
		(0.048)	(0.044)	(0.016)	(0.072)
Crisis		0.197***	0.314***	-0.085***	0.920***
		(0.035)	(0.05)	(0.032)	(0.126)
Libor	-0.036	-0.054**	-0.105***	-0.034	-0.152***
	(0.023)	(0.023)	(0.019)	(0.023)	(0.023)
Amihud	0.665***	0.413***	0.498***	0.667***	0.447***
	(0.11)	(0.101)	(0.104)	(0.11)	(0.113)
VIX_{t-1}	0.089***	0.087***	0.079***	0.089***	0.080***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Ret^2_{t-1}	-0.805**	-0.940**	-1.082***	-0.822**	-1.397***
	(0.36)	(0.414)	(0.368)	(0.362)	(0.421)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Obs.	253,847	253,847	253,847	253,847	253,847
Adj. R^2	0.709	0.715	0.734	0.709	0.746

Table 7
The Impact of Amplification on Monthly Volatility: Crisis Subsamples

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: 30 Day *SD(Ret)* $_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =	SD2)	+SD (2)	-SD(2)	COVID	
Amplification	0.054***	0.062***	0.064***	0.034***	0.013***
	(0.005)	(0.006)	(0.005)	(0.003)	(0.004)
× Crisis	0.217***	0.250***	0.141**	0.472***	
	(0.048)	(0.062)	(0.066)	(0.072)	
× preCOVID					0.042
					(0.082)
× inCOVID					-0.586***
					(0.105)
× postCOVID					0.532***
					(0.028)
Crisis	0.197***	0.083	0.140***	0.920***	
	(0.035)	(0.077)	(0.049)	(0.126)	
preCOVID					-0.470***
					(0.174)
inCOVID					2.570***
					(0.458)
postCOVID					-0.189**
					(0.092)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	253,847	253,847	253,847	253,847	253,847
Adj. R^2	0.715	0.712	0.711	0.746	0.734

Table 8
The Impact of Amplification on Market Efficiency: Panel Variance Ratio Regressions

This table explores the relationship between the moderation-amplification ratio and 5-day variance ratios using panel regressions. The dependent variable is the 5-day variance ratio on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret_{t-1}^2) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent Variable: Variance Ratio$_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =		SD (2)	NBER	GRec2008	COVID
Amplification	-0.002	0.006	0.007	-0.003	0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
× Crisis		-0.136***	-0.139***	0.071***	-0.213***
		(0.028)	(0.026)	(0.017)	(0.045)
Crisis		0.102***	-0.026**	-0.009	-0.057**
		(0.008)	(0.013)	(0.015)	(0.022)
Libor	0.039***	0.036***	0.044***	0.039***	0.048***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.01)
Amihud	0.139***	0.084***	0.150***	0.138***	0.155***
	(0.024)	(0.024)	(0.024)	(0.024)	(0.025)
VIX_{t-1}	0.001**	0.001*	0.002***	0.001**	0.002***
	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)
Ret_{t-1}^2	0.343***	0.345***	0.359***	0.343***	0.386***
	(0.065)	(0.061)	(0.063)	(0.065)	(0.061)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Obs.	253,454	253,454	253,454	253,454	253,454
Adj. R^2	0.035	0.039	0.037	0.035	0.038

Table 9
The Impact of Amplification on Market Efficiency: Panel Variance Ratio Regressions by Crisis Subsamples

This table explores the relationship between the moderation-amplification ratio and market efficiency using panel regressions. The dependent variable is the 5-day variance ratio on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent Variable: Variance Ratio$_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =	SD (2)	+SD (2)	-SD (2)	COVID	
Amplification	0.006	0.002	0.002	0.006	0.013***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
× Crisis	-0.136***	-0.182***	-0.108***	-0.213***	
	(0.028)	(0.041)	(0.028)	(0.045)	
× preCOVID					-0.091
					(0.105)
× inCOVID					0.029
					(0.023)
× postCOVID					-0.172***
					(0.018)
Crisis	0.102***	0.076***	0.098***	-0.057**	
	(0.008)	(0.01)	(0.008)	(0.022)	
preCOVID					-0.02
					(0.031)
inCOVID					-0.153***
					(0.044)
postCOVID					-0.101***
					(0.022)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Fund FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	253,454	253,454	253,454	253,454	253,454
Adj. R^2	0.039	0.036	0.038	0.038	0.039

Table 10
The Aggregate Impact of Amplification on Expected Volatility

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: VIX_t				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =		SD(2)	NBER	GRec2008	COVID
Amplification	2.049***	2.309***	1.179***	1.230***	2.107***
	(0.15)	(0.143)	(0.135)	(0.142)	(0.146)
× Crisis		-2.272***	1.551***	2.895***	-1.062
		(0.429)	(0.42)	(0.493)	(0.689)
Crisis		0.200***	0.222***	0.172***	0.249***
		(0.028)	(0.019)	(0.021)	(0.048)
Libor	-0.056***	-0.063***	-0.071***	-0.051***	-0.068***
	(0.014)	(0.012)	(0.013)	(0.014)	(0.013)
Amihud	0.780***	0.679***	0.670***	0.702***	0.750***
	(0.041)	(0.052)	(0.041)	(0.038)	(0.042)
VIX_{t-1}	0.343***	0.315***	0.344***	0.331***	0.333***
	(0.054)	(0.054)	(0.048)	(0.051)	(0.053)
Ret^2_{t-1}	0.011***	0.011***	0.009***	0.010***	0.010***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Obs.	3,564	3,564	3,564	3,564	3,564
Adj. R^2	0.762	0.769	0.781	0.78	0.765

Table 11
The Aggregate Impact of Amplification on Expected Volatility: Crisis Subsamples

This table explores the relationship between the moderation-amplification ratio and market volatility using panel regressions. The dependent variable is the value of VIX on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels. Both the dependent and independent variable of interest are standardized.

	Dependent Variable: VIX_t				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =	SD (2)	+SD (2)	-SD (2)	COVID	
Amplification	2.309***	2.125***	2.227***	2.107***	1.846***
	(0.143)	(0.149)	(0.145)	(0.146)	(0.134)
× Crisis	-2.272***	-2.053**	-1.664***	-1.062	
	(0.429)	(0.845)	(0.473)	(0.689)	
× preCOVID					-4.258**
					(1.994)
× inCOVID					-4.617
					(8.49)
× postCOVID					1.186***
					(0.278)
Crisis	0.200***	0.026	0.261***	0.249***	
	(0.028)	(0.06)	(0.029)	(0.048)	
preCOVID					0.377***
					(0.113)
inCOVID					0.905
					(0.944)
postCOVID					0.420***
					(0.033)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	3,564	3,564	3,564	3,564	3,564
Adj. R^2	0.769	0.764	0.771	0.765	0.773

Table 12
The Aggregate Impact of Amplification on Market Efficiency: Variance Ratio Regressions

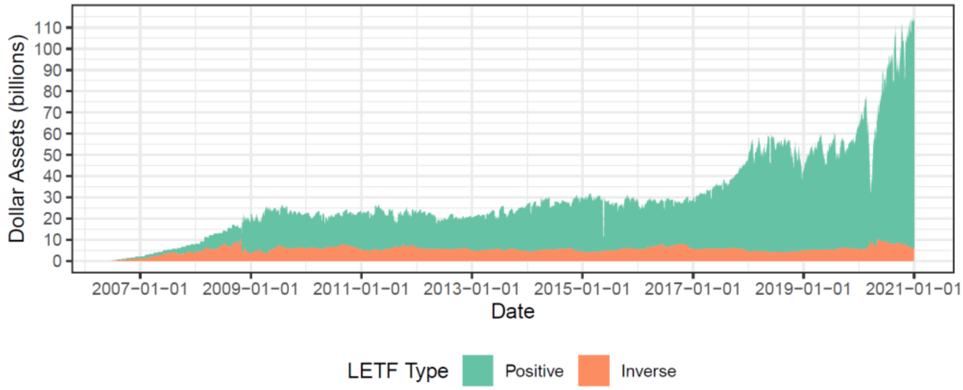
This table explores the market-wide relationship between the moderation-amplification ratio and 5-day variance ratios using panel regressions. The dependent variable is the 5-day variance ratio on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent Variable: Market Variance Ratio$_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =		SD (2)	NBER	GRec2008	COVID
Amplification	-2.400***	-2.309***	-1.876***	-2.099***	-2.256***
	(0.167)	(0.18)	(0.142)	(0.159)	(0.163)
× Crisis		-1.078***	-2.805***	-2.742***	-1.786***
		(0.384)	(0.417)	(0.515)	(0.544)
Crisis		-0.018	0.031	0.028	0.089
		(0.026)	(0.036)	(0.039)	(0.071)
Libor	0.001	0.004	-0.003	-0.006	-0.001
	(0.013)	(0.012)	(0.015)	(0.014)	(0.014)
Amihud	-0.204***	-0.159***	-0.178***	-0.190***	-0.203***
	(0.035)	(0.04)	(0.036)	(0.035)	(0.035)
VIX_{t-1}	0.004***	0.005***	0.006***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ret^2_{t-1}	-0.004***	-0.004***	-0.004***	-0.005***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Obs.	3,533	3,533	3,533	3,533	3,533
Adj. R^2	0.153	0.154	0.159	0.156	0.154

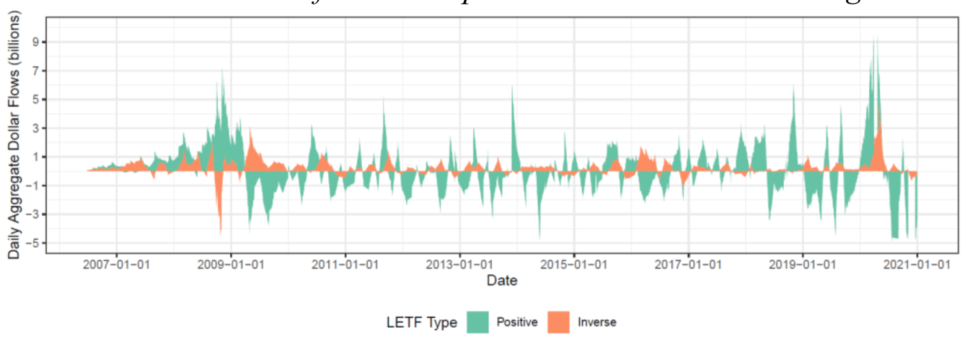
Table 13
The Aggregate Impact of Amplification on Market Efficiency: Variance Ratio Regressions by Crisis Subsamples

This table explores the market-wide relationship between the moderation-amplification ratio and market efficiency using panel regressions. The dependent variable is the 5-day variance ratio on day t. The independent variable of interest is the amplification ratio on day t. In columns (2) through (5), we study this relationship during times of market stress. The dummy *SD (2)* takes on a value of 1 if the return on day t is 2 standard deviations away from the index mean. The dummy *NBER* takes on a value of 1 if the observations are realized during the Great Financial Crisis of 2008 (July 1, 2007 – August 30, 2009) or during the COVID-19 crash (February 19, 2020 – April 30, 2020). The dummy *GRec2008* takes on a value of 1 if the observation is realized during the Great Financial Crisis of 2008. The dummy *COVID* takes on a value of 1 if the observation is realized during the COVID-19 crash. We include *Libor*, *Amihud* illiquidity, the lagged VIX (VIX_{t-1}), and lagged squared market returns (Ret_{t-1}^2) as controls. The data is daily at the fund level and include fund, month, and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are double clustered at the fund and day level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent Variable: Market Variance Ratio$_t$				
	(1)	(2)	(3)	(4)	(5)
Crisis Definition =	SD (2)	+SD (2)	-SD (2)	COVID	
Amplification	-2.309***	-2.377***	-2.339***	-2.256***	-2.209***
	(0.18)	(0.168)	(0.176)	(0.163)	(0.17)
× Crisis	-1.078***	-0.788	-1.009**	-1.786***	
	(0.384)	(0.538)	(0.468)	(0.544)	
× preCOVID					-3.901**
					(1.577)
× inCOVID					0.501
					(3.721)
× postCOVID					-2.332***
					(0.459)
Crisis	-0.018	-0.009	-0.005	0.089	
	(0.026)	(0.044)	(0.025)	(0.071)	
preCOVID					0.250***
					(0.062)
inCOVID					-0.024
					(0.417)
postCOVID					0.477***
					(0.052)
Year FE	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Obs.	3,533	3,533	3,533	3,533	3,533
Adj. R^2	0.154	0.153	0.153	0.154	0.166

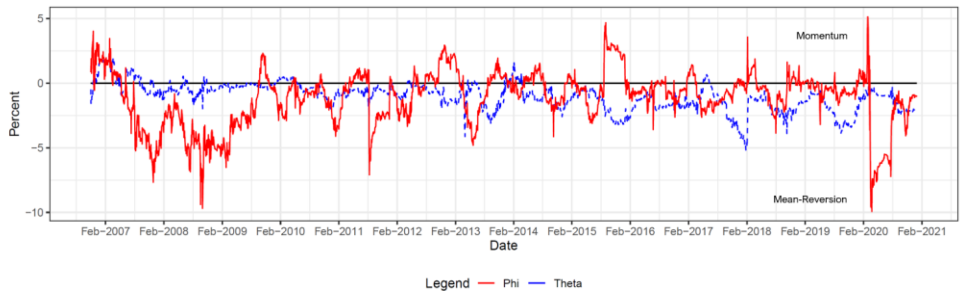


Panel A: Time Series of Fund Inception and Assets Under Management



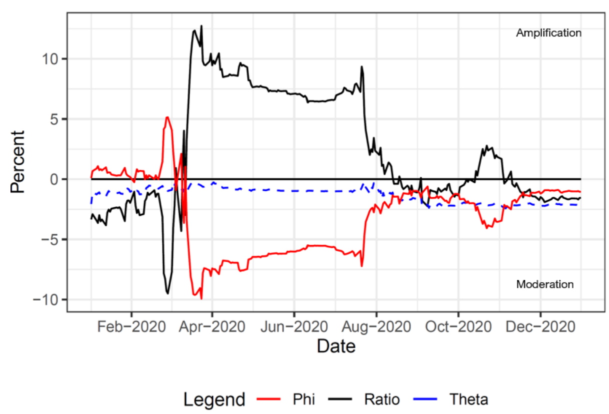
Panel B: Time Series of Aggregate Fund Flows

Figure 1. Trends in Levered and Inverse Exchange Traded Funds. In panel A, we plot The assets under management for positively and inverse LETFs in billions of USD. In panel B, we provided aggregate dollar fund flows in billions USD.



Panel A: Return Autocorrelation and LETF Investor Behavior

Panel B: The Moderation Ratio



Panel C: The 2020 Subsample

Figure 2. Time series of Aggregate Investor Behavior, Autocorrelation, and Amplification Ratio. This figure plots a time series of the investor behavior parameter θ (where a positive number means momentum and a negative number means contrarian) in the dotted blue line; the aggregate underlying auto-correlation in the red dashed line; and the ratio between investor behavior and autocorrelation in the black solid line.

Internet Appendix

Of Seesaws and Swings: The Impact of Return and Flow Dynamics on LETF Rebalancing and Market Volatility

Contents

This Internet Appendix provides a more detailed description of the data and includes additional results that are referenced in the main text. In addition, it reports ancillary results that do not appear in the main paper.

A. Descriptive Statistics

The tables are as follows

- Table A1 – Summary Statistics for Crisis Subsamples. We break down the summary statistics by the two crisis periods that occur during our sample period.
- Table A2 – Rebalancing Demand Cross-tabulation by Index Return and Fund Flow. Reports the average rebalancing demand tabulated across benchmark return and fund flow quintiles.
- Table A3 – Momentum and Contrarian Behavior Summarized Using Return Portfolios. Reports the proportion of 25 portfolios that display momentum behavior and contrarian behavior by subsample.
- Table A4 - The Decomposition of Rebalancing Demand. Reports the coefficient estimates for the four components of rebalancing demand.

The figures are as follows

- Figure A1 – Time-series of Median Rebalancing Demand
- Figure A2 – Flow and Return Distributions
- Figure A3 – Rebalancing Demand Cross-tabulation by Index Return and Fund Flow
- Figure A4 – Flows as a Function of Returns

Table A1
Summary Statistics for Crisis Subsamples

This table reports summary statistics for ETF-level size, returns, fund flows, and rebalancing demand. Panel A shows the number of funds in our entire sample, which includes inverse ($m < 1$), positively levered ($m > 1$), and unlevered ($m = 1$) ETFs, as well as the total number of fund-day observations. Panel B shows the summary statistics for the inverse LETF subsample ($m \in \{-3, -2, -1\}$). Panel C focuses on ETFs that have positive leverage multiples ($m \in \{+2, +3\}$). The mean, standard deviation, 1st percentile, 50th percentile, and 99th percentile are presented for our entire sample period beginning in June 2006 until December 2020 and for the crisis subsample. The crisis subsample includes the Great Financial Crisis of 2008 starting July 1, 2007 and ends August 30, 2009 and the COVID-19 crisis starting February 19,2020 to April 30, 2020.

			Panel A. Full Sample Size				
	Leverage	$m = -3$	m	m	$m = 1$	$m = 2$	$m = 3$
ETFs	97	18	18	13	727	20	28
Obs. (Fund-	260,584	39,774	62,486	37,722	1,321,61	67,448	53,154
			Panel B. Inverse LETFs ($m < 1$)				
Recession of 2008 Subsample		Obs.	Mean	St. Dev.	$P_{1\%}$	$P_{50\%}$	$P_{99\%}$
Rebalancing Demand (%)		139,982	-0.09	16.36	-50.67	0.36	43.65
Flow (%)		139,982	0.18	4.36	-5.40	0.00	10.58
Benchmark Return (%)		139,982	0.04	1.58	-4.53	0.08	4.52
Fund Return (%)		139,982	-0.10	3.42	-10.02	-0.15	10.16
Shares Outstanding (m)		139,982	3.48	11.29	0.00	0.34	57.63
log(Market Cap. [$m])		139,982	3.99	1.83	0.83	3.90	7.73
COVID-19 Subsample							
Rebalancing Demand (%)		13,239	-1.06	27.65	-95.47	-0.02	78.51
Flow (%)		13,239	0.39	6.55	-8.72	0.00	25.45
Benchmark Return (%)		13,239	-0.08	3.36	-10.11	-0.01	9.40
Fund Return (%)		13,239	0.11	6.62	-19.38	0.00	19.74
Shares Outstanding (m)		13,239	2.12	9.10	0.00	0.19	46.65
log(Market Cap. [$m])		13,239	4.50	1.74	1.08	4.34	8.06
			Panel C. Positively Levered ETFs ($m > 1$)				
Recession of 2008 Subsample		Obs.	Mean	St. Dev.	$P_{1\%}$	$P_{50\%}$	$P_{99\%}$
Rebalancing Demand (%)		120,602	0.32	12.12	-29.65	0.23	31.28
Flow (%)		120,602	0.05	3.74	-7.10	0.00	5.68
Benchmark Return (%)		120,602	0.05	1.59	-4.53	0.08	4.51
Fund Return (%)		120,602	0.11	3.92	-11.33	0.20	11.21
Shares Outstanding (m)		120,602	17.84	48.51	0.01	3.02	213.98
log(Market Cap. [$m])		120,597	4.68	1.69	1.23	4.76	7.92
COVID-19 Subsample							
Rebalancing Demand (%)		10,684	0.93	19.47	-49.74	0.06	68.1
Flow (%)		10,684	0.54	5.87	-1.95	0.00	27.60
Benchmark Return (%)		10,684	-0.08	3.41	-10.29	-0.01	9.66
Fund Return (%)		10,684	-0.24	7.78	-23.81	-0.01	21.92
Shares Outstanding (m)		10,684	43.45	121.72	0.04	3.51	691.20
log(Market Cap. [$m])		10,679	4.35	1.72	1.25	4.22	8.09

Table A2
Rebalancing Demand Cross-tabulation by Index Returns and Fund Flows

This table reports the average rebalancing demand (in percent) tabulated across benchmark return and fund flow quintiles. The "Unconditional Mean" column/row reports the average rebalancing demand in percent for each benchmark return/flow quintile ignoring fund flows/returns. Panel A focuses on ETFs with negative leverage multiples (-3, -2, -1). Panel C focuses on ETFs with positive leverage multiples (+2, +3). The time-period of this analysis runs from June 2006 until December 2020.

Panel A. Inverse LETFs ($m < 1$)							
			Fund Flows				
			Low	Q2	Q3	Q4	High
		Uncond. Mean	-15	-3.04	1.73	7.14	28.20
Underlying Return	Low	-1.46	19.42	-3.98	-18.57	-27.01	-81.99
	Q2	-0.49	23.32	2.93	-8.06	-19.10	-67.80
	Q3	-0.03	28.81	5.09	-3.75	-15.69	-60.61
	Q4	0.46	36.34	10.40	0.06	-10.84	-54.14
	High	1.42	46.11	20.65	9.20	-3.37	-46.88
Panel B. Positively Levered ETFs ($m > 1$)							
			Fund Flows				
			Low	Q2	Q3	Q4	High
		Uncond. Mean	-14.3	-4.17	-0.80	2.27	18.80
Underlying Return	Low	-1.53	-41.56	-15.11	-7.85	-0.43	50.19
	Q2	-0.50	-37.18	-11.99	-3.69	4.28	35.09
	Q3	-0.02	-33.80	-10.32	-2.39	5.42	44.30
	Q4	0.47	-34.74	-7.98	-0.20	8.17	44.89
	High	1.45	-30.76	-4.84	4.22	12.86	61.67

Table A3
Momentum and Contrarian Behavior Summarized Using Return Portfolios

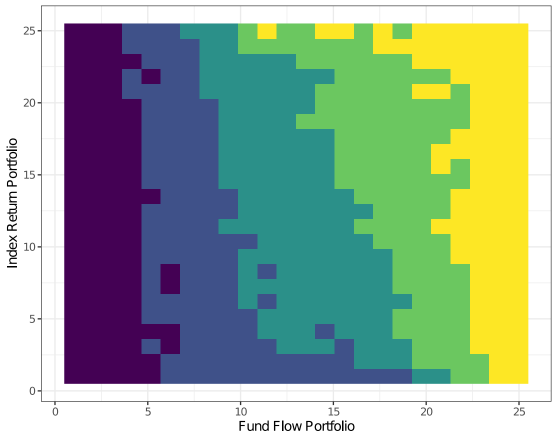
This table reports the number (proportion) of the twenty-five portfolios that displayed momentum behavior (sign of the underlying index return and flows are equivalent) and contrarian (different signs between the underlying return and flows). We create 25 portfolios by evenly partitioning the sample based on returns and taking the average fund flows for the portfolios. We additionally multiply the returns for the inverse levered ETFs to help ease the interpretation. We additionally provide the implication of the behavior towards the rebalancing demand. Corresponds to the results plotted in Figure B4.

	Overall	Normal	Recession	2008 Crash	COVID
			Panel A. Inverse LETFs ($m < 1$)		
Obs.	6,031	5,495	536	368	168
Momentum	13	13	17	16	18
	(52%)	(0.52)	(0.68)	(0.64)	(0.72)
Contrarian	12	12	8	9	7
	(0.48)	(0.48)	(0.32)	(0.36)	(0.28)
Behavior	Mix	Mix	Momentum	Momentum	Momentum
Implication	-	-	Amplification	Amplification	Amplification
			Panel B. Positively Levered ETFs ($m > 1$)		
Obs.	5,741	5,330	411	246	165
Momentum	18	15	11	12	11
	(0.72)	(0.6)	(0.44)	(0.48)	(0.44)
Contrarian	7	10	14	13	14
	(0.28)	(0.4)	(0.56)	(0.52)	(0.56)
Behavior	Momentum	Momentum	Contrarian	Mix	Contrarian
Implication	Amplification	Amplification	Moderation	-	Moderation

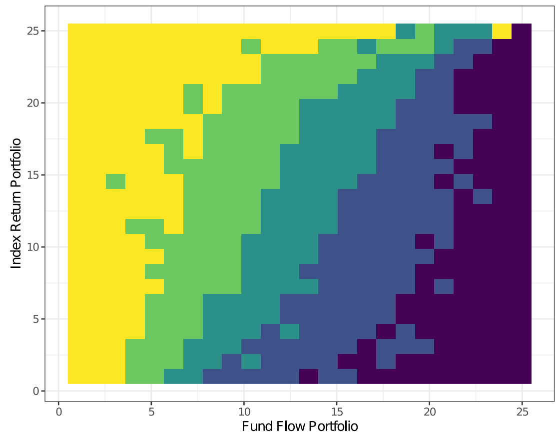
Table A4
The Decomposition of Rebalancing Demand

This table presents the empirical parameter estimates from equation (9). In column (4), we run the regression for the unlevered ETFs based on the same underlying index as the LETFs as a benchmark for comparison. Rebalancing demand is defined as the growth of assets under management in excess of the benchmark return scaled by the leverage multiple. Flows are defined as the percentage growth in shares outstanding of the fund. We include year fixed effects to capture unobservable time-varying market characteristics and cluster the standard errors at the ETF level to control for serial correlation. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

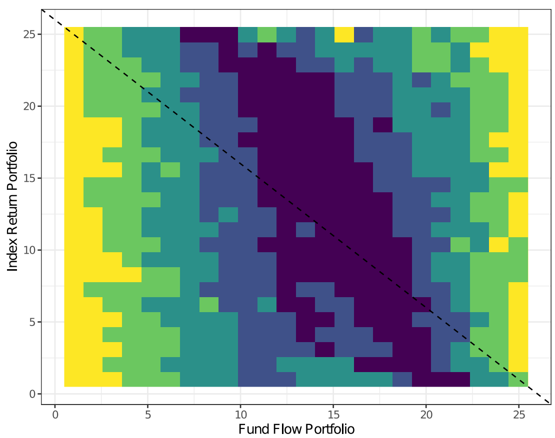
	Dependent Variable: Rebalancing Demand					
Leverage Multiple (m)	$m=-3$	$m=-2$	$m=-1$	$m=1$	$m=2$	$m=3$
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.000**	0.001***	0.000***	-0.000***	0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Benchmark Return	12.040***	5.991***	1.997***	-0.013***	1.998***	5.983***
	(0.009)	(0.002)	(0.001)	(0.000)	(0.001)	(0.009)
Flows	-2.995***	-2.000***	-1.000***	1.000***	2.000 ***	2.993***
	(0.004)	(0.001)	(0.001)	(0.000)	(0.000)	(0.005)
× Returns	9.922***	3.993***	1.007***	0.993***	4.047***	9.802***
	(0.146)	(0.047)	(0.033)	(0.005)	(0.016)	(0.197)
× Risk-free Rate	-88.727	1.219	2.703	-1.534	3.635	131.848
	(91.957)	(13.203)	(9.067)	(1.171)	(4.378)	(119.967)
Obs.	39,774	62,486	37,722	132,1619	67,448	53,154
Adj. R^2	0.988	0.994	0.995	0.996	0.999	0.952



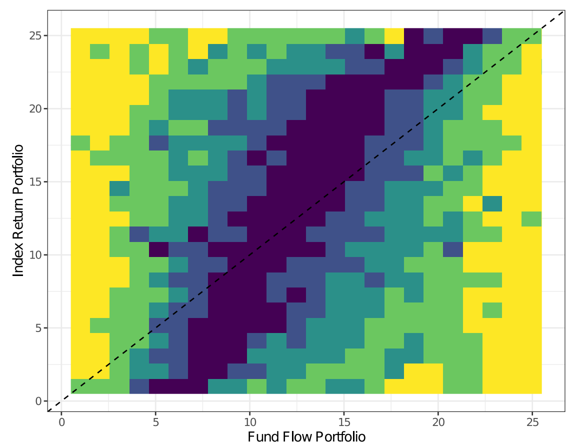
(a) Signed Rebalancing Demand for Positively Leveraged Funds



(b) Signed Rebalancing Demand for Inverse Leveraged Funds

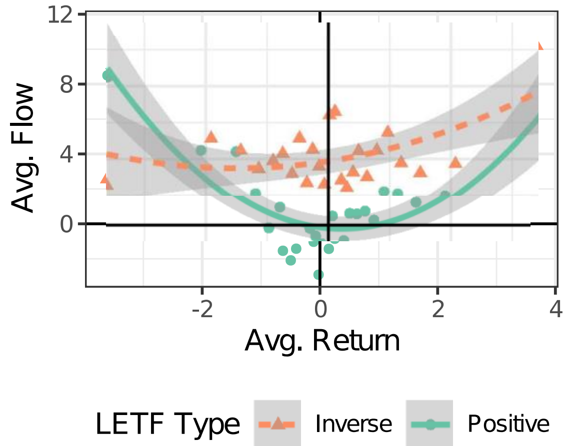


(c) Absolute Rebalancing Demand for Positively Leveraged Funds

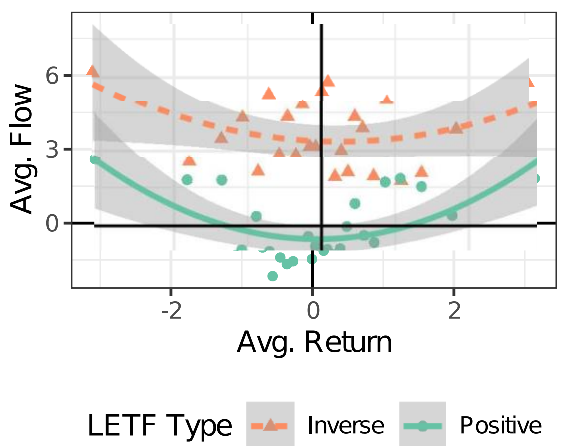


(d) Absolute Rebalancing Demand for Inverse Leveraged Funds

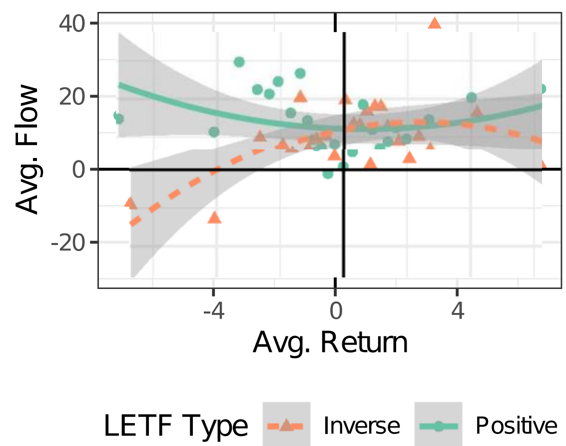
Figure A3. Rebalancing Demand Cross-Tabulation by Index Returns and Fund Flow. Twenty-five portfolios are created by evenly partitioning the sample based on returns and flows and plot the grids with the fill color representing the level of signed and absolute rebalancing demand (which we partition into 5 portfolios). We also plot a 45 degree line for the absolute rebalancing demand figures.



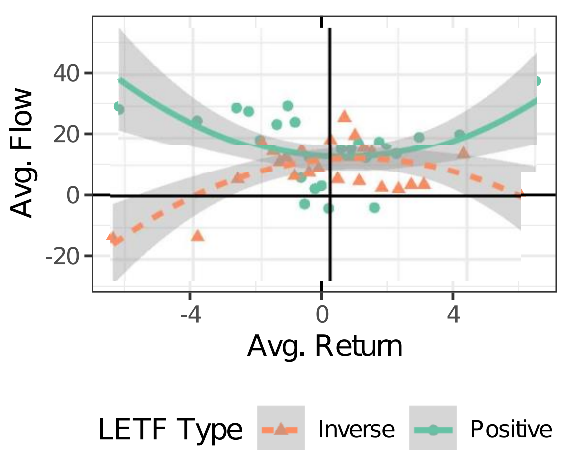
(a) Overall Sample



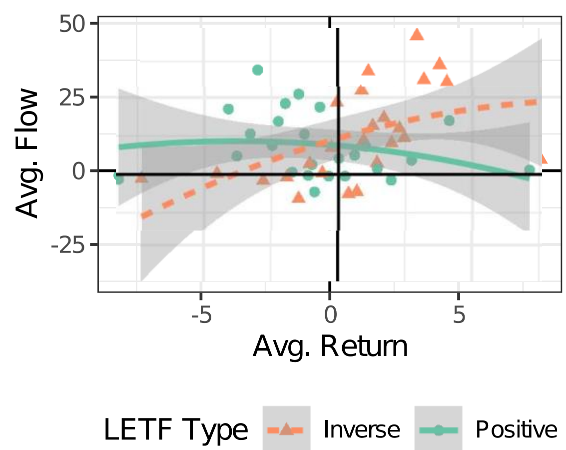
(b) Nonrecession Subsample



(c) Recession Subsample



(d) 2008 Crash Subsample



(e) COVID-19 Crash Subsample

(Continued on next page)

Figure A4. Returns and Fund Flows We create 25 portfolios by evenly partitioning the sample based on returns and taking the average fund flows for the portfolios. We then plot a quadratic curve and corresponding to 95% standard error bands to capture the general relationship. We additionally multiply the returns for the inverse levered ETFs to help ease the interpretation. Momentum behavior is captured by the upper right quadrant while contrarian behavior is captured by the upper-left quadrant

B. Supplementary Results

*Comparing the Interactive Model to the Baseline Model***.** We define the difference in absolute value of the two models as the relative amplification of volatility due to the investment gap,

$$\text{Amplification} = |\Delta| - |\Delta^L|$$

where L references the returns and flow-based models in the literature without the interaction. This variable is greater than zero when our model predicts higher absolute rebalancing and negative when we predict lower absolute rebalancing. The amplification effect of our model relative to the currently accepted flow-based models depends on whether the flows exhibit momentum or contrarian behavior:

$$|\Delta| - |\Delta^L| = \begin{cases} +\text{sgn}[(m^2 - m)r + mf]|m^2 rf\ |, & \text{if sgn}(r) = \text{sgn}(f) \\ -\text{sgn}[(m^2 - m)r + mf]|m^2 rf\ |, & \text{if sgn}(r) \neq \text{sgn}(f) \end{cases}$$

There exists a region where one component dominates over the other, causing the interaction term to switch signs. For a given flow, this kinked region in Figure 5 is defined by a threshold that is an inverse function of the relative weights of both components,

$$\text{Kinked Region: } \left[-\frac{m}{m^2 - m} f, 0\right].$$

The panels in Figures D2 and D3 plots these highly nonlinear relations. In our regressions, we expect a positive sign for subsamples when $|\Delta| > |\Delta^L|$ and a negative sign when $|\Delta^L| > |\Delta|$.

The tables are as follows:

- Table B1 – Difference in Means Test Between the Interactive and Noninteractive Model
- Table B2 – Difference in Means Test Between the Interactive and Noninteractive Model by Subsamples
- Table B3 – The Impact of Rebalancing Demand on Index Volatility
- Table B4 – The Impact of Rebalancing Demand on Market-wide Volatility
- Table B5 – The Impact of the Investment Gap on Index Volatility
- Table B6 – The Impact of the Investment Gap on Market-wide Volatility
- Table B7 – The Impact of Rebalancing Demand on Index Volatility Controlling for Option Markets
- Table B8 – The Impact of Rebalancing Demand on Market-wide Volatility Controlling for Option Markets
- Table B9 – The Impact of the Investment Gap on Index Volatility Controlling for Option Markets
- Table B10 – The Impact of the Investment Gap on Market-wide Volatility Controlling for Expected Volatility
- Table B11 – The Impact of Rebalancing Demand on Index Volatility Controlling for Expected Volatility
- Table B12 – The Impact of Rebalancing Demand on Market-wide Volatility Controlling for Expected Volatility

- Table B13 – The Impact of the Investment Gap on Index Volatility Controlling for Expected Volatility
- Table B14 – The Impact of the Investment Gap on Market-wide Volatility Controlling for Expected Volatility
- Table B15 – Investor Behavior and Autocorrelation Parameters: Robustness

The figures are as follows:

- Figure B1 – Comparative Statics of the Interactive Model.
- Figure B2 – Amplification and Moderation of the Return Approximation of Rebalancing Demand Across Different Leverage Multiples Relative to Cheng and Madhavan (2009).
- Figure B2 – Amplification and Moderation of the Return Approximation of Rebalancing Demand Across Different Leverage Multiples Relative to Ivanov and Lenkey (2009).

Table B1
Difference in Means Test Between the Interactive and Noninteractive Model

This table presents difference in means *t*-tests between the interactive rebalancing model and the flow approximation of Ivanov and Lenkey (2018). We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	*t*-stat.	
Panel A. Overall Sample						
LETF	260,584	6.578	6.541	0.037	9.205	***
Positive	120,602	5.021	4.995	0.026	3.798	***
Inverse	139,982	7.919	7.873	0.046	10.209	***
-3	39,774	14.929	14.807	0.121	8.230	***
-2	62,486	6.828	6.813	0.015	4.488	***
-1	37,722	2.336	2.319	0.017	10.519	***
2	67,448	2.670	2.664	0.006	4.818	***
3	53,154	8.004	7.953	0.051	3.310	***
Panel B. Recession Subsample						
	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	*t*-stat.	
LETF	23,923	12.402	12.342	0.060	2.703	***
Positive	10,684	9.016	9.012	0.127	0.127	
Inverse	13,239	15.135	15.030	0.105	3.489	***
-3	1,682	38.540	38.184	0.356	1.740	*
-2	7,853	14.698	14.610	0.088	3.502	***
-1	3,704	5.433	5.405	0.027	2.097	**
2	8,277	5.533	5.526	0.007	0.866	
3	899	20.993	20.998	-0.005	-0.037	
Panel C. Non-recession Subsample						
	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	*t*-stat.	
LETF	236,661	5.989	5.955	0.034	9.115	***
Positive	109,918	4.633	4.605	0.028	4.142	***
Inverse	126,743	7.165	7.126	0.040	10.370	***
-3	38,092	13.887	13.775	0.112	8.888	***
-2	54,633	5.696	5.692	0.004	4.225	***
-1	34,018	1.999	1.983	0.016	15.314	***
2	59,171	2.270	2.264	0.006	6.421	***
3	50,747	7.388	7.334	0.054	3.669	***

Table B2
Difference in Means Test Between the Interactive and Noninteractive Model by Subsamples

This table presents difference in means *t*-tests between the interactive rebalancing model and the flow approximation of Ivanov and Lenkey (2018). We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	SE	
Panel A. 2008 Crash Subsample						
LETF	18,011	9.6188	9.5896	0.030	0.0127	**
Positive	7,766	6.3459	6.3593	-0.0134	0.0120	
Inverse	10,245	12.0998	12.0383	0.0614	0.0035	***
-3	604	28.9618	29.1205	-0.1586	0.0891	*
-2	6,739	13.7122	13.6195	0.0927	0.0291	***
-1	2,902	4.8458	4.8111	0.0347	0.0163	**
2	7,044	5.3581	5.3423	0.0158	0.0092	*
3	722	15.9832	16.2817	-0.2985	0.0922	***
Panel B. COVID-19 Crash Subsample						
	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	SE	
LETF	3,162	29.2710	28.7345	0.5367	0.1450	***
Positive	1,557	22.7055	22.2600	0.4455	0.2075	**
Inverse	1,605	35.6400	35.0150	0.6251	0.2030	***
-3	586	61.8335	60.0935	1.7403	0.5530	***
-2	593	28.2190	28.2165	0.0026	0.0235	
-1	426	9.9390	9.9815	-0.0425	0.0230	*
2	658	9.3780	9.4435	-0.0657	0.0115	***
3	899	32.4605	31.6410	0.8197	0.3590	**
Panel C. Post COVID-19 Crash Subsample						
	N	$\lvert\Delta\rvert$	$\lvert\Delta^L\rvert$	Diff.	SE	
LETF	17,701	9.1180	9.5745	-0.4565	0.0190	***
Positive	8,777	7.0490	7.5240	-0.4750	0.0275	***
Inverse	8,924	11.1530	11.5915	-0.4383	0.0270	***
-3	3,248	19.2880	20.5465	-1.2585	0.0710	***
-2	3,285	8.8765	8.8515	0.0252	0.0105	**
-1	2,391	3.2305	3.1915	0.0389	0.0085	***
2	3,654	2.9110	2.9090	0.0016	0.0050	
3	5,123	10.0010	10.8160	-0.8150	0.0460	***

Table B3
The Impact of Rebalancing Demand on Index Volatility: Standardized Coefficients

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest. Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF and year fixed effects to control for omitted variables and cluster the standard errors at the underlying index level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Pre-COVID-19 Subsample								
$\|\Delta\|$	0.224***	0.134***	0.250***	0.275***	0.257***	0.099**	0.122**	0.216***
	(0.004)	(0.004)	(0.005)	(0.000)	(0.005)	(0.004)	(0.005)	(0.001)
Obs.	239,445	110,141	129,304	35,871	58,549	34,884	63,083	47,058
Adj. R^2	0.376	0.368	0.384	0.372	0.390	0.305	0.374	0.329
Panel B. COVID-19 Crash Subsample								
$\|\Delta\|$	0.489***	0.371***	0.512***	0.490***	0.549***	0.379***	0.513***	0.373***
	(0.003)	(0.008)	(0.003)	(0.004)	(0.002)	(0.018)	(0.011)	(0.007)
Obs.	3,159	1,555	1,604	585	593	426	658	897
Adj. R^2	0.187	0.109	0.208	0.248	0.296	0.120	0.246	0.140
Panel C. Post COVID-19 Crash Subsample								
$\|\Delta\|$	0.287***	0.336***	0.299***	0.305**	0.332***	0.272***	0.380***	0.333***
	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.023)	(0.004)
Obs.	17,677	8,767	8,910	3,239	3,280	2,391	3,649	5,118
Adj. R^2	0.231	0.296	0.169	0.189	0.177	0.126	0.214	0.327

Table B4
The Impact of Rebalancing Demand on Market-wide Volatility: Standardized Coefficients

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest. Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF and year fixed effects to control for omitted variables and cluster the standard errors at the underlying index level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Pre-COVID-19 Subsample				
$\|\Delta\|$	0.216***	0.120***	0.240***	0.257***	0.244***	0.108*	0.113***	0.174***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)	(0.002)	(0.001)
Obs.	239449	110143	129306	35873	58549	34884	63083	47060
Adj. R^2	0.289	0.303	0.289	0.351	0.302	0.167	0.306	0.257
				Panel B. COVID-19 Crash Subsample				
$\|\Delta\|$	0.495***	0.357***	0.527***	0.508***	0.566***	0.378***	0.505***	0.362***
	(0.004)	(0.009)	(0.004)	(0.004)	(0.003)	(0.018)	(0.007)	(0.007)
Obs.	3159	1555	1604	585	593	426	658	897
Adj. R^2	0.177	0.090	0.191	0.229	0.294	0.114	0.229	0.118
				Panel C. Post COVID-19 Crash Subsample				
$\|\Delta\|$	0.275***	0.262***	0.295***	0.307**	0.275***	0.257***	0.323***	0.265***
	(0.003)	(0.004)	(0.003)	(0.004)	(0.005)	(0.011)	(0.014)	(0.003)
Obs.	17677	8767	8910	3239	3280	2391	3649	5118
Adj. R^2	0.070	0.056	0.077	0.091	0.070	0.061	0.099	0.064

Table B5
The Impact of the Investment Gap on Index Volatility: Standardized Coefficients

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper ($|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF and year fixed effects to control for omitted variables and cluster the standard errors at the underlying index level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Pre-COVID-19 Subsample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	-0.000	0.050**	-0.053***	0.041	-0.029***	-0.221***	0.060***	0.094***
	(0.012)	(0.010)	(0.026)	(0.016)	(0.016)	(0.035)	(0.018)	(0.003)
Obs.	239445	110141	129304	35871	58549	34884	63083	47058
Adj. R^2	0.331	0.353	0.330	0.304	0.329	0.343	0.363	0.293
Panel B. COVID-19 Crash Subsample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	0.076***	0.107***	0.056***	0.067***	0.115	-0.023*	-0.277***	0.143***
	(0.005)	(0.006)	(0.006)	(0.006)	(1.390)	(0.085)	(0.542)	(0.005)
Obs.	3159	1555	1604	585	593	426	658	897
Adj. R^2	0.020	0.004	0.003	0.010	0.003	-0.027	0.055	0.021
Panel C. Post COVID-19 Crash Subsample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	-0.117***	-0.163***	-0.018	-0.034	0.088***	0.010	-0.047	-0.184***
	(0.020)	(0.021)	(0.024)	(0.024)	(0.011)	(0.095)	(0.300)	(0.021)
Obs.	17677	8767	8910	3239	3280	2391	3649	5118
Adj. R^2	0.168	0.217	0.088	0.098	0.076	0.052	0.074	0.244

Table B6
The Impact of the Investment Gap on Market-wide Volatility: Standardized Coefficients

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper ($|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF and year fixed effects to control for omitted variables and cluster the standard errors at the underlying index level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Pre-COVID-19 Subsample				
$|\Delta| - |\Delta^L|$	-0.006	0.049**	-0.061***	0.042**	-0.038***	-0.221***	0.073***	0.072***
	(0.010)	(0.007)	(0.019)	(0.011)	(0.012)	(0.010)	(0.006)	(0.001)
Obs.	239445	110141	129304	35871	58549	34884	63083	47058
Adj. R^2	0.331	0.353	0.330	0.304	0.329	0.343	0.363	0.293
				Panel B. COVID-19 Crash Subsample				
$|\Delta| - |\Delta^L|$	0.111***	0.143***	0.092***	0.111***	0.116	-0.022**	-0.272***	0.193***
	(0.009)	(0.008)	(0.011)	(0.011)	(1.290)	(0.053)	(0.634)	(0.008)
Obs.	3159	1555	1604	585	593	426	658	897
Adj. R^2	0.020	0.004	0.003	0.010	0.003	-0.027	0.055	0.021
				Panel C. Post COVID-19 Crash Subsample				
$|\Delta| - |\Delta^L|$	0.004	-0.005	0.024	0.026	0.041***	-0.002	-0.049	-0.005
	(0.007)	(0.007)	(0.016)	(0.017)	(0.012)	(0.035)	(0.230)	(0.007)
Obs.	17677	8767	8910	3239	3280	2391	3649	5118
Adj. R^2	0.168	0.217	0.088	0.098	0.076	0.052	0.074	0.244

Table B7
The Impact of Rebalancing Demand on Index Volatility: Controlling for Option Markets

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest. Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include year fixed effects to control for omitted variables and cluster the standard errors at the year level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
|Δ|	0.224***	0.134***	0.250***	0.275***	0.257***	0.099**	0.122**	0.216***
	(0.004)	(0.004)	(0.005)	(0.000)	(0.005)	(0.004)	(0.005)	(0.001)
Options	-0.018	-0.047	0.004	-0.003*	0.008	-0.018***	-0.049	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Exp. Day	0.018*	0.002	0.022**	0.008***	0.038***	-0.019	0.003	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)
Obs.	260,281	120,463	139,818	39,695	62,422	37,701	67,390	53,073
Adj. R^2	0.300	0.293	0.309	0.342	0.335	0.122	0.307	0.214
Panel B. Non-Recession Subsample								
|Δ|	0.179***	0.147***	0.188***	0.350***	0.198***	0.156***	0.075***	0.294***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)	(0.003)
Options	-0.037	-0.103	-0.003	-0.006*	0.001	-0.017***	-0.123	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Exp. Day	0.013	-0.006	0.018	0.003*	0.048**	-0.025	-0.007	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Obs.	236,385	109,794	126,591	38,023	54,569	33,999	59,115	50,679
Adj. R^2	0.073	0.095	0.072	0.258	0.070	0.069	0.079	0.156
Panel C. Recession Subsample								
|Δ|	0.401***	0.269***	0.454***	0.316***	0.476***	0.345***	0.271***	0.362***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.004)	(0.023)	(0.004)	(0.007)
Options	0.022	0.054*	0.013	-0.006***	0.016	-0.022**	0.056*	0.000
	(0.002)	(0.004)	(0.002)	(0.001)	(0.002)	(0.001)	(0.004)	(0.000)
Exp. Day	0.043***	0.018*	0.051***	0.010	0.055***	0.036***	0.021**	-0.029***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
Obs.	23,896	10,669	13,227	1,672	7,853	3,702	8,275	2,394
Adj. R^2	0.191	0.101	0.233	0.256	0.256	0.173	0.103	0.164

Table B8
The Impact of Rebalancing Demand on Market-wide Volatility: Controlling for Option Markets

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest corresponding. Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include year fixed effects to control for omitted variables and cluster the standard errors at year level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Overall Sample				
|Δ|	0.210***	0.125***	0.235***	0.332***	0.249***	0.114*	0.112***	0.214***
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.005)	(0.002)	(0.002)
Options	-0.036***	-0.057***	-0.018**	-0.000	-0.020**	-0.002*	-0.059**	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Exp. Day	0.026***	-0.006*	0.035***	0.005***	0.055***	-0.001	-0.005	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	260285	120465	139820	39697	62422	37701	67390	53075
Adj. R^2	0.275	0.287	0.276	0.342	0.302	0.146	0.295	0.235
				Panel B. Non-Recession Subsample				
|Δ|	0.149***	0.079***	0.163***	0.280***	0.191***	0.101**	0.051***	0.167***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)
Options	-0.054***	-0.111***	-0.005	-0.002**	-0.006	-0.000	-0.123***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp. Day	0.031***	-0.017***	0.043***	-0.001	0.082***	-0.005	-0.017**	-0.014***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	236389	109796	126593	38025	54569	33999	59115	50681
Adj. R^2	0.079	0.090	0.078	0.246	0.093	0.055	0.071	0.166
				Panel C. Recession Subsample				
|Δ|	0.333***	0.233***	0.370***	0.318***	0.385***	0.322***	0.224***	0.347***
	(0.003)	(0.002)	(0.004)	(0.002)	(0.004)	(0.015)	(0.002)	(0.006)
Options	-0.023**	0.020***	-0.034***	-0.003***	-0.037***	-0.008**	0.021***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Exp. Day	0.038***	0.008*	0.047***	0.005	0.050***	0.034***	0.011**	-0.040***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	23896	10669	13227	1672	7853	3702	8275	2394
Adj. R^2	0.148	0.079	0.177	0.258	0.177	0.164	0.075	0.159

Table B9
The Impact of the Investment Gap on Index Volatility: Controlling for Option Markets

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper ($|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include year fixed effects to control for omitted variables and cluster the standard errors at the year level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
$\|\Delta\| - \|\Delta^L\|$	-0.001	0.050**	-0.052**	0.068**	-0.028**	-0.245***	0.049**	0.096**
	(0.015)	(0.011)	(0.035)	(0.019)	(0.019)	(0.041)	(0.021)	(0.007)
Options	-0.011	-0.048	0.007	-0.005*	0.010	-0.018***	-0.053	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.000)	(0.001)	(0.000)
Exp. Day	0.010	-0.004	0.015	-0.009***	0.026**	-0.020	-0.002	-0.019***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Obs.	260281	120463	139818	39695	62422	37701	67390	53073
Adj. R^2	0.242	0.268	0.241	0.217	0.258	0.155	0.290	0.128
Panel B. Non-Recession Subsample								
$\|\Delta\| - \|\Delta^L\|$	-0.005	0.070**	-0.103**	0.064	-0.017	-0.285***	0.038	0.108**
	(0.017)	(0.007)	(0.045)	(0.022)	(0.028)	(0.041)	(0.022)	(0.006)
Options	-0.031	-0.105	-0.002	-0.007**	0.002	-0.018***	-0.127	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
Exp. Day	0.008	-0.012	0.014	-0.013***	0.040**	-0.025	-0.010	-0.018***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Obs.	236385	109794	126591	38023	54569	33999	59115	50679
Adj. R^2	0.041	0.078	0.047	0.143	0.031	0.126	0.075	0.083
Panel C. Recession Subsample								
$\|\Delta\| - \|\Delta^L\|$	0.001	0.089***	-0.031	0.061**	-0.039*	-0.017***	0.104***	0.045
	(0.009)	(0.034)	(0.026)	(0.013)	(0.029)	(0.018)	(0.017)	(0.018)
Options	0.029	0.061*	0.019	-0.006***	0.023	-0.027***	0.063*	0.000
	(0.003)	(0.004)	(0.003)	(0.001)	(0.003)	(0.001)	(0.004)	(0.000)
Exp. Day	0.026***	0.007	0.032***	-0.006	0.034***	0.018***	0.010	-0.047***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
Obs.	23896	10669	13227	1672	7853	3702	8275	2394
Adj. R^2	0.032	0.037	0.033	0.167	0.034	0.057	0.041	0.036

Table B10
The Impact of the Investment Gap on Market-wide Volatility: Controlling for Option Markets

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper ($|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include year fixed effects to control for omitted variables and cluster the standard errors at the year level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
$|\Delta| - |\Delta^L|$	-0.003	0.052**	-0.057**	0.060***	-0.038***	-0.224***	0.076***	0.069***
	(0.010)	(0.008)	(0.024)	(0.008)	(0.012)	(0.013)	(0.005)	(0.001)
Options	-0.030***	-0.058***	-0.016**	-0.002***	-0.018**	-0.003**	-0.065***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Exp. Day	0.020***	-0.011***	0.028***	-0.010***	0.044***	-0.001	-0.010**	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	260,285	120,465	139,820	39,697	62,422	37,701	67,390	53,075
Adj. R^2	0.233	0.274	0.228	0.244	0.244	0.183	0.289	0.194
Panel B. Non-Recession Subsample								
$|\Delta| - |\Delta^L|$	-0.010	0.073**	-0.113***	0.031**	-0.051**	-0.278***	0.114***	0.077***
	(0.011)	(0.006)	(0.026)	(0.006)	(0.027)	(0.014)	(0.007)	(0.001)
Options	-0.050***	-0.113***	-0.004	-0.003***	-0.005	-0.001	-0.134***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exp. Day	0.027***	-0.020***	0.040***	-0.015***	0.074***	-0.003	-0.021**	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	236,389	109,796	126,593	38,025	54,569	33,999	59,115	50,681
Adj. R^2	0.057	0.089	0.065	0.171	0.059	0.122	0.081	0.144
Panel C. Recession Subsample								
$|\Delta| - |\Delta^L|$	0.001	0.082***	-0.027	0.092***	-0.041**	-0.018***	0.085***	0.110**
	(0.011)	(0.011)	(0.019)	(0.013)	(0.018)	(0.013)	(0.009)	(0.015)
Options	-0.017	0.026***	-0.029**	-0.004***	-0.031**	-0.013***	0.027***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Exp. Day	0.024***	-0.002	0.031***	-0.010	0.034***	0.018***	0.001	-0.058***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	23,896	10,669	13,227	1,672	7,853	3,702	8,275	2,394
Adj. R^2	0.039	0.033	0.045	0.173	0.033	0.063	0.032	0.051

Table B11
The Impact of Rebalancing Demand on Index Volatility: Controlling for Expected Volatility

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest. Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF, year, month, and day of week fixed effects to capture unobservable fund and cluster the standard errors at the underlying index fund level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
$\lvert\Delta\rvert$	0.114***	0.075***	0.125***	0.127***	0.125***	0.074**	0.064**	0.128***
	(0.002)	(0.003)	(0.002)	(0.001)	(0.003)	(0.005)	(0.003)	(0.002)
VIX_{t-1}	0.556***	0.598***	0.538***	1.092***	0.529***	0.313**	0.566***	0.746***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.267***	0.220*	0.288***	-0.229***	0.282***	0.402**	0.275*	-0.014
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	203502	94189	109313	31007	48821	29485	52721	41468
Adj. R^2	0.635	0.627	0.640	0.690	0.641	0.662	0.639	0.558
Panel B. Non-Recession Subsample								
$\lvert\Delta\rvert$	0.104***	0.069**	0.113***	0.177***	0.109***	0.075*	0.036	0.142***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.005)	(0.001)	(0.002)
VIX_{t-1}	0.571***	0.566***	0.574***	0.805***	0.762***	0.165	0.541***	0.554***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.132**	0.091*	0.148**	-0.093***	0.011	0.281**	0.124*	0.053
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	184894	85883	99011	29708	42705	26598	46276	39607
Adj. R^2	0.485	0.477	0.491	0.559	0.447	0.649	0.481	0.478
Panel C. Recession Subsample								
$\lvert\Delta\rvert$	0.145***	0.076***	0.162***	0.013	0.173***	0.064*	0.077***	0.052***
	(0.003)	(0.002)	(0.003)	(0.000)	(0.003)	(0.008)	(0.002)	(0.001)
VIX_{t-1}	0.568***	0.666***	0.508***	1.129***	0.421***	0.839***	0.651***	1.117***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.106	-0.054*	0.185**	-0.665***	0.258***	-0.072	-0.020	-0.770***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	18608	8306	10302	1299	6116	2887	6445	1861
Adj. R^2	0.619	0.615	0.621	0.782	0.619	0.697	0.614	0.728

Table B12
The Impact of Rebalancing Demand on Market-wide Volatility: Controlling for Expected Volatility

This table presents standardized estimates from regressing index volatility on rebalancing demand for the three subsamples of interest. Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF, year, month, and day of week fixed effects to capture unobservable fund and cluster the standard errors at the underlying index fund level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
$\lvert\Delta\rvert$	0.084***	0.050***	0.092***	0.106***	0.088***	0.071**	0.044***	0.064***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.003)	(0.001)	(0.001)
VIX_{t-1}	0.823***	0.882***	0.800***	1.184***	0.799***	0.492***	0.821***	1.095***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.130***	0.071	0.153***	-0.272***	0.143***	0.335***	0.153**	-0.161***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	203506	94191	109315	31009	48821	29485	52721	41470
Adj. R^2	0.700	0.706	0.700	0.718	0.718	0.649	0.715	0.666
Panel B. Non-Recession Subsample								
$\lvert\Delta\rvert$	0.101***	0.050***	0.111***	0.145***	0.107***	0.080**	0.040**	0.069***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
VIX_{t-1}	0.776***	0.753***	0.774***	0.945***	0.927***	0.331***	0.662***	0.965***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.038	0.052	0.044	-0.146***	-0.066**	0.238***	0.105	-0.096***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	184898	85885	99013	29710	42705	26598	46276	39609
Adj. R^2	0.566	0.540	0.581	0.568	0.624	0.591	0.550	0.548
Panel C. Recession Subsample								
$\lvert\Delta\rvert$	0.076***	0.048***	0.082***	0.017**	0.086***	0.047**	0.047***	0.032*
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.004)	(0.000)	(0.001)
VIX_{t-1}	0.807***	0.966***	0.733***	1.161***	0.620***	0.916***	0.942***	1.184***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.012	-0.111***	0.073	-0.701***	0.164***	-0.109**	-0.061**	-0.787***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	18608	8306	10302	1299	6116	2887	6445	1861
Adj. R^2	0.707	0.696	0.710	0.797	0.707	0.724	0.691	0.816

Table B13
The Impact of the Investment Gap on Index Volatility: Controlling for Expected Volatility

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper ($|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Index volatility is the 5-day rolling standard deviation of the underlying benchmark return. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF, year, month, and day of week fixed effects to capture unobservable fund and cluster the standard errors at the underlying index fund level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. Overall Sample				
$\|\Delta\| - \|\Delta^L\|$	0.003	0.041**	-0.039***	0.003	-0.031***	-0.105**	0.056**	0.055***
	(0.007)	(0.008)	(0.018)	(0.009)	(0.015)	(0.028)	(0.018)	(0.003)
VIX_{t-1}	0.586***	0.612***	0.567***	1.148***	0.558***	0.279*	0.593***	0.769***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.264***	0.221	0.289***	-0.236***	0.283***	0.449**	0.255*	0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	203502	94189	109313	31007	48821	29485	52721	41468
Adj. R^2	0.624	0.624	0.628	0.676	0.627	0.664	0.638	0.546
				Panel B. Non-Recession Subsample				
$\|\Delta\| - \|\Delta^L\|$	0.009	0.051***	-0.049**	0.003	-0.009	-0.130**	0.043*	0.067***
	(0.006)	(0.004)	(0.021)	(0.012)	(0.008)	(0.027)	(0.010)	(0.003)
VIX_{t-1}	0.591***	0.572***	0.590***	0.859***	0.794***	0.124	0.557***	0.571***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.125**	0.090*	0.144**	-0.090**	-0.006	0.312**	0.110	0.065
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	184894	85883	99011	29708	42705	26598	46276	39607
Adj. R^2	0.475	0.475	0.481	0.531	0.436	0.655	0.481	0.464
				Panel C. Recession Subsample				
$\|\Delta\| - \|\Delta^L\|$	-0.002	0.053***	-0.024***	0.006	-0.029***	-0.027***	0.061***	-0.029*
	(0.009)	(0.015)	(0.010)	(0.016)	(0.011)	(0.018)	(0.009)	(0.008)
VIX_{t-1}	0.597***	0.680***	0.527***	1.133***	0.418***	0.846***	0.659***	1.149***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.123	-0.055*	0.210*	-0.672***	0.305***	-0.070	-0.026	-0.800***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	18608	8306	10302	1299	6116	2887	6445	1861
Adj. R^2	0.601	0.612	0.600	0.782	0.595	0.694	0.611	0.727

Table B14
The Impact of the Investment Gap on Market-wide Volatility: Controlling for Expected Volatility

This table presents standardized estimates from regressing index volatility on the difference between the absolute rebalancing demand derived in this paper (see Equation 7, $|\Delta|$) and the flow approximation of Ivanov and Lenkey (2018) for the three subsamples of interest ($|\Delta^L|$). Market-wide volatility is the 5-day rolling standard deviation of the value-weight return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ. All models are weighted by the square root of the total LETF assets tracking the index. We drop any ETF with less than 60 days of data and remove two-days before and after split dates. We include ETF and year fixed effects to capture unobservable fund and cluster the standard errors at the fund and year level. We use *, **, and *** to indicate significance at the 10%, 5%, and 1% level, respectively.

				Leverage Multiple				
	LETF	Positive	Inverse	-3	-2	-1	2	3
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Overall Sample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	-0.003	0.052**	-0.057**	0.060***	-0.038***	-0.224***	0.076***	0.069***
	(0.010)	(0.008)	(0.024)	(0.008)	(0.012)	(0.013)	(0.005)	(0.001)
VIX_{t-1}	-0.030***	-0.058***	-0.016**	-0.002***	-0.018**	-0.003**	-0.065***	0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.020***	-0.011***	0.028***	-0.010***	0.044***	-0.001	-0.010**	-0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	260,285	120,465	139,820	39,697	62,422	37,701	67,390	53,075
Adj. R^2	0.233	0.274	0.228	0.244	0.244	0.183	0.289	0.194
Panel B. Non-Recession Subsample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	-0.010	0.073**	-0.113***	0.031**	-0.051**	-0.278***	0.114***	0.077***
	(0.011)	(0.006)	(0.026)	(0.006)	(0.027)	(0.014)	(0.007)	(0.001)
VIX_{t-1}	-0.050***	-0.113***	-0.004	-0.003***	-0.005	-0.001	-0.134***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
FSI_{t-1}	0.027***	-0.020***	0.040***	-0.015***	0.074***	-0.003	-0.021**	-0.023***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	236,389	109,796	126,593	38,025	54,569	33,999	59,115	50,681
Adj. R^2	0.057	0.089	0.065	0.171	0.059	0.122	0.081	0.144
Panel C. Recession Subsample								
$\lvert\Delta\rvert - \lvert\Delta^L\rvert$	0.001	0.082***	-0.027	0.092***	-0.041**	-0.018***	0.085***	0.110**
	(0.011)	(0.011)	(0.019)	(0.013)	(0.018)	(0.013)	(0.009)	(0.015)
VIX_{t-1}	-0.017	0.026***	-0.029**	-0.004***	-0.031**	-0.013***	0.027***	0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
FSI_{t-1}	0.024***	-0.002	0.031***	-0.010	0.034***	0.018***	0.001	-0.058***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Obs.	23,896	10,669	13,227	1,672	7,853	3,702	8,275	2,394
Adj. R^2	0.039	0.033	0.045	0.173	0.033	0.063	0.032	0.051

Table B15
The Impact of Rebalancing on Volatility: Instrumented Aggregate Regressions

This table explores the relationship between rebalancing demand on date t (b_t) and market volatility by using 2SLS regressions. Columns (1) through (3) present the first stage results while columns (4) through (5) present the second stage results. In columns (1) and (4), we present the results using the aggregate moderation-amplification ratio as an instrument for rebalancing demand, as suggested by our structural model. The remaining columns exploit the idiosyncratic shocks to large LETFs by constructing granular instrumental variables (Gabaix and Koijen, 2022). In column (2) and (5), we use the difference between the value-weighted average of the leverage multiples in the LETF space and the equal-weighted average, denoted Δm. In columns (3) and (6), we use the difference between the value-weighted average of fund flows and the equal-weighted average of fund flows, denoted Δf. We include *Libor*, *Amihud* illiquidity, the lagged changes in VIX (ΔVIX_{t-1}), and lagged squared market returns (Ret^2_{t-1}) as controls. The data is daily and we include month and year fixed effects. Standard errors, which are in parenthesis under the point estimates, are clustered at year level. We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

	Dependent Variable:							
	First Stage: Rebalancing Demand$_t$				Second Stage: Change in VIX$_t$			$\lvert \text{dVIX}_t \rvert$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
θ_t/ϕ_t	0.035							
	(0.027)							
Δm		0.098***						
		(0.014)						
Δf			2.538***					
			(0.218)					
$\left(\frac{m\theta}{(m-1)\phi}\right)\Delta f$				0.006***				
				(0.001)				
Rebalancing					-1.478**	-0.498***	-0.040**	-0.306**
					(0.498)	(0.084)	(0.019)	(0.080)
Libor	-0.004	0.018**	-0.010**	-0.004	0.005	0.010***	0.012***	0.008
	(0.007)	(0.007)	(0.003)	(0.005)	(0.009)	(0.003)	(0.003)	(0.005)
Amihud	-0.022	-0.016	-0.030	-0.020	0.036*	0.054***	0.062***	0.166***
	(0.020)	(0.017)	(0.018)	(0.017)	(0.019)	(0.013)	(0.015)	(0.023)
ΔVIX_{t-1}	0.067**	0.078**	0.048	0.065**	0.007	-0.057**	-0.087***	0.103***
	(0.030)	(0.030)	(0.028)	(0.030)	(0.041)	(0.019)	(0.022)	(0.017)
Ret^2_{t-1}	0.001***	0.001***	0.001***	0.001***	0.001	0.000	-0.001***	0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Month FE	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	3,564	3,564	3,564	3,565	3,564	3,564	3,564	3,564
Adj. R^2	0.012	0.052	0.261	0.012	-0.57	0.335	0.061	0.127

Table B15
Investor Behavior and Autocorrelation Parameters: Robustness

This table reports the estimated parameters from a Fama-Macbeth two-stage estimation of the investors' momentum versus contrarian behavior parameter θ and the underlying index return autocorrelation parameter ϕ. In the first stage, we run the following regressions on a fund-by-bund basis,

$$f_t = \alpha + \theta m r_{t-1} + \sum_{j=1}^{3} \delta_j f_{t-j} + \sum_{j=1}^{3} \gamma_j r_{t-j} + u_{t+1},$$

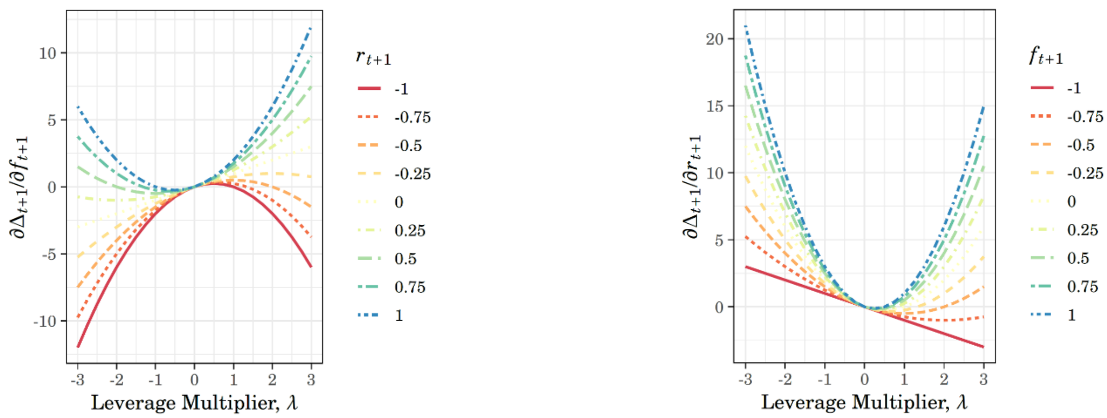
$$r_t = \kappa + \phi r_{t-1} + e_{t+1},$$

using a 90-day rolling window. This allows use to extract a time-series of both parameters. We linearly interpolate all zero flow days. We include three days of lagged flows and two additional days of lagged returns in the flow regression to correct for any autocorrelation induced by the procedure and to control for the findings of Broman (2022) and Evans et al. (2021), who show that additional return lags may play a role in explaining flows and that sponsors strategically delay the creation of new shares. We then aggregate the investor behavior θ and return auto-correlation ϕ parameter values by taking the asset weighted sum for each day,

$$\Theta_t = \sum_j \frac{a_{j,t}}{A_t} \Theta_{j,t}$$

where a_{jt} is the assets under management of fund j, the sum $A_t = \sum_j a_{j,t}$ is the total assets under management in the leveraged ETF space, $\Theta_{j,t}$ is the estimated parameter for fund j on day t, and Θ_t is the aggregate parameter value on day t. In the second stage, we estimate the average of our time-series and use the $\log(1+\Theta)$ transformation to scale the parameter values. We use pre-whitened Newey-West (1987) standard errors with the optimal bandwidth selection procedure from Newey-West (1994). We use *, **, and *** to denote statistical significance at the 1%, 5%, and 10% levels.

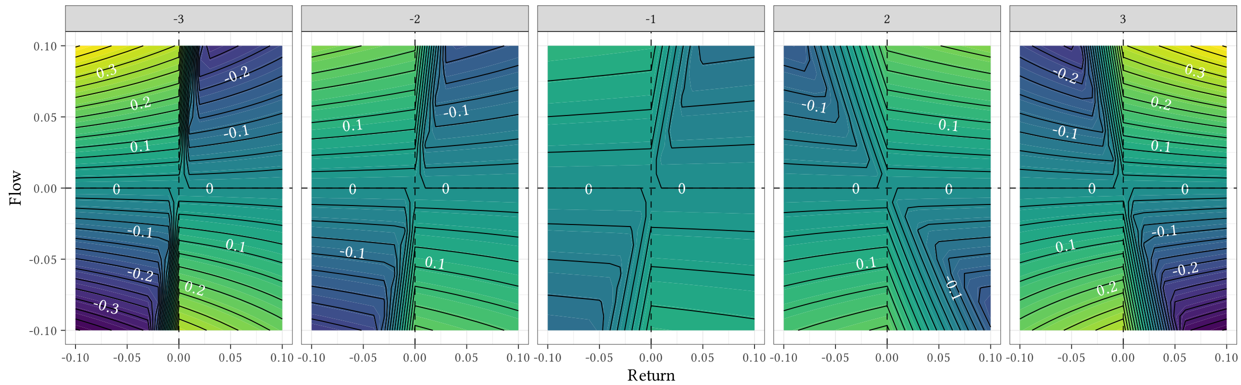
		Leverage (m)				
	Aggregate	-3	-2	-1	2	3
θ	-0.692***	0.220***	0.100*	-0.046	-0.351*	-3.792**
	(0.24)	(0.059)	(0.06)	(0.029)	(0.183)	(1.507)
ϕ	-1.154***	-0.165***	-0.736**	-0.381***	-1.867***	-1.829**
	(0.312)	(0.048)	(0.299)	(0.112)	(0.583)	(0.721)
ζ	0.56	0.289***	0.570**	0.170***	3.189***	-3.012
	(0.585)	(0.055)	(0.25)	(0.059)	(1.18)	(2.05)
N	3,564	2,965	3,548	3,564	3,564	2,965



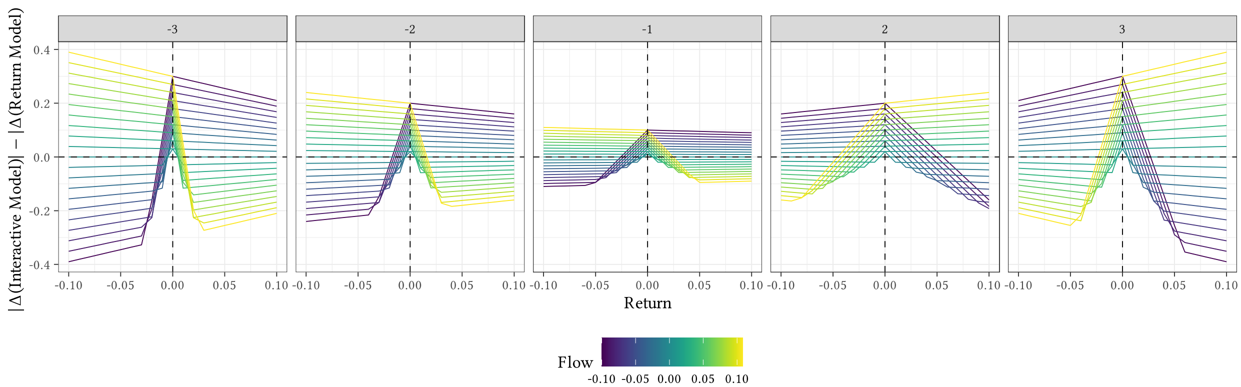
Panel (A). Response to Flow Shocks

Panel (B). Response to Return Changes

Figure B1. Comparative Statistics. We plot the impact of benchmark returns and flows on rebalancing demand.

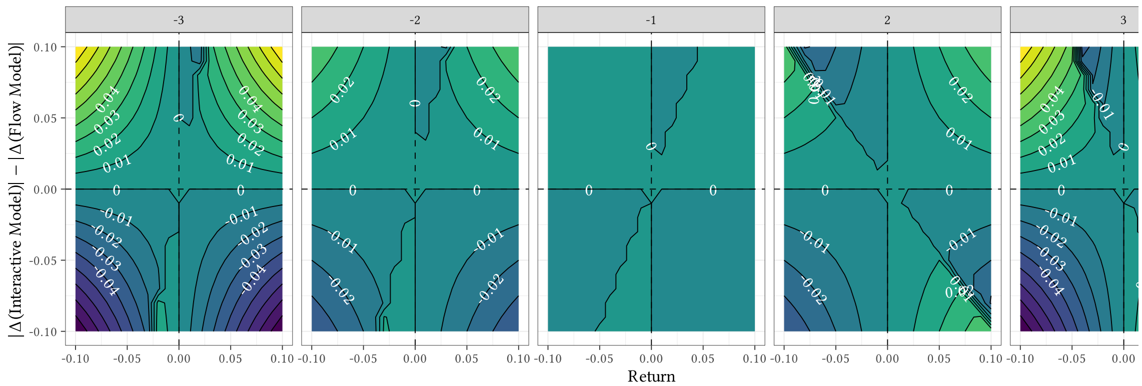


Panel (A). Amplification and Moderation Contour Plot by Leverage Multiple

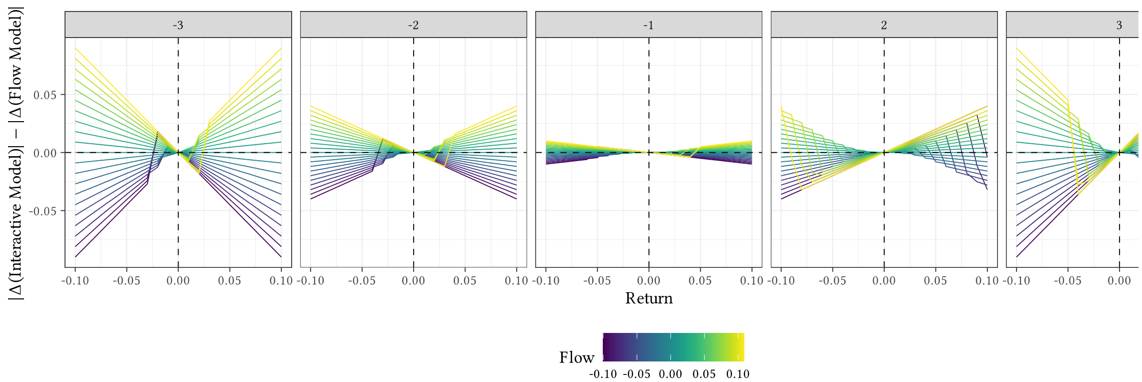


Panel (B). Amplification and Moderation at Different Levels of Flows by Leverage Multiple

Figure B2. Amplification and Moderation of the Return Approximation of Rebalancing Demand Across Different Leverage Multiples Relative to CM (2009). Panel (A) plots amplification/moderation effect of the interactive model relative to the return approximation on the y-axis and underlying benchmark returns on the x -axis. Amplification/Moderation is defined as the difference in the absolute value of the interactive rebalancing demand model and the return model derived by Cheng and Madhavan (2009). A positive number means that the return approximation is underestimating rebalancing demand (i.e., actual rebalancing demand is amplified) while a negative number means that the return approximation is overestimating rebalancing demand (i.e., actual rebalancing demand is moderated).



Panel (A). Amplification and Moderation Contour Plot by Leverage Multiple



Panel (B). Amplification and Moderation at Different Levels of Flows by Leverage Multiple

Figure B3. Amplification and Moderation of the Flow Approximation of Rebalancing Demand Across Different Leverage Multiples. Panel (A) plots amplification/moderation effect of the interactive model relative to the flow approximation. Amplification/Moderation is defined as the difference in the absolute value of the interactive rebalancing demand model and the return model derived by Ivanov and Lenkey (2018). A positive number means that the flow approximation is underestimating rebalancing demand (i.e., actual rebalancing demand is amplified) while a negative number means that the flow approximation is overestimating rebalancing demand (i.e., actual rebalancing demand is moderated).