# Speculation Sentiment*

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### Abstract

I provide a novel and direct test that shows speculative demand shocks push asset prices away from fundamentals. I form the *Speculation Sentiment Index* using observable arbitrage trades in leveraged exchange-traded funds (ETFs). Arbitrage activity originates from unobservable speculative demand shocks that create relative mispricing between a leveraged ETF and its underlying derivative securities. The index proxies for the direction and magnitude of market-wide speculative demand shocks. The Speculation Sentiment Index predicts aggregate asset return reversals and it is associated with market-wide mispricing and arbitrage activity.



*Keywords: Return predictability, leveraged exchange-traded fund, non-fundamental demand

# 1 Introduction

> ...defining investment speculation and gambling is an interesting question...It's a tricky definition. You know, it's like pornography, and that famous quote on that. But I look at it in terms of the intent of the person engaging in the transaction
>
> —Warren Buffett, May 26, 2010
>
> Testimony to United States of America Financial Crisis Inquiry Commission[1]

On the continuum of ways one can allocate capital to risky endeavors, investing lies at one extreme and gambling lies at the other. Somewhere in-between lies speculation and, as articulated by Mr. Buffett, the distinction between speculation and gambling is blurry. In this paper, I focus on traders' motives around this blurry boundary and I define speculation sentiment as a gambling-like, non-fundamental belief about the future direction of the market. Similar to the beliefs of the gambler who looks at the roulette wheel and wagers which color will result on the next spin, speculation sentiment is the mood of an uninformed trader who looks at the market and wagers on its short-run performance.

Does speculative sentiment from individual traders aggregate in a meaningful way and, if it does, do changes in this speculative demand move asset prices away from fundamentals? To date, the answers to these questions have been elusive because speculative demand shocks are difficult to identify. However, in this paper, I provide a novel and direct means of measuring aggregate speculative demand shocks and I provide credible evidence that the shocks distort asset prices. The measure is based on observable arbitrage trades in correcting relative mispricing in the Leveraged Exchange-Traded Funds (ETFs) market. I coin the measure the *Speculation Sentiment Index* ($SSI$) and the index predicts aggregate asset return reversals and the relation is economically meaningful: A one standard deviation increase in the monthly index is associated with a 1.1%-1.9% decline in broad market indices the following month. The results are robust to the inclusion of sentiment proxies and market controls.

A leveraged ETF's shares provide magnified, short-horizon exposure to a market benchmark, for example, the S&P 500 index. The shares trade intraday in the secondary market and are characterized by high trade volume (relative to non-leveraged ETFs and single-name stocks). Leveraged ETF shares are primarily traded among individuals and short-horizon traders and, unlike margin

[1] Mr. Buffett's use of the phrase "it's like pornography, and that famous quote on that," is in reference to the colloquial expression "I know it when I see it." The phrase originated in 1964 when United States Supreme Court Justice Potter Stewart used it to describe his threshold test for obscenity (see Jacobellis v. Ohio).

accounts or option trading which require special approvals, any trader may purchase a leveraged ETF share in his or her brokerage account (and also in many retirement accounts). As a pooled investment vehicle, the intrinsic value of a leveraged ETF share is determined by the value of an underlying basket of derivative securities and cash holdings. The underlying derivative securities are traded primarily by institutions and for several purposes, such as, risk management and hedging. Consequently, there are different investor clienteles trading the shares and trading the underlying derivative securities. I argue that these two distinct clienteles cause there to be a difference in the demand for the leveraged ETF shares and the demand for the underlying derivative securities. In particular, my identifying assumption is that leveraged ETF share demand is relatively more sensitive to short-horizon, gambling-like demand shocks than the underlying derivative security demand.

Under my identifying assumption that leveraged ETF share demand is relatively more sensitive to speculative demand shocks than the underlying derivative security demand, the realization of a shock gives rise to a relative mispricing. Importantly, remnants of mispricing are observable in the leveraged ETF market unlike other settings in which mispricing may be quickly exploited by arbitrageurs leaving no evidence for the empiricist. Observable remnants are due to a unique feature of the ETF market: Arbitrageurs exploit relative mispricing in a primary market by creating and redeeming ETF shares. This process allows the empiricist to observe arbitrage activity via changes in shares outstanding. Thus, leveraged ETFs provide a special setting to directly observe a proxy of speculative demand shocks. To see this, consider the example in Figure 1. At $t = 0$, a small relative mispricing exists between the leveraged ETF shares and the underlying net asset value (NAV), but it is not large enough to attract arbitrageurs due to transaction costs. At $t = 1$, a latent speculative demand shock is realized, and the demands for the ETF shares and the underlying derivative securities are affected to different degrees, generating a larger mispricing. At $t = 2$, arbitrageurs exploit the mispricing and their trades are observable.

I form the measure of speculation sentiment ($SSI$) using the first leveraged ETFs offered to traders, which were introduced by ProShares in the summer of 2006. Using the original leveraged ETFs, three that provide 2x long exposure and three that provide 2x short exposure to market indices, I calculate $SSI$ at the monthly frequency. The index is calculated by taking the difference between share change in the 2x leveraged-long ETFs and share change in the 2x leveraged-short ETFs. $SSI$ provides a glimpse into the mood of speculators; If the number is large and positive, speculators heavily demanded leveraged-long exposure, so much so that the ETF share prices drifted above NAVs leading to arbitrage opportunities. If the number is large and negative, speculators heavily demanded leveraged-short exposure. Finally, if the number is near zero, the demand for leveraged-long and leveraged-short ETFs effectively canceled out or the speculative demand shock was small. Taking the difference between share change in the leveraged-long and leveraged-short ETFs also mitigates arbitrage activity that may be due to other non-fundamental shocks that generate relative mispricing between leveraged ETFs and their underlying derivative securities (for example, limited arbitrage capital).

The empirical results are consistent with my identifying assumption and $SSI$ predicts asset return reversals. I focus the predictive analysis on three benchmark indices: (i) the CRSP equal-weighted index, (ii) the CRSP value-weighted index, and (iii) the S&P 500 index. To begin, I perform a rudimentary test to motivate predictive regressions. I examine the relation between the sign on lagged $SSI$ and the sign on the index return for each of the three benchmark indices. I sort $SSI$ into quartiles and focus on the first and fourth quartiles, which represent the largest negative realizations and the largest positive realizations of the index. Lagged $SSI$ correctly predicts the sign on the return 68.33% of the time for the CRSP equal-weighted index, 61.67% of the time for the CRSP value-weighted index, and 60.00% of the time for the S&P 500 index. As a point of reference, the probabilities of successfully predicting at that frequency or greater with a coin flip are 0.31%, 4.62% and 7.75% respectively. The results of the rudimentary test suggest a negative relation between lagged $SSI$ and subsequent index returns.

Motivated by the rudimentary test, I perform predictive regressions with index returns as the dependent variable and lagged $SSI$ along with a set of sentiment proxies and market controls. A one standard deviation increase in lagged $SSI$ is associated with a statistically significant 1.6%-1.9% decline in the CRSP equal-weighted index, a 1.3%-1.4% decline in the CRSP value-weighted index, and a 1.1%-1.2% decline in the S&P 500 index. The predictive power of $SSI$ is not driven by the 2008 financial crisis; Repeating the analysis beginning in January 2010, the coefficients remain relatively stable in magnitude with statistically significant p-values.

To conclude the analysis, I study the relation between $SSI$ and contemporaneous arbitrage activity across a universe of over 1,000 ETFs.[2] Arbitrage activity in other ETFs is not necessarily due to speculative demand shocks as there are many sources of non-fundamental demand that generate relative mispricing. However, I document a strong relation between $SSI$ and market-wide ETF arbitrage activity. I perform fund-by-fund regressions in which share change (i.e., arbitrage activity) is the dependent variable and $SSI$ along with a set of controls are the independent variables. On a

[2]The sample universe of ETFs represented nearly two and a half trillion dollars in assets at the end of 2016 and covered nearly every asset category (equities, bonds, currencies, real estate, commodities, and even volatility) and asset market (developed markets and emerging markets).

value-weighted (equal-weighted) basis, 17%-22% (7%-10%) of ETFs have sensitivities to $SSI$ that are statistically significant with a 1% p-value threshold. In a subset of 146 leveraged ETFs, the results are stronger: On a value-weighted (equal-weighted) basis, 36%-50% (22%-34%) of leveraged ETFs have sensitivities to $SSI$ that are statistically significant with a 1% p-value threshold. The results document a strong statistical relation between $SSI$ and ETF arbitrage activity, particularly in other speculative, leveraged ETFs.

The magnitudes of the fund-level sensitivities to $SSI$ are also of economic importance. Consider SPY, which is the largest ETF and accounts for almost 10% of the value in all ETFs. A one standard deviation increase in $SSI$ is associated with 28.8% of a standard deviation increase in SPY's monthly arbitrage activity, or approximately 5 billion dollars of arbitrage activity.[3] In the entire sample set of non-leveraged ETFs, the median effect is between 13%-14% of a standard deviation. In leveraged ETFs, the median effect is over twice as large at 29% of a standard deviation, again suggesting that leveraged ETFs are relatively more sensitive to speculative demand shocks. Finally, the signs on the sensitivities themselves provide additional evidence that $SSI$ captures both the magnitude and direction of speculation sentiment. In a subset of 100, equity-focused, leveraged ETFs, $SSI$ systematically loads positively on the leveraged-long equity ETFs and negatively on the leveraged-short equity ETFs; 84% of leveraged-long equity assets have a positive coefficient and 95% of leveraged-short equity assets have a negative coefficient.

The main contribution of this paper is in providing a clean measure of speculation sentiment based on the arbitrage activity it generates. $SSI$ provides insights regarding the role of speculative demand on price formation; I show that $SSI$ negatively predicts asset returns, which is consistent with speculative traders bidding up asset prices that subsequently revert to their fundamental values over the span of a few weeks.[4] In this sense, my measure of speculation sentiment relates to "micro-bubbles," as opposed to full-blown speculative bubbles that, as described by Robert Shiller in his Nobel Prize Lecture and book *Irrational Exuberance*, are rare situations requiring widespread psychological contagion, price feedback, and massive misvaluation (Shiller, 2014).

Speculation sentiment is one dimension of broader *investor sentiment*.[5] I argue that speculation

[3]During the sample, the monthly standard deviation of percent change in shares outstanding is 7.64% for SPY and SPY's market capitalization on 12/30/2016 was 225 billion dollars: $28.8\% \times 7.65\% \times 225B = 5B$.

[4]Other empirical research also shows that demand for assets, unrelated to fundamentals, creates price dislocations that do not immediately revert. The sources of these non-fundamental demand shocks are numerous: Index rebalancing (Shleifer, 1986), liquidity needs (Coval & Stafford, 2007), investor sentiment measured by mutual fund flows (Ben-Rephael, Kandel, & Wohl, 2012), stale information (Huberman & Regev, 2001; DellaVigna & Pollet, 2007; Hong, Torous, & Valkanov, 2007), and investor inattention (DellaVigna & Pollet, 2009; Hirshleifer, Lim, & Teoh, 2009).

[5]Baker and Wurgler (2007) defines investor sentiment as "a belief about future cash flows and investment risk that is not justified by the facts at hand." As such, investor sentiment is inherently multi-dimensional as sentiment is

sentiment is a gambling-like, short-horizon dimension of investor sentiment. While I focus on a single dimension of investor sentiment in this paper, there are many other established proxies relating to a host of investor sentiment dimensions, for example, the mood of traders suffering from external disappointment (Edmans, Garcia, & Norli, 2007) or sadness (Saunders, 1993). With many dimensions to investor sentiment, there is not a shortage of sentiment proxies in the literature.[6] Importantly, sentiment measures need not compete with each other as "the sentiment" measure; Given numerous dimensions to investor sentiment, observing many measures does not imply that most measures are wrong.

Finally, this paper adds to a growing literature that uses exchange-traded funds as a laboratory to study non-fundamental demand. Ben-David, Franzoni, and Moussawi (2018) documents the transmission of non-fundamental demand volatility for ETF shares to the ETF's underlying assets via the ETF primary market mechanism. In a similar spirit, Brown, Davies, and Ringgenberg (2018) show that market participants fail to incorporate the information contained in observable arbitrage activity and that conditioning on ETF share changes yields return predictability.[7] Brown et al. (2018) focuses on fund-level return predictability and is agnostic regarding the types of the implicit demand shocks. Conversely, I focus on a subset of ETFs that cater to short-horizon traders to isolate speculative demand shocks and I examine the relation between these demand shocks and asset prices. Leveraged ETFs have also been of interest to academics. Cheng and Madhavan (2009) show that the daily rebalancing dynamics of leveraged ETFs, that is, maintaining the target leverage exposure, supports the claim that leveraged ETFs lead to greater end-of-day market volatility; For example, to maintain 2x exposure to an index, the leveraged ETF must always rebalance in the direction of that day's price movement. Empirically, however, there is debate to how much excess volatility leveraged ETFs generate: Shum, Hejazi, Haryanto, and Rodier (2015) and Tuzun (2013) provide new evidence that leveraged ETF rebalancing exacerbates market volatility while Ivanov and Lenkey (2014) suggests excess volatility concerns are overblown. Furthermore, Bessembinder (2015) argues that end-of-day rebalancing leads to predictable order flow, which should have minimal effects on long term prices. While I study a set of leveraged ETFs to formulate $SSI$, my focus is on the arbitrage activity associated with investor demand and not

related to the behaviors of individual traders and there are many well documented behavioral biases. See Hirshleifer (2001) and Barberis and Thaler (2003) for surveys of the behavioral finance literature.

[6] See Baker and Wurgler (2007) for a survey of investor sentiment measures. See also DeVault, Sias, and Starks (2017) for an analysis of existing sentiment measures relation to institutional demand versus individual demand.

[7] See also Staer (2016), which shows that ETF arbitrage activity is associated with contemporaneous price pressure and subsequent return reversals. Furthermore, see Ben-David, Franzoni, and Moussawi (2016) for a survey of the ETF literature.

the daily rebalancing activities in leveraged ETFs.

# 2 Background

On June 21, 2006, ProShares announced a set of four exchange-traded funds (ETFs) designed to make it easier for investors to get magnified exposure to an index. The four ETFs' daily objective is to provide 2x exposure to well-known indices like the S&P 500 and the Dow Jones Industrial Average (before fees and expenses). Three weeks later, on July 13, 2006, ProShares announced a set of four additional ETFs designed to provide magnified *short* exposure to well-known market indices. The set of leveraged ETFs announced during the summer of 2006 are provided in Figure 2. These eight ETFs sponsored by ProShares represent the first set of leveraged ETFs offered. Since the original eight launched in the summer of 2006, nearly 300 additional leveraged ETFs have been offered to investors. There are now leveraged ETFs providing magnified exposures to bond indices, commodities, currencies, emerging markets, and market volatility indices.

## 2.1 The Exchange-Traded Fund Market and Mechanism

The universe of Exchange-Traded Products (ETPs) is comprised of exchange-traded notes (ETNs), exchange-traded commodities (ETCs) and exchange-traded funds (ETFs). The majority of exchange-traded products fall into the ETF category and the term "ETF" is commonly used as a synonym for all exchange-traded products. Consequently, I use the label ETF throughout the paper unless a distinction is necessary.

The ETF market is large; With over three trillion dollars under management, ETFs collectively hold more assets than hedge funds (Madhavan, 2016). ETFs are also ingrained into nearly every asset market, both domestic and foreign.[8] Furthermore, ETFs are accessible to novice and professional investors alike.[9]

ETFs are a pooled investment vehicle, like a mutual fund, which allows investors to buy a basket of assets at once.[10] Like a closed-end mutual fund, investors can buy or sell an ETF share on a secondary market just as they would buy or sell a stock. However, unlike a closed-end mutual

[8] With over 2,000 publicly traded ETFs in the United States, investors may construct portfolios with both domestic and international exposures and invest in everything from equities to real estate. For example, ETFs utilized nearly 100 unique Lipper objective codes in 2015. Lipper's objective codes are assigned based on the language that the fund uses in its prospectus to describe how it intends to invest. Lipper codes range from broad U.S domestic equities, for example, "S&P 500 Index Objective Funds" to more exotic categories like "International Small-Cap Funds."

[9] ETFs are a popular investment choice within individual retirement plans, for example, 401Ks, and also a popular investment for professional managers to "equitize" cash in their funds' benchmarks (Antoniewicz & Heinrichs, 2014).

[10] Like mutual funds, most ETFs are formally registered with the SEC as investment companies under the Investment Company Act of 1940.

fund, shares in an ETF are added or removed on a primary market via the actions of third party arbitrageurs called authorized participants (APs). APs, who are pre-qualified by the fund sponsor (e.g., ProShares), are allowed to exchange shares of the ETF for shares of the underlying assets (an in-kind transaction) or for cash. Similarly, APs may deliver the underlying assets or cash in exchange for the ETF shares. This process, which is designed to equilibrate supply and demand for shares in the ETF, allows APs to enforce the law of one price. For example, if an ETF price gets too high relative to the value of the underlying assets, an AP short-sells the ETF shares and purchases the underlying assets. At the end of the day, the AP delivers the underlying assets (for in-kind transactions) or delivers cash in exchange for new ETF shares. The AP then covers the short position in the ETF with the new the shares. The AP conducts the opposite trade if an ETF price gets too low relative to the value of the underlying assets, removing ETF shares from the market.

## 2.2 Leveraged ETFs

Leveraged ETFs are similar in most ways to traditional, non-leveraged ETFs, but they also have unique features. First, unlike most non-leveraged ETFs, leveraged ETFs replicate their intended benchmark via derivatives.[11] For example, to obtain 2x or -2x exposure to an index, the ETF sponsor enters into total return swaps, which are rolled on a daily basis. Second, while most non-leveraged ETFs adhere to a static policy of in-kind transactions (84% of ETFs based on end of 2016 AUM), the creation and redemption process conducted between the leveraged ETF sponsor and APs always includes an element of cash in the exchange of shares.

Leveraged ETFs are designed for short-horizon trades as they replicate benchmark indices effectively in a given day but longer-term returns exhibit tracking error. Borrowing an example from Cheng and Madhavan (2009), consider a leveraged ETF that intends to provide 2x exposure to a particular index. The ETF begins with an initial NAV of $100. The benchmark index that starts at 100, falls by 10% one day and then goes up by 10% the next. Over the two-day period, the index declines by 1% (down to 90 and then up to 99). One might expect that the leveraged ETF would provide a return of -2%. Instead, it declines by 4%; Doubling the index's 10% fall pushes the ETF's NAV to $80 on the first day. The next day, the fund's NAV climbs to $96.

[11] All ETFs replicate their intended benchmark via one of three methods: Full replication, optimized replication, and derivative replication. The vast majority of ETFs are fully replicated, meaning that the ETF physically holds the underlying assets in the intended benchmark. Optimized replication is similar, but does not require the ETF to hold every asset. Instead, the ETF sponsor may hold a representative sample that minimizes tracking error while avoiding difficult to obtain or illiquid securities. Based on end of 2016 assets under management, 67% of ETFs were fully replicated and 30% were optimized, the remaining 3% were derivative based.

Consistent with being designed for short-horizon trades, leveraged ETFs exhibit greater trade volume than their non-leveraged counterparts based on average turnover, which is measured as average volume divided by end of month shares outstanding. Figure 3 compares the ProShares leveraged ETFs to their largest, non-leveraged, comparable ETFs. Share turnover in the leveraged ETFs SSO and SDS, which provide 2x and -2x exposure to the S&P 500 index respectively, were 6.3 and 4.2 times more than that in the non-leveraged ETF SPY (which is the largest non-leveraged ETF providing exposure to the S&P 500). To put this in perspective, if all shares in SPY were to transact once during a period of time, all shares in SSO would have transacted 6.3 times and all shares in SDS would have transacted 4.2 times during that same period. For the other ProShares leveraged ETFs, the numbers are similar.

Leveraged ETFs are also traded among retail investors relatively more than non-leveraged ETFs or single-name stocks. For example, institutional ownership in leveraged ETFs relative to non-leveraged counterparts is low. Figure 3 also provides the ratio of percent of shares held by institutional investors in the ProShares leveraged ETFs as compared to their largest, non-leveraged, comparable ETFs.[12] For example, SSO and SDS exhibit only 39.9% and 17.4% of the percent of shares held by institutional investors in SPY. For the other original six leveraged ETFs, the ratios are comparable.

Finally, leveraged ETFs' are small in size as compared to their non-leveraged counterparts. Returning to Figure 3, SSO represents just 1.6% of AUM as compared to SPY and SDS represents only 2.3% of SPY. Across the other ProShares leveraged ETFs, the ratios are similar.

# 3 Data and Index Construction

## 3.1 Data

To construct and study $SSI$, I combine data from Bloomberg, ProShares, Compustat, CRSP, Jeffrey Wurgler's website, Robert Stambaugh's website, Asaf Manela's website, Matthew Ringgenberg's website, Robert Shiller's website, Kenneth French's website, the University of Michigan Survey of Consumer's website, and the U.S. Treasury's website. From Bloomberg, I get daily data on ETF shares outstanding, share changes, prices, NAVs, total returns, and trade volumes.[13] From Bloomberg I also get weekly data on ETF institutional ownership and ETF characteristics, that is,

[12]Data for percent of shares held by institutions comes from Bloomberg. Institutional ownership is defined as *Percentage of Shares Outstanding held by institutions. Institutions include 13Fs, US and International Mutual Funds, Schedule Ds (US Insurance Companies) and Institutional stake holdings that appear on the aggregate level. Based on holdings data collected by Bloomberg.*

[13]Ben-David et al. (2018) shows that Bloomberg provides the most accurate daily ETF data.

expense ratios, stated benchmark, leverage quantities and direction (for leveraged ETFs), and asset focus (e.g., bonds, equities, or commodities). From ProShares and Compustat, I get ETF shares outstanding data, which are used to crosscheck the Bloomberg data. From CRSP, I get return data on the CRSP equal-weighted, CRSP value-weighted, and S&P 500 indices and I get data on the CRSP stock universe, which includes prices, returns, trade volume, and shares outstanding. Finally, I clean the ETF data based on the methodology provided in the data appendix of Brown et al. (2018).

To control for broader investor sentiment, I use the Baker-Wurgler Investor Sentiment Index (Baker & Wurgler, 2006), which is obtained from Jeffrey Wurgler's website and I use the Survey of Consumer Confidence, which is taken from the University of Michigan Survey of Consumer's website. To control for market conditions, I use VIX index data, which is obtained from Bloomberg. I control for aggregate liquidity using the Pastor-Stambaugh liquidity series (Pástor & Stambaugh, 2003), which is obtained from Robert Stambaugh's website and intermediary liquidity using the He-Kelly-Manela intermediary liquidity series (He, Kelly, & Manela, 2017), which is obtained from Asaf Manela's website. I control for short interest as a proxy for ETF arbitrageur liquidity using the Short Interest Index (Rapach, Ringgenberg, & Zhou, 2016), which is obtained from Matthew Ringgenberg's website. Additionally, I control for other predictors of returns including aggregate dividends-to-price and cyclically adjusted earnings-to-price ratios, which are obtained from Robert Shiller's website. Term spread and short-rate data are obtained from the U.S. Treasury's website. Finally, I add information on the three factor (Fama & French, 1993), three factor plus momentum (Carhart, 1997), and five factors models (Fama & French, 2015) from Kenneth French's website. From each data source, I obtain data series from 2006 through the end of 2016, with the exception of the Baker-Wurgler Investor Sentiment Index, which is only available through September 2015.

### 3.2 Speculation Sentiment Index Construction

I construct the index using six of the eight original leveraged ETFs offered by ProShares: Three leveraged-long ETFs (QLD, SSO, and DDM) and three leveraged-short ETFs (QID, SDS, and DXD). Each long-short pair tracks an intended index: QLD and QID provide 2x exposure to the NASDAQ-100 index, SSO and SDS provide 2x exposure to the S&P 500 index, and DDM and DXD provide 2x exposure to the Dow Jones Industrial Average. The two excluded ETFs, MVV and MZZ, are a long-short pair that provide exposure to the S&P MidCap 400 Index. MVV and MZZ are excluded due to their inability to gain traction among investors from 2006 through 2016, in particular MZZ. Aside from excluding MVV and MZZ, I use the remaining six original leveraged

ETFs (three 2x and three -2x) to avoid cherry-picking based on realized outcomes.

The index is constructed in the following manner. Of the six leveraged ETFs, $J$ denotes the set of leveraged-long ETFs and $K$ denotes the set of leveraged-short ETFs. In each month $t$, ETF $i$'s percent share change is computed as,

$$\Delta_{i,t} = \frac{SO_{i,t}}{SO_{i,t-1}} - 1, \tag{1}$$

in which $SO_{i,t}$ is the ETF's shares outstanding in month $t$ and $t-1$ denotes the previous month. $\Delta_{i,t}$ can be negative valued (ETF shares are redeemed in net) or $\Delta_{i,t}$ can be positive valued (ETF shares are created in net). Both negative and positive values of $\Delta_{i,t}$ imply net arbitrage activity, with the sign on $\Delta_{i,t}$ providing the direction.

Once percent share changes are computed, the first stage of month $t$'s index level is computed as the net difference in share changes for leveraged-long ETFs and leveraged-short ETFs,

$$net_t = \sum_{i \in J} \Delta_{i,t} - \sum_{i \in K} \Delta_{i,t}. \tag{2}$$

Eqn. 2 represents the net demand shock in the set of leveraged ETFs. For example, if $net_t$ is near zero then the implicit demand shock that generates mispricing is either small or it affects leveraged-long and leverage-short ETFs equally. Conversely, if $net_t$ is large and positive, the demand shock favors leveraged-long products. If $net_t$ is large and negative, the demand shock favors leveraged-short products. Additionally, by netting the leveraged-long ETFs' share change and the leveraged-short ETFs' share change, other non-fundamental demand shocks are netted. For example, if there a non-fundamental shock to arbitrageurs' liquidity, the shock should affect leveraged-long and leveraged-short ETF share change in the same direction. Thus, netting share change would also net out the non-fundamental shock to arbitrageur liquidity.

$net_t$ exhibits autocorrelation.[14] In the Online Appendix, Panel A of Table OA1 presents the results of the regression of $net_t$ on five of its lagged values,

$$net_t = a + \beta_1 net_{t-1} + \beta_2 net_{t-2} + \beta_3 net_{t-3} + \beta_4 net_{t-4} + \beta_5 net_{t-5} + \epsilon_t. \tag{3}$$

In the regression, the first lagged value $net_{t-1}$ carries a coefficient of approximately 0.3 and is statistically significant with a 1% p-value threshold. Given serial correlation across months, the final step in forming the index is to estimate $net_t$ as an $AR(1)$ process,

$$net_t = a + \gamma net_{t-1} + SSI_t, \tag{4}$$

[14] $net_t$ is stationary; An Augmented Dickey-Fuller test rejects the null hypothesis that a unit root is present with a p-value smaller than 1% in the time series of $net_t$.

in which $a$ is a constant, $\gamma$ is the $AR(1)$ coefficient on $net_{t-1}$, and $SSI_t$ is the innovation to the index. After estimating the parameters $a$ and $\gamma$, the series of innovations are given by,

$$SSI \equiv \{SSI_1, \ldots, SSI_T\}. \tag{5}$$

The time series $SSI$ forms the *Speculation Sentiment Index*.[15] Notably, $SSI_t$ and $net_t$ are highly correlated (correlation coefficient of 0.960). The analysis hereafter is qualitatively the same using $net_t$.[16] $SSI$ is depicted in Figure 4.[17] Notably, the index exhibits the most pronounced swings just prior, during, and immediately after the 2008 Financial Crisis.

While the economics of $SSI$ are examined in the subsequent sections, it is worth highlighting one feature of the index here as it relates to the methodology. $SSI$ is basic to construct as one only needs to observe monthly shares outstanding for six ETFs. While simple, the method appears to capture the main driver of share change in the set of ETFs; A more sophisticated method using a principal components analysis (PCA) yields nearly identical results. If one performs PCA on monthly percent share changes in the six ETFs, the first principal component explains over 50% of the joint variation (if share changes across the six ETFs were independent, the first principal component would explain $1/6^{th}$ of the joint variation or 16.7%). Furthermore, the linear weights associated with forming the first principal component from the original data are approximately equal in magnitude; Three are positive valued with values between 0.40 and 0.46 and three are negative valued with values between -0.30 and -0.50. The three positive valued linear weights are assigned to the leveraged-long ETFs and the three negative valued linear weights are assigned to the leveraged-short ETFs. The first principal component has a correlation coefficient of 0.96 with $SSI$ and the first principal component is nearly perfectly correlated with $net_t$. Because PCA is agnostic to economic interpretation, in many settings it is difficult to explain which economic force a particular principal component embodies. In this setting, however, the interpretation is straightforward: The speculation sentiment measured by the difference between leveraged-long and leveraged-short ETFs' share change is the primary driver of fund-level arbitrage activity.

[15] In the Online Appendix, Panel B of Table OA1 provides the $AR(1)$ estimation. Panel C of Table OA1 presents the results of the regression of $SSI_t$ on five of its lagged values, $SSI_t = a + \beta_1 SSI_{t-1} + \beta_2 SSI_{t-2} + \beta_3 SSI_{t-3} + \beta_4 SSI_{t-4} + \beta_5 SSI_{t-5} + \epsilon_t$. The results do not exhibit autocorrelation.

[16] In the Online Appendix, Table OA7 provides the baseline return predictability analysis using $net_t$ in place of $SSI_t$.

[17] While this paper relies on a monthly construction of $SSI$, it is possible to compute the index at a daily and weekly frequency because share change data are available daily. However, in the Online Appendix, I provide a detailed description about shortcomings in daily and weekly measures due to stale data, inconsistencies in reported daily data across data providers, and strategic delay by authorized participants in creating new ETF shares. The monthly measure does not suffer from these shortcomings.

# 4 Return Predictability

Under my identifying assumption that leveraged ETF share demand is relatively more sensitive to speculative demand shocks, $SSI$ proxies for speculative demand shocks. In this section, I examine the relation between $SSI$ and future asset returns. Under the null hypothesis, $SSI$ should not predict asset returns. However, I find that $SSI$ has substantial predictive power, which is consistent with $SSI$ measuring speculative demand shocks that distort asset prices and lead to return reversals.

I focus the predictability analysis on three benchmark indices: (i) the CRSP equal-weighted index, (ii) the CRSP value-weighted index, and (iii) the S&P 500 index. Figure 5, provides scatter plots of each index's monthly return versus lagged $SSI$. In each plot, the vertical axis represents the index's return and the horizontal axis represents lagged $SSI$. Panel A corresponds to the CRSP equal-weighted index, Panel B corresponds to the CRSP value-weighted index, and Panel C corresponds to the S&P 500 index. In all three scatter plots, a trend line is included. The scatter plots depict a negative relation between lagged $SSI$ and index returns.

Motivated by the scatter plots, I perform a rudimentary test. I evaluate the frequency at which the sign on lagged $SSI$ correctly predicts the sign on the index's return for each benchmark index. I sort $SSI$ into quartiles and focus on the first and fourth quartiles, which represent the largest negative realizations and the largest positive realizations of the index. The results are provided in each panel of Figure 5 under the heading "Extreme Quartiles." Lagged $SSI$ correctly predicts the sign on CRSP equal-weighted index 68.33% of the time, the sign on the CRSP value-weighted index 61.67% of the time, and the sign on the S&P 500 index 60.00% of the time. To put these frequencies into context, the probability of successfully predicting at least as many months with a fair coin flip are 0.31%, 4.62% and 7.75% respectively. Furthermore, a Bayesian model comparison is performed under two hypotheses. The null hypothesis is that $SSI$ is uninformative, that is, the probability that it correctly predicts the sign on the next month's return is 50.00%. The alternative hypothesis is that $SSI$ is informative. Under the alternative hypothesis, I assume lagged $SSI$ predicts the next month's return with probability $\tilde{p}$, in which $\tilde{p}$ is distributed according to the PDF $y(\tilde{p}) = 2\tilde{p}$ on the support $[0, 1]$. Under the assumed distribution of priors $E[\tilde{p}] = \frac{2}{3}$, which is approximately equal to the observed frequencies. The Bayes factor, that is, the likelihood ratio, in comparing the alternative hypothesis to the null hypothesis is given by,

$$\frac{\binom{N}{s} \int_0^1 \tilde{p}^s (1-\tilde{p})^{N-s} 2\tilde{p} \, \mathrm{d}\tilde{p}}{\binom{N}{s} \frac{1}{2}^s (1-\frac{1}{2})^{N-s}}, \tag{6}$$

in which $N$ is the number of monthly observations and $s$ is the number of observations in which lagged $SSI$ correctly predicts the index's return. The Bayes factor for the CRSP equal-weighted index is 12.52, the Bayes factor for the CRSP value-weighted index is 11.33, and the Bayes factor for the S&P 500 index is 11.03. The evidence against the null is strong using the Jeffreys criteria (Jeffreys, 1961) and the evidence against the null is positive using the Kass-Raftery criteria (Kass & Raftery, 1995). In addition to looking at the extreme quartiles, the analysis is repeated using the full sample and the results are provided under the heading "Full Sample" in Figure 5. The full sample results are consistent with the extreme quartiles results, however, the results are weaker statistically and weaker with respect to the Bayes factors.

The scatter plots and rudimentary results in Figure 5 show a negative relation between lagged $SSI$ and broad market index returns. To formalize the results, I perform predictive regressions. The baseline regression examines the ability of lagged $SSI$ to predict the next month's return in each of the three indices,

$$r_t = a + \beta SSI_{t-1} + \epsilon_t, \tag{7}$$

in which $r_t$ is either the CRSP equal-weighted monthly return, the CRSP value-weighted monthly return, or the S&P 500 monthly return in month $t$, $a$ is the regression intercept, $SSI_{t-1}$ is the one month lagged value of $SSI$, $\beta$ is the regression coefficient, and $\epsilon_t$ is the regression error term. The results for the regressions are reported in Table 1 as regression (1). Results for the CRSP equal-weighted index are reported in Panel A, results for the CRSP value-weighted index are reported in Panel B, and results for the S&P 500 index are reported in Panel C. The sample's index returns run from December 2006 through December 2016. $SSI$ is standardized and index returns are reported as percentages so that $\beta$ may be interpreted as the effect of a one standard deviation in $SSI$ on subsequent returns. In regression (1), the coefficient $\beta$ is statistically significant with a 1% p-value threshold for each of the three indices; For the CRSP equal-weighted index, a one standard deviation increase in lagged $SSI$ is associated with a 1.9% decline in the index. For the CRSP value-weighted index, the effect is smaller with a decline of 1.4%. For the S&P 500, the effect is also smaller with a decline of 1.2%.

To control for market conditions, I perform the predictive regression,

$$r_t = a + \beta SSI_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t, \tag{8}$$

in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. The additional controls include lagged index return $r_{t-1}$ and lagged VIX $vix_{t-1}$ to control for market conditions. Furthermore, because leveraged ETF arbitrage activity is an equilibrium outcome, the controls also include lagged innovation to aggregate liquidity $\Delta liq_{t-1}$ (Pástor & Stambaugh, 2003), lagged short interest $short_{t-1}$ (Rapach et al., 2016), and lagged intermediary capital risk factor $intc_{t-1}$ (He et al., 2017). The controls also include other predictors of returns: Lagged dividend-to-price $dp_{t-1}$ and cyclically adjusted earnings-to-price $caep_{t-1}$, lagged term spread $term_{t-1}$ and short-rate $rate_{t-1}$, and lagged consumer confidence level $conf_{t-1}$ and change $\Delta conf_{t-1}$. Finally, dummy variables for return month are included to control for seasonality (e.g., the January effect). The results for the regressions are reported in Table 1 as regression (2). The coefficient $\beta$ is statistically significant with a 5% p-value threshold for each of the three indices. For the CRSP equal-weighted index, a one standard deviation increase in lagged $SSI$ is associated with a 1.6% decline in the index. For the CRSP value-weighted index, the effect is smaller with a decline of 1.3%. For the S&P 500, the effect is also smaller with a decline of 1.1%.

The specification reported as regression (2) in Table 1 is one of many specifications one could construct using the set of controls. For example, I do not include the Baker-Wurgler Investor Sentiment Index due to it not being available for the entirety of the sample (the index ends in September 2015). To demonstrate the robustness of the return predictability analysis to alternative specifications, I provide specification curves (Simonsohn, Simmons, & Nelson, 2015) in Figure 6, Figure 7, and Figure 8, which correspond to the CRSP equal-weighted index, the CRSP value-weighted index, and the S&P 500 index respectively. Each figure presents coefficient estimates for $\beta$ across 1,024 alternative specifications that use different combinations of controls: (i) lagged index return $r_{t-1}$, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$ and change $\Delta sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$ and change $\Delta conf_{t-1}$, (iv) lagged VIX $vix_{t-1}$, (v) lagged innovation to aggregate liquidity $\Delta liq_{t-1}$, (vi) lagged short interest $short_{t-1}$, (vii) lagged intermediary capital risk factor $intc_{t-1}$, (viii) lagged dividend-to-price $dp_{t-1}$ and cyclically adjusted earnings-to-price $caep_{t-1}$, (ix) lagged term spread $term_{t-1}$ and short-rate $rate_{t-1}$, and (x) month of year dummies $D_{mon}$. Furthermore, each data point is colored according to its associated p-value. Out of the 1,024 specifications plotted, $\beta$ remains relatively stable in the CRSP equal-weighted index, CRSP value-weighted index, and S&P 500 regressions. Furthermore, $\beta$ is statistically significant with a 5% p-value threshold for 991 of 1024 (97%) of the CRSP equal-weighted index regressions, 956 of 1024 (93%) of the CRSP value-weighted index regressions, and 763 of 1024 (75%) of the S&P 500 index regressions.

Regression (3) in Table 1 includes all controls from regression (2) but excludes the primary variable of interest, lagged $SSI$. Comparing regression (3) to regression (2) provides a measure of marginal explanatory power. For the CRSP equal-weighted index regressions, including $SSI_{t-1}$ increases the adjusted $R^2$ from 0.230 to 0.271 representing an increase of 18%. For the CRSP value-weighted index regressions, including $SSI_{t-1}$ increases the adjusted $R^2$ from 0.193 to 0.231 representing an increase of 20%. Finally, for the S&P 500 index regressions, including $SSI_{t-1}$ increases the adjusted $R^2$ from 0.213 to 0.239 representing an increase of 12%.

The 2008 financial crisis falls during the sample. One may be concerned that the market volatility that characterized the 2008 financial crisis is responsible for the results in regressions (1) and (2). As a robustness check, the monthly analysis is repeated with a start date of January 1, 2010 to avoid the market volatility of 2008 and 2009. The results from the post-2009 analysis are reported as regressions (4)-(6) in Table 1. The coefficients are less stable in comparing $\beta$ in regression (4) to $\beta$ in regression (5), but remain statistically significant in both regressions and for each of the three benchmark indices.

The results in this section show a meaningful relation, both statistically and economically, between lagged values of $SSI$ and subsequent index returns. The results are not driven by the 2008 financial crisis and the results are robust to the inclusion of controls. Moreover, within each regression specification, the coefficient on $SSI$ with CRSP equal-weighted index returns is the largest in magnitude and the coefficient on $SSI$ with S&P 500 index returns is the smallest in magnitude. The rank order of coefficients suggests that speculative demand shocks disproportionately affect small capitalization stocks. Collectively, the results of this section are consistent with speculative demand shocks moving asset prices away from fundamentals.

### 4.1 Betting Against Speculation Sentiment

The return predictability results suggest that one could construct a trading strategy to exploit speculation sentiment. In this subsection, I provide a trading strategy conditioned on $SSI$ that generates excess returns that survive standard risk adjustments. The strategy is a standard long-short equity portfolio based on stocks' sensitivities to $SSI$.[18]

I begin with the set of all NYSE traded stocks and the time series of $SSI$ from January 2007 to December 2016. For each stock, I estimate its monthly sensitivity to lagged $SSI_{t-1}$ using rolling 36 month windows. For example, the first sensitivity is calculated in January 2010 using data from January 2007 through December 2009 and the second sensitivity is calculated in February 2010

[18] The previous section demonstrates the ability to predict index returns based on $SSI$. In the Online Appendix, I also provide a trading strategy based on entering into total return swaps in which the CRSP value-weighted index or the CRSP equal-weighted index is the reference entity. The trading strategy yields similar excess returns to the long-short equity portfolio studied in this section.

using data from February 2007 through January 2010.[19] Each stock's sensitivity is estimated using the regression,

$$r_{i,t} = a_{i,\tau} + \beta_{i,\tau} SSI_{t-1} + \epsilon_{i,t}, \tag{9}$$

in which $r_{i,t}$ is the monthly return on stock $i$ in month $t$, $a_{i,\tau}$ is the regression intercept, $SSI_{t-1}$ is the lagged one month value of $SSI$, $\beta_{i,\tau}$ is stock $i$'s sensitivity to lagged $SSI$ on date $\tau$ based on the previous 36 months of data, and $\epsilon_{i,t}$ is the error term.

The regression analysis yields 84 monthly sets of $\beta_{i,\tau}$. In each month $\tau$, individual stocks are sorted into quintiles based on that month's sensitivity to $SSI$. A long-short portfolio is constructed using quintiles one and five. The position in the long-short portfolio, that is, which quintile is the long leg and which is the short leg, depends on the previous month's realization of $SSI$; If $SSI$ is positive valued at $\tau - 1$, the long-short portfolio formed at date $\tau$ consists of the fifth quintile forming the long leg and the first quintile forming the short leg. Instead, if $SSI$ is negative valued at $\tau - 1$, the long-short legs are flipped. Furthermore, the portfolio itself is scaled by the magnitude of $SSI$; If the absolute value of $SSI$ is small, the exposure of the portfolio is small and a fraction of the portfolio is held in cash. Conversely, when the absolute value of $SSI$ is large, the exposure of the portfolio is increased using leverage. I normalize $SSI$ so that the average leverage is equal to zero.

Equal-weighted and value-weighted portfolios are formed in which value-weights are determined by the stocks' market capitalizations in month $\tau$. The returns from the trading strategy yield abnormal returns that cannot be explained by canonical risk factors. Table 2 reports the equal-weighted and value-weighted portfolio returns regressed on four risk models. Across all risk models, the abnormal returns are statistically different from zero with a p-value threshold of 5% for the equal-weighted portfolio and with a p-value threshold of 10% for value-weighted portfolio. Moreover, the intercepts are stable: For the equal-weighted portfolio, the intercept equals between 1.45% and 1.60%, and for the value-weighted portfolio, the intercept equals between 1.35% and 1.53%. These monthly abnormal returns imply annualized abnormal returns in the range of 18.9%-21.0% for the equal-weighted portfolio and 17.5%-20.0% for the value-weighted portfolio.

# 5 Contemporaneous Mispricing and Speculation Sentiment

Under my identifying assumption that leveraged ETF share demand is relatively more sensitive to speculative demand shocks, $SSI$ proxies for speculative demand shocks. In this section, I

[19] To avoid a look ahead bias, the $AR(1)$ process used to formulate $SSI$ is estimated using only data from prior to January 2010.

examine the relation between $SSI$ and contemporaneous mispricing in other assets. Under the null hypothesis, $SSI$ should not be related to contemporaneous mispricing in other assets. However, I find that $SSI$ has substantial explanatory power, which is consistent with $SSI$ being a proxy for aggregate speculative demand shocks.

A natural setting to look at contemporaneous mispricing is in the universe of other ETFs. Observed arbitrage activity in ETFs is symptomatic of non-fundamental demand shocks that give rise to relative mispricing. I perform fund level regressions on the broad universe of all ETFs using monthly data. The sample for the regression analysis is November 2006-December 2016 and an ETF is included at the point in which it surpasses $50MM in assets under management for the first time.[20] Furthermore, ETFs are required to have at least 30 months of observations to be included in the sample. The baseline regression run on each ETF is of the form,

$$\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}, \tag{10}$$

in which $\Delta_{i,t}$ is the percent change in shares outstanding for fund $i$ on date $t$, $a_i$ is the regression intercept, $SSI_t$ is the value of $SSI$ on date $t$, $\beta_i^{SSI}$ is fund $i$'s loading on $SSI_t$, and $\epsilon_{i,t}$ is an error term. The univariate regression in Eqn. 10 relates $SSI_t$ to contemporaneous arbitrage activity in ETF $i$. In addition to the regression outlined in Eqn. 10, additional regressions are run with added monthly controls including lagged percent change in shares outstanding ($\Delta_{i,t-1}$), lagged ETF returns ($r_{i,t-1}$), and contemporaneous ETF returns ($r_{i,t}$). All variables in the regressions are standardized.

To provide a snapshot of the results, Table 3 provides the regression results for two representative ETFs: SPY and VXX.[21] $SSI_t$ loads significantly with a 1% p-value threshold for SPY and VXX in the baseline regression. Because all variables in the regression analysis are standardized, the coefficients may be interpreted as the effect of a one standard deviation move in $SSI$ on share change in the given ETF. For SPY, which provides non-leveraged exposure to the S&P 500, a one standard deviation increase in $SSI$ is associated with 28.8% of a standard deviation increase in $\Delta_{i,t}$. Therefore, when speculative demand favors leveraged-long products (i.e., a positive value of $SSI$) there is greater arbitrage activity in SPY in the direction of share creations. VXX, which provides investor exposure to the VIX index, loads negatively on $SSI$; A one standard deviation

[20] The $50MM cutoff is consistent with a number of papers in the ETF literature and its purpose is to mitigate the impact of illiquidity and possible non-synchronous prices due to infrequent trading.

[21] SPY is managed by State Street Global Advisors and it provides investors exposure to the S&P 500. SPY is also the largest equity ETF based on 2016 assets under management (moreover, it is the largest ETF across all asset categories and is also the oldest ETF). VXX is managed by Barclays iPath and it provides investors exposure to a daily rolling long position in the first and second month VIX futures contracts. VXX is the largest alternative ETN.

increase in $SSI$ is associated with 75.2% of a standard deviation reduction in $\Delta_{i,t}$. Thus, when speculative demand favors leveraged-long products, VXX's arbitrage activity associated with share creations is dampened. Notably, VIX is often viewed as a fear index and tends to reflect bearish beliefs regarding the equity markets. Across other specifications with added controls of lagged share change $\Delta_{i,t-1}$, lagged ETF return $r_{i,t-1}$, and contemporaneous ETF return $r_{i,t}$, the baseline findings are robust.

Turing to the distribution of coefficient estimates for $\beta_i^{SSI}$, Table 4 provides a summary regarding the coefficients' p-values. First, Panel A summarizes the p-values for $\beta_i^{SSI}$ in all 1,006 ETFs used in the monthly regressions. $\beta_i^{SSI}$ is statistically significant with a 1% p-value threshold in regression (1) for nearly 9% of the sample based on equal-weighting. In regressions (2) - (4) with added controls, between 7%-10% of ETFs have a coefficient estimate that is significant with a 1% p-value threshold. The value-weighted results are stronger; Using end of 2016 assets under management for each ETF to calculate value-weights, $\beta_i^{SSI}$ loads significantly with a 1% p-value threshold for 17% of the sample in regression (1). With added controls in regressions (2) - (4), between 17% and 22% of ETFs have a coefficient estimate that is significant with a 1% p-value threshold.

Panel B in Table 4 provides the results in the subset of leveraged ETFs. For regression (1), with a 1% p-value threshold, 28% of funds have a significant coefficient based on equal-weights and 40% based on value-weights. Regressions (2)-(4) provide similar results with between 22%-34% of the coefficient estimates being significant with a 1% p-value threshold based on equal-weights and between 36%-50% of the coefficient estimates being significant with a 1% p-value threshold based on value-weights. The results show that $SSI$ is related to arbitrage activity in a large fraction of ETFs and the effect is stronger in the subset of leveraged ETFs.

While statistically strong, the coefficient estimates themselves are also economically meaningful. Table 5 provides the percentile breaks across the estimates of $\beta_i^{SSI}$.[22] Beginning with Panel A, the threshold values of $\beta_i^{SSI}$ that separate decile groups are reported across the asset categories of non-leveraged equity, non-leveraged fixed income, non-leveraged commodity, and all leveraged ETFs. For non-leveraged equity ETFs, 20% of the sample have a coefficient estimates smaller than -0.176 meaning that these ETFs exhibit at least 17.6% of a standard deviation decline in share creations (increase in share redemptions) given a one standard deviation increase in $SSI$. Furthermore, 20% of the non-leveraged equity ETFs have coefficient estimates larger than 0.127

[22]The number of leveraged ETFs in Table 4 and in Table 5 differ by four (146 versus 150). The difference is due to four ETFs that were closed prior to 2016 and did not have end-of-2016 assets to be included in the weighted sample of Panel B in Table 4.

meaning that these ETFs exhibit at least 12.7% of a standard deviation increase in share creations given a one standard deviation increase in $SSI$. For non-leveraged fixed income and commodity ETFs, the threshold values are similar. Leveraged ETF thresholds are more pronounced; 20% of the sample has coefficient estimates smaller than -0.388 and 20% have coefficient estimates larger than 0.312. The results in Panel A show that variation in $SSI$ is related to sizable changes in arbitrage activity across other ETFs. Furthermore, the economic magnitudes are more pronounced in leveraged ETFs.

Panel B of Table 5 provides a summary of percentile breaks, but for the absolute value of the coefficient estimate $|\beta_i^{SSI}|$. Because $SSI$ captures both the magnitude and direction of speculation sentiment, taking the absolute value of coefficient estimates provides insights regarding the economic importance of $SSI$ on overall arbitrage activity. For non-leveraged equity ETFs, the median effect is 0.125, implying that over half of non-leveraged equity ETFs exhibit more than 12.5% of a standard deviation change in arbitrage activity when $SSI$ moves by a standard deviation. The median effects for non-leveraged fixed income and commodity ETFs are larger with values of 0.142 and 0.135 respectively. Leveraged ETFs, again, are more pronounced having a median effect of 0.289.

Table 6 provides a breakdown of the coefficient signs for leveraged equity ETFs only. If $SSI$ is related to bullish and bearish short-horizon, gambling-like trading, coefficients on the leveraged-long equity ETFs will carry a positive sign and coefficients on the leveraged-short equity ETFs will carry a negative sign. For both equal-weighted and value-weighted results, leveraged-long equity ETFs systematically load positively on $SSI$ and leveraged-short equity ETFs systematically load negatively: Of leveraged-long equity ETFs, 75% have positive coefficients on an equal-weighted basis and 84% on a value-weighted basis. Of leveraged-short equity ETFs, 88% have negative coefficients on an equal-weighted basis and 95% on a value-weighted basis. The direction of the leverage correctly predicts the coefficient's sign on 81 of the 100 leveraged equity ETFs; Of the 51 leveraged-long equity ETFs, 38 have a positive coefficient and, of the 49 leveraged-short equity ETFs, 43 have a negative coefficient. The probability that leverage direction correctly predicts at least 81 of the 100 ETFs by chance is 3.04e-11. The results of Table 6 are illustrated in Figure 9: The coefficient estimates of $\beta_i^{SSI}$ for each leveraged equity ETF are illustrated across three dimensions. The horizontal axis represents the coefficient estimate, the vertical axis represents the p-value associated with the estimate and each observation's size is scaled by end of 2016 assets under management. The figure depicts a strong split between positive and negative loadings on $SSI$; Leveraged-short ETFs are drawn to the lower left-hand corner of the graph and leveraged-long ETFs are drawn to the lower right-hand corner.

The analysis of this section documents a strong relation, both economically and statistically, between $SSI$ and market-wide mispricing. The results are strongest in other leveraged ETFs, which are more sensitive to speculative demand shocks. The evidence is consistent with $SSI$ measuring aggregate speculation sentiment.

## 6 Conclusion

I provide a novel measure of speculative demand shocks. I coin the measure the Speculation Sentiment Index and I show that it predicts aggregate asset return reversals. A trading strategy based on $SSI$ earns significant excess returns after controlling for standard risk factors. Finally, speculative demand shocks, measured by $SSI$, are related to market-wide mispricing and arbitrage activity. The results provide direct and credible evidence that speculative demand shocks push asset prices away from fundamentals and the dislocations are meaningful.

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**Table 1:** Return predictability and $SSI$. Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value: $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $SSI_{t-1}$ is the lagged Speculation Sentiment Index value, $\beta$ is the estimated coefficient on $SSI_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta SSI_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the lagged Speculation Sentiment Index value. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.893$^{***}$ | -1.566$^{**}$ | | -1.157$^{***}$ | -2.451$^{***}$ | |
| | (4.214) | (2.554) | | (2.688) | (4.354) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.130 | 0.411 | 0.371 | 0.081 | 0.455 | 0.283 |
| Adjusted $R^2$ | 0.123 | 0.271 | 0.230 | 0.070 | 0.246 | 0.024 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel B: VW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.419$^{***}$ | -1.312$^{**}$ | | -0.928$^{**}$ | -1.904$^{***}$ | |
| | (3.576) | (2.420) | | (2.318) | (3.560) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.097 | 0.378 | 0.341 | 0.061 | 0.447 | 0.330 |
| Adjusted $R^2$ | 0.089 | 0.231 | 0.193 | 0.050 | 0.235 | 0.089 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel C: S&P 500

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.234$^{***}$ | -1.072$^{**}$ | | -0.818$^{**}$ | -1.720$^{***}$ | |
| | (3.207) | (2.084) | | (2.090) | (3.286) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.080 | 0.385 | 0.357 | 0.051 | 0.448 | 0.348 |
| Adjusted $R^2$ | 0.072 | 0.239 | 0.213 | 0.039 | 0.236 | 0.113 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

*Note:* $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$

**Table 2:** Trading strategy abnormal returns from January 2010 through December 2016. Panel A provides the returns from a long-short portfolio based on the sign and magnitude of previous month's level of the Speculation Sentiment Index $SSI_{t-1}$ regressed on priced factors. Model (1) consists of the market factor. Model (2) consists of the market factor, size factor, and value factor. Model (3) consists of the market factor, size factor, value factor and momentum factor. Model (4) consist of the market factor, size factor, value factor, profitability factor, and investment factor. Panel B provides characteristics of the equal-weighted and value-weighted portfolios during the sample and it also includes the same characteristics for the S&P 500 index as a benchmark.

Panel A: Excess Returns

| | Equal-Weighted | | | | Value-Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Intercept | 1.449** | 1.454** | 1.595** | 1.518** | 1.351* | 1.368* | 1.531** | 1.476* |
| | (2.082) | (2.058) | (2.261) | (2.093) | (1.841) | (1.836) | (2.063) | (1.935) |
| Mkt-Rf | 0.214 | 0.209 | 0.177 | 0.197 | 0.147 | 0.123 | 0.085 | 0.097 |
| | (1.209) | (1.054) | (0.894) | (0.954) | (0.789) | (0.585) | (0.409) | (0.446) |
| SMB | | 0.048 | 0.089 | 0.038 | | 0.110 | 0.157 | 0.080 |
| | | (0.143) | (0.268) | (0.109) | | (0.312) | (0.451) | (0.216) |
| HML | | -0.071 | -0.236 | 0.029 | | -0.023 | -0.213 | 0.114 |
| | | (-0.227) | (-0.718) | (0.071) | | (-0.069) | (-0.615) | (0.260) |
| MOM | | | -0.364 | | | | -0.420* | |
| | | | (-1.569) | | | | (-1.720) | |
| CMA | | | | -0.289 | | | | -0.416 |
| | | | | (-0.432) | | | | (-0.590) |
| RMW | | | | -0.092 | | | | -0.214 |
| | | | | (-0.175) | | | | (-0.387) |
| $R^2$ | 0.018 | 0.018 | 0.048 | 0.022 | 0.008 | 0.009 | 0.045 | 0.017 |
| Adjusted $R^2$ | 0.006 | -0.018 | 0.000 | -0.041 | -0.005 | -0.028 | -0.004 | -0.046 |
| N | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

*Note:* $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$

Panel B: Portfolio Characteristics

| | Equal-Weighted | Value-Weighted | S&P 500 |
|---|---|---|---|
| SHARPE RATIO | 0.928 | 0.768 | 0.826 |
| MAX MONTHLY LOSS | -11.304% | -8.923% | -8.198% |
| STDEV MONTHLY RETURN | 6.145% | 6.449% | 3.659% |
| SEMI STDEV MONTHLY RETURN | 2.626% | 2.721% | 2.266% |
| MAX LEVERAGE | 1.878x | 1.878x | NA |
| AVG LEVERAGE | 0.000x | 0.000x | NA |
| STDEV LEVERAGE | 0.726x | 0.726x | NA |

**Table 3:** The relation between share creation/redemption activity and the contemporaneous $SSI_t$ index level for two representative ETFs. For each of the two ETFs, four regressions are run with monthly data. The data begin in November 2006 for SPY and in May 2009 for VXX and the data conclude in December 2016. Regression (1) is given by $\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}$ in which $\Delta_{i,t}$ is fund $i$'s percent share change in month $t$, $a_i$ is an intercept, $SSI_t$ is the level of $SSI_t$, and $\epsilon_{i,t}$ is an error term. Regression (2) includes lagged share change $\Delta_{i,t-1}$. Regression (3) includes lagged ETF return $r_{i,t-1}$. Finally, regression (4) includes contemporaneous ETF return $r_{i,t}$.

| | Monthly Share Change Regressions | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SPY | | | | VXX | | | |
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Intercept | -0.013 | -0.001 | 0.000 | -0.011 | -0.054 | -0.056 | -0.062 | -0.036 |
| | (-0.148) | (-0.017) | 0.000 | (-0.135) | (-0.575) | (-0.620) | (-0.695) | (-0.417) |
| $SSI_t$ | 0.288*** | 0.348*** | 0.282*** | 0.483*** | -0.752*** | -0.789*** | -0.905*** | -0.499*** |
| | (3.321) | (3.953) | (3.238) | (4.719) | (-4.681) | (-5.183) | (-5.765) | (-3.158) |
| $\Delta_{i,t-1}$ | | -0.231*** | | | | 0.287*** | | |
| | | (-2.628) | | | | (3.205) | | |
| $r_{i,t-1}$ | | | -0.126 | | | | -0.308*** | |
| | | | (-1.444) | | | | (-3.325) | |
| $r_{i,t}$ | | | | 0.336*** | | | | -0.403*** |
| | | | | (3.288) | | | | (-4.338) |
| $R^2$ | 0.084 | 0.134 | 0.100 | 0.160 | 0.196 | 0.289 | 0.295 | 0.336 |
| Adjusted $R^2$ | 0.077 | 0.120 | 0.085 | 0.146 | 0.187 | 0.273 | 0.279 | 0.321 |
| $N$ | 122 | 122 | 122 | 122 | 92 | 91 | 91 | 92 |

*Note:* $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

**Table 4:** The statistical significance of each ETF's loading on $SSI$ in explaining contemporaneous share creation/redemption activity. For each ETF with at least 30 months of data and after surpassing $50MM in assets under management, four regressions are run with monthly data (beginning in November 2006 and ending in December 2016). Regression (1) is given by $\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}$ in which $\Delta_{i,t}$ is fund $i$'s percent share change in month $t$, $a_i$ is an intercept, $SSI_t$ is the level of $SSI$, and $\epsilon_{i,t}$ is an error term. Regression (2) includes lagged share change $\Delta_{i,t-1}$. Regression (3) includes lagged ETF return $r_{i,t-1}$. Regression (4) includes contemporaneous ETF return $r_{i,t}$. The table provides the percentage of ETFs for which $\beta_i^{SSI}$ loads significantly with p-value thresholds of 1% and 5%. Panel A provides the analysis for all ETFs, weighted equally and weighted by 2016 ETF market capitalizations. Panel B provides the analysis for only leveraged ETFs, weighted equally and weighted by 2016 ETF market capitalizations.

| Panel A: Broad Universe of ETFs | | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | Equal-Weighted Analysis | | | |
| $p < 0.01$ | 8.748% | 10.239% | 9.742% | 6.958% |
| $p < 0.05$ | 17.197% | 19.980% | 17.992% | 13.718% |
| | Value-Weighted Analysis | | | |
| $p < 0.01$ | 17.387% | 16.633% | 17.022% | 22.475% |
| $p < 0.05$ | 28.066% | 28.844% | 29.487% | 28.398% |
| N=1006 | | | | |
| **Panel B: Leveraged ETFs** | | | | |
| | Equal-Weighted Analysis | | | |
| $p < 0.01$ | 28.082% | 30.822% | 33.562% | 21.918% |
| $p < 0.05$ | 44.521% | 41.781% | 42.466% | 30.822% |
| | Value-Weighted Analysis | | | |
| $p < 0.01$ | 39.823% | 50.169% | 47.482% | 35.926% |
| $p < 0.05$ | 58.868% | 53.932% | 54.057% | 48.160% |
| N=146 | | | | |

**Table 5:** Percentile breaks for coefficient estimates of $\beta_i^{SSI}$ across ETF categories. For each ETF with at least 30 months of data and after surpassing \$50MM in assets under management, a univariate regression is run with monthly data (beginning in November 2006 and ending in December 2016). The regression is of the form $\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}$ in which $\Delta_{i,t}$ is fund $i$'s percent share change in month $t$, $a_i$ is an intercept, $SSI_t$ is the level of $SSI$, and $\epsilon_{i,t}$ is an error term. The table provides the $n^{th}$ percentile coefficient estimates across deciles and across four categories of ETFs: Non-leveraged equity ETFs, non-leveraged fixed income ETFs, non-leveraged commodity ETFs, and leveraged ETFs.

Panel A: Percentile Values for $\beta_i^{SSI}$

| | Percentile | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $10^{th}$ | $20^{th}$ | $30^{th}$ | $40^{th}$ | $50^{th}$ | $60^{th}$ | $70^{th}$ | $80^{th}$ | $90^{th}$ | Observations |
| Non-leveraged Equity | -0.258 | -0.176 | -0.124 | -0.081 | -0.036 | 0.013 | 0.059 | 0.127 | 0.243 | 637 |
| Non-leveraged Fixed Income | -0.311 | -0.207 | -0.139 | -0.086 | -0.042 | -0.020 | 0.058 | 0.147 | 0.219 | 145 |
| Non-leveraged Commodity | -0.270 | -0.210 | -0.182 | -0.119 | -0.065 | -0.013 | 0.048 | 0.104 | 0.194 | 55 |
| Leveraged | -0.585 | -0.388 | -0.235 | -0.121 | -0.025 | 0.046 | 0.187 | 0.312 | 0.518 | 150 |

Panel B: Percentile Values for $|\beta_i^{SSI}|$

| | Percentile | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $10^{th}$ | $20^{th}$ | $30^{th}$ | $40^{th}$ | $50^{th}$ | $60^{th}$ | $70^{th}$ | $80^{th}$ | $90^{th}$ | Observations |
| Non-leveraged Equity | 0.025 | 0.047 | 0.074 | 0.099 | 0.125 | 0.157 | 0.201 | 0.249 | 0.332 | 637 |
| Non-leveraged Fixed Income | 0.034 | 0.049 | 0.077 | 0.107 | 0.142 | 0.171 | 0.215 | 0.287 | 0.353 | 145 |
| Non-leveraged Commodity | 0.025 | 0.062 | 0.082 | 0.112 | 0.135 | 0.187 | 0.207 | 0.239 | 0.303 | 55 |
| Leveraged | 0.035 | 0.083 | 0.142 | 0.218 | 0.289 | 0.364 | 0.462 | 0.561 | 0.715 | 150 |

**Table 6:** The sign on leveraged equity-focused ETFs' loadings on $SSI$ level in explaining contemporaneous share creation/redemption activity. For each leveraged equity-focused ETF with at least 30 months of data and after surpassing \$50MM in assets under management, a univariate regression is run using monthly data (beginning in November 2006 and ending in December 2016). The regression is of the form $\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}$ in which $\Delta_{i,t}$ is fund $i$'s percent share change in month $t$, $a_i$ is an intercept, $SSI_t$ is the level of $SSI$, and $\epsilon_{i,t}$ is an error term. The results are reported based on equal-weights and based on 2016 ETF market capitalization weights.

Panel A: Leveraged Equity ETFs

| | Equal-Weighted Analysis | | |
|---|---|---|---|
| Leveraged ETF Type | % Negative Coefficient | % Positive Coefficient | N |
| Long | 25.490% | 74.510% | 51 |
| Short | 87.755% | 12.245% | 49 |

| | Value-Weighted Analysis | | |
|---|---|---|---|
| Leveraged ETF Type | % Negative Coefficient | % Positive Coefficient | N |
| Long | 15.988% | 84.012% | 51 |
| Short | 95.240% | 4.760% | 49 |

**Figure 1:** Speculative demand shocks on the leveraged ETF shares and the leveraged ETF underlying derivative securities.

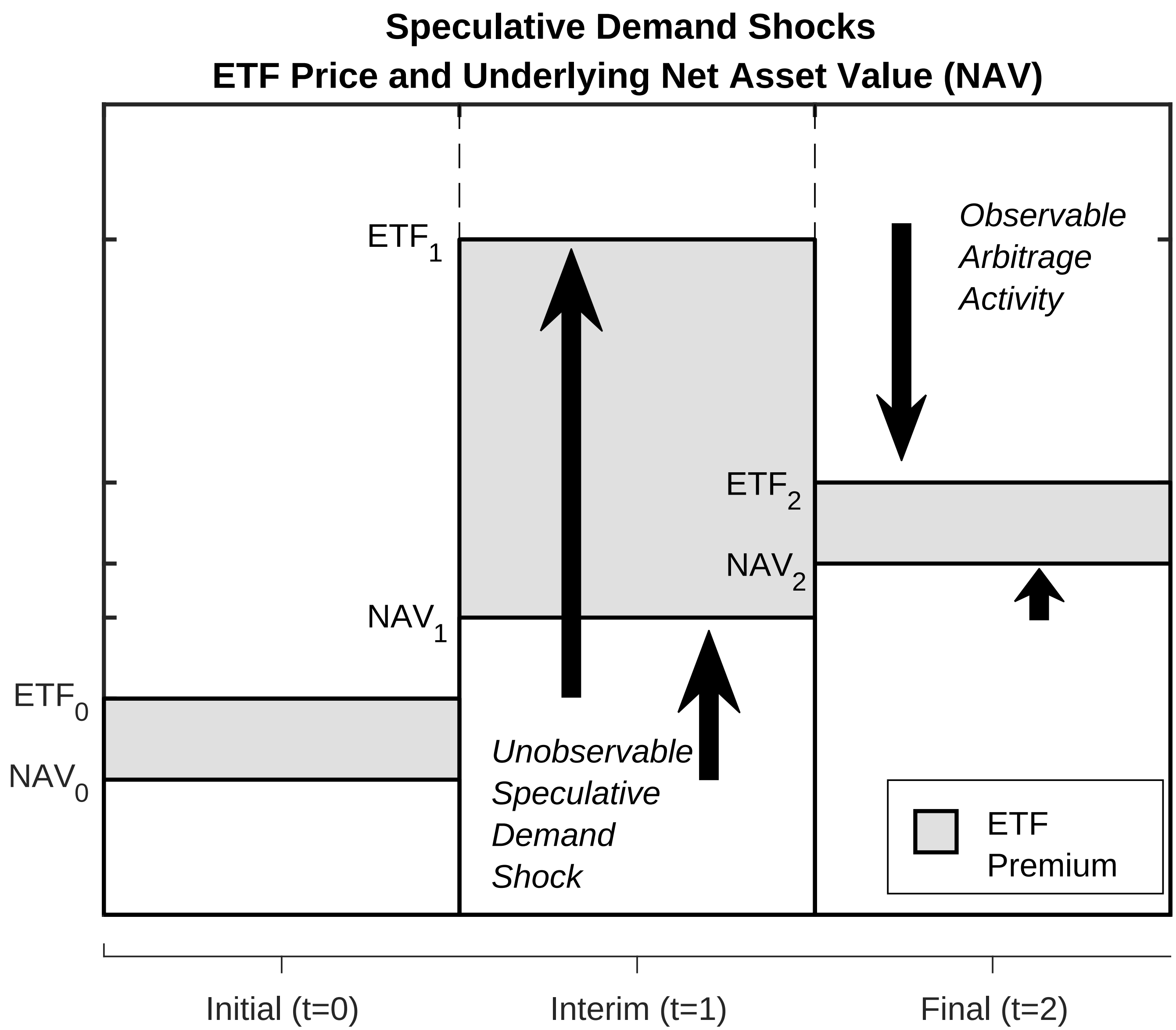


**Figure 2:** The following table provides the set of leveraged ETFs launched by ProShares during the summer of 2006. The first set of ETFs provides 2x long exposure to pre-specified indices and the second set of ETFs provices 2x short exposure to the same indices.

| **Panel A: Set of ETFs announced on June 21, 2006** | | |
|---|---|---|
| Fund Name | Daily Objective | Ticker |
| Ultra QQQ ProShares | Double the NASDAQ-100 Index | QLD |
| Ultra S&P 500 ProShares | Double the S&P 500 Index | SSO |
| Ultra Dow30 ProShares | Double the Dow Jones Industrial Average | DDM |
| Ultra MidCap400 ProShares | Double the S&P MidCap 400 | MVV |
| **Panel A: Set of ETFs announced on July 13, 2006** | | |
| UltraShort QQQ ProShares | Double the inverse of the NASDAQ-100 Index | QID |
| UltraShort S&P 500 ProShares | Double the inverse of the S&P 500 Index | SDS |
| UltraShort Dow30 ProShares | Double the inverse of the Dow Jones Industrial Average | DXD |
| UltraShort MidCap400 ProShares | Double the inverse of the S&P MidCap 400 | MZZ |

**Figure 3:** Comparison of leveraged ETFs to comparable, non-leveraged ETFs. The table compares leveraged ETFs to non-leveraged ETFs along the dimensions of institutional ownership, monthly turnover, and size. Data for percent of fund shares held by institutions comes from Bloomberg and is available beginning in 2010. Monthly turnover is calculated as monthly volume divided by end-of-month shares outstanding.

| Comparable ETF | SPY | | QQQ | | DIA | | IJH | |
|---|---|---|---|---|---|---|---|---|
| Leveraged ETF | SSO | SDS | QID | QLD | DDM | DXD | MVV | MZZ |
| Average Percent of Institutional Ownership in Leveraged to Non-leveraged | 39.9% | 17.4% | 25.3% | 21.9% | 24.7% | 20.2% | 42.0% | 28.7 % |
| | | | | | | | | March 28, 2010 - December 25, 2016 |
| Average Percent of Monthly Turnover in Leveraged to Non-leveraged | 631.4% | 420.5% | 635.0% | 386.6% | 685.6% | 602.9% | 2,451.9% | 1,197.0% |
| | | | | | | | | January 31, 2007 - December 31, 2016 |
| Average Percent of Assets Under Management in Leveraged to Non-leveraged | 1.6% | 2.3% | 3.4% | 3.5% | 3.3% | 4.0% | 1.9% | 1.0% |
| | | | | | | | | January 31, 2007 - December 31, 2016 |

**Figure 4:** Speculation Sentiment Index from October 2006 through December 2016.

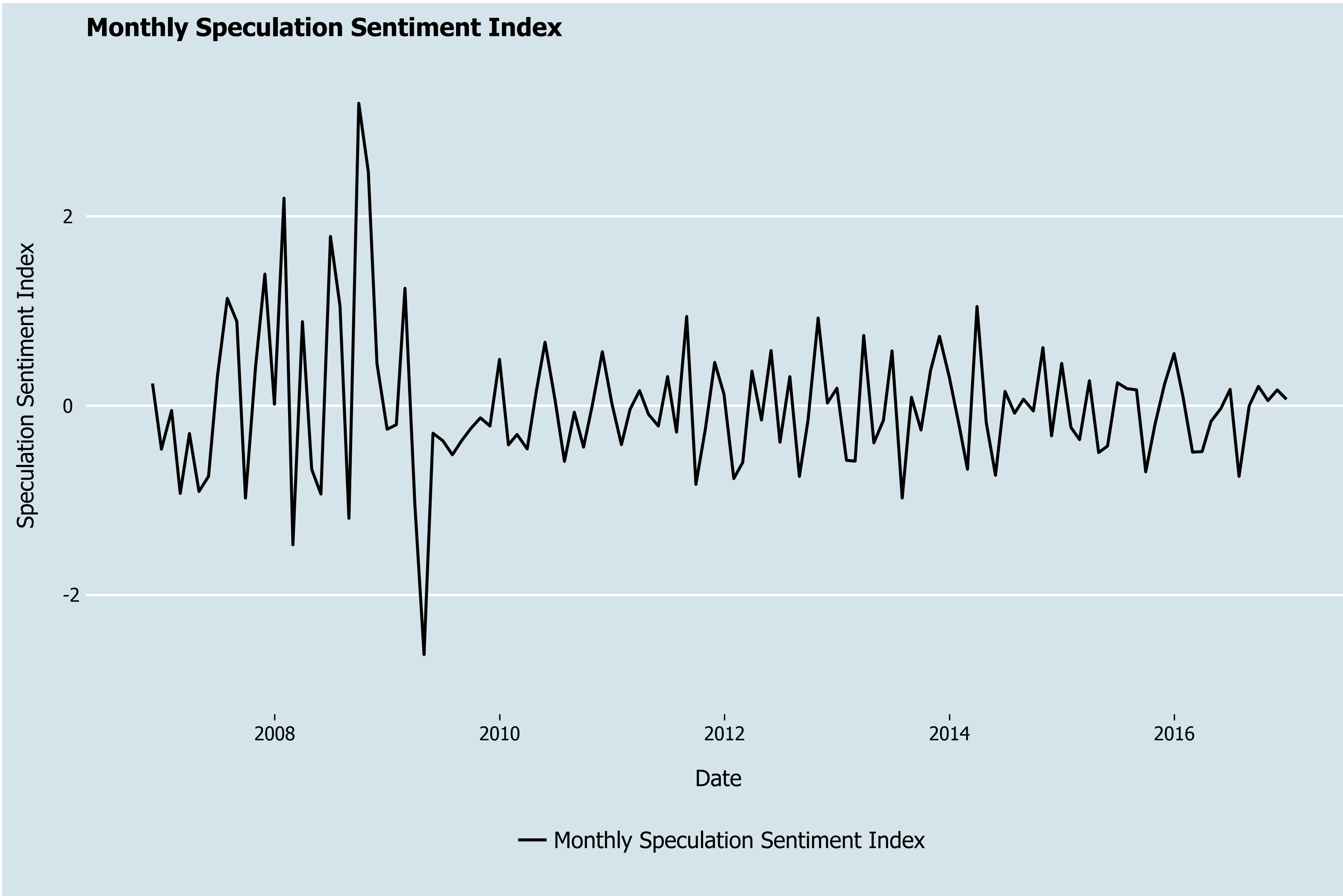
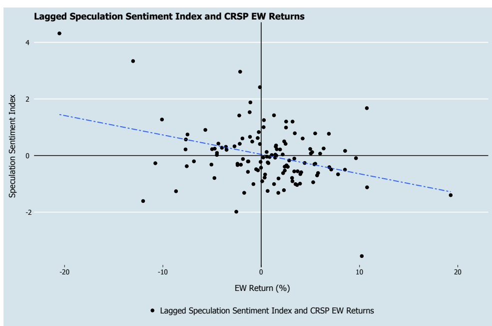
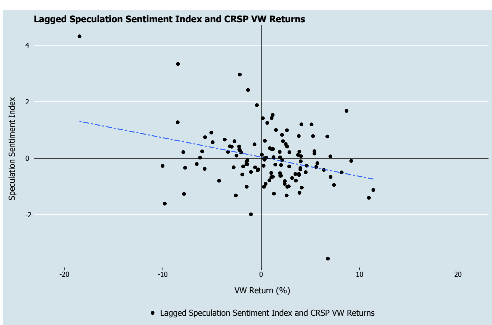


**Figure 5:** Scatter plots and the ability of the sign on $SSI_{t-1}$ to predict the sign on $r_t$. In each panel, a scatter plot of $r_t$ versus $SSI_{t-1}$ is presented in which Panel A depicts the equal-weighted CRSP index, Panel B depicts the value-weighted CRSP index, and Panel C depicts the S&P 500 index. The dotted line in each scatter plot is the trend line. Also in each panel, a table analyzing the ability of the sign on $SSI_{t-1}$ to predict the sign on $r_t$ is provided. The first column represents the smallest quartile of $SSI_{t-1}$ observations (30 observations) and the largest quartile of $SSI_{t-1}$ observations (30 observations) from December 2007 - December 2016. The second column represents the entire sample of 121 months from December 2007 - December 2016. The first row provides the percentage of the sample for which $SSI_{t-1}$ correctly predicts the sign on the next month's return (positive $SSI_{t-1}$ predicts negative $r_t$ and vice versa). The second row provides the probability, under a binomial distribution with $p = 0.5$ (i.e., a fair coin flip), that one would see at least as many correct observations as what is observed in the data. The final row provides the Bayes factor (i.e., the likelihood ratio) if the precision of the signal in $SSI$ is distributed according to the PDF $y(\tilde{p}) = 2\tilde{p}$ (with $E[\tilde{p}] = \frac{2}{3}$) as compared to a completely uninformative signal. The specific calculation for the Bayes factor is given by $\frac{\binom{N}{s}\int_0^1 \tilde{p}^s(1-\tilde{p})^{N-s}2\tilde{p}\,\mathrm{d}\tilde{p}}{\binom{N}{s}\frac{1}{2}^s(1-\frac{1}{2})^{N-s}}$ in which $N$ is the number of monthly observations and $s$ is the number of correct predictions.



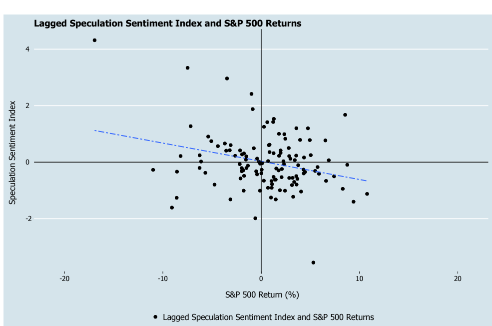

| | CRSP EW | |
|---|---|---|
| | Extreme Quartiles | Full Sample |
| Percent of Sample Sign on $SSI_{t-1}$ Predicts Sign on $r_t$ | 68.33% | 60.33% |
| $\Pr(x \geq \text{Observed})$ Using Binomial Dist. Characterized by $p = .5$ | 0.31% | 1.44% |
| Bayes Factor for Prior Distributed by $2\tilde{p}$ compared to $p = 0.5$ | 12.52 | 1.80 |
| N | 60 | 121 |

(a) CRSP Equal-Weighted Index Returns versus Lagged $SSI$




| | CRSP VW | |
|---|---|---|
| | Extreme Quartiles | Full Sample |
| Percent of Sample Sign on $SSI_{t-1}$ Predicts Sign on $r_t$ | 61.67% | 56.20% |
| $\Pr(x \geq \text{Observed})$ Using Binomial Dist. Characterized by $p = .5$ | 4.62% | 10.15% |
| Bayes Factor for Prior Distributed by $2\tilde{p}$ compared to $p = 0.5$ | 11.33 | 1.68 |
| N | 60 | 121 |

(b) CRSP Value-Weighted Index Returns versus Lagged $SSI$




| | S&P 500 | |
|---|---|---|
| | Extreme Quartiles | Full Sample |
| Percent of Sample Sign on $SSI_{t-1}$ Predicts Sign on $r_t$ | 60.00% | 56.20% |
| $\Pr(x \geq \text{Observed})$ Using Binomial Dist. Characterized by $p = .5$ | 7.75% | 10.15% |
| Bayes Factor for Prior Distributed by $2\tilde{p}$ compared to $p = 0.5$ | 11.03 | 1.68 |
| N | 60 | 121 |

(c) S&P 500 Index Returns versus Lagged $SSI$

**Figure 6:** Specification curves for return predictability analysis - EW CRSP. This figure presents coefficient estimates for $\beta$ across 1,024 subsamples that use different combinations of controls: (i) lagged index return $r_{t-1}$, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$ and change $\Delta sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$ and change $\Delta conf_{t-1}$, (iv) lagged VIX $vix_{t-1}$, (v) lagged innovation to aggregate liquidity $\Delta liq_{t-1}$, (vi) lagged short interest $short_{t-1}$, (vii) lagged intermediary capital risk factor $intc_{t-1}$, (viii) lagged dividend-to-price $dp_{t-1}$ and cyclically adjusted earnings-to-price $caep_{t-1}$, (ix) lagged term spread $term_{t-1}$ and short-rate $rate_{t-1}$, and (x) month of year dummies $D_{mon}$. Each data point is colored according to its associated p-value.

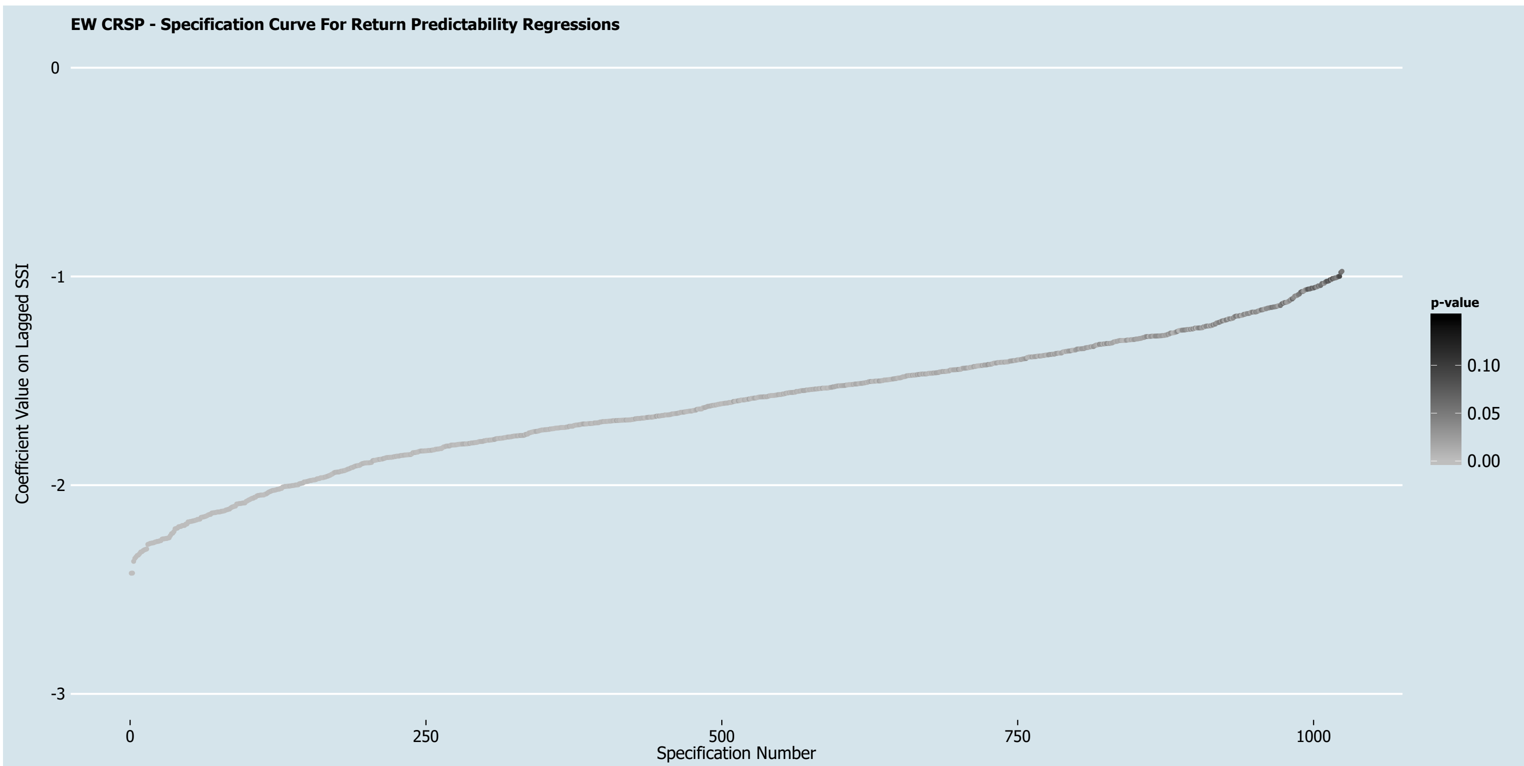


**Figure 7:** Specification curves for return predictability analysis - VW CRSP. This figure presents coefficient estimates for $\beta$ across 1,024 subsamples that use different combinations of controls: (i) lagged index return $r_{t-1}$, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$ and change $\Delta sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$ and change $\Delta conf_{t-1}$, (iv) lagged VIX $vix_{t-1}$, (v) lagged innovation to aggregate liquidity $\Delta liq_{t-1}$, (vi) lagged short interest $short_{t-1}$, (vii) lagged intermediary capital risk factor $intc_{t-1}$, (viii) lagged dividend-to-price $dp_{t-1}$ and cyclically adjusted earnings-to-price $caep_{t-1}$, (ix) lagged term spread $term_{t-1}$ and short-rate $rate_{t-1}$, and (x) month of year dummies $D_{mon}$. Each data point is colored according to its associated p-value.

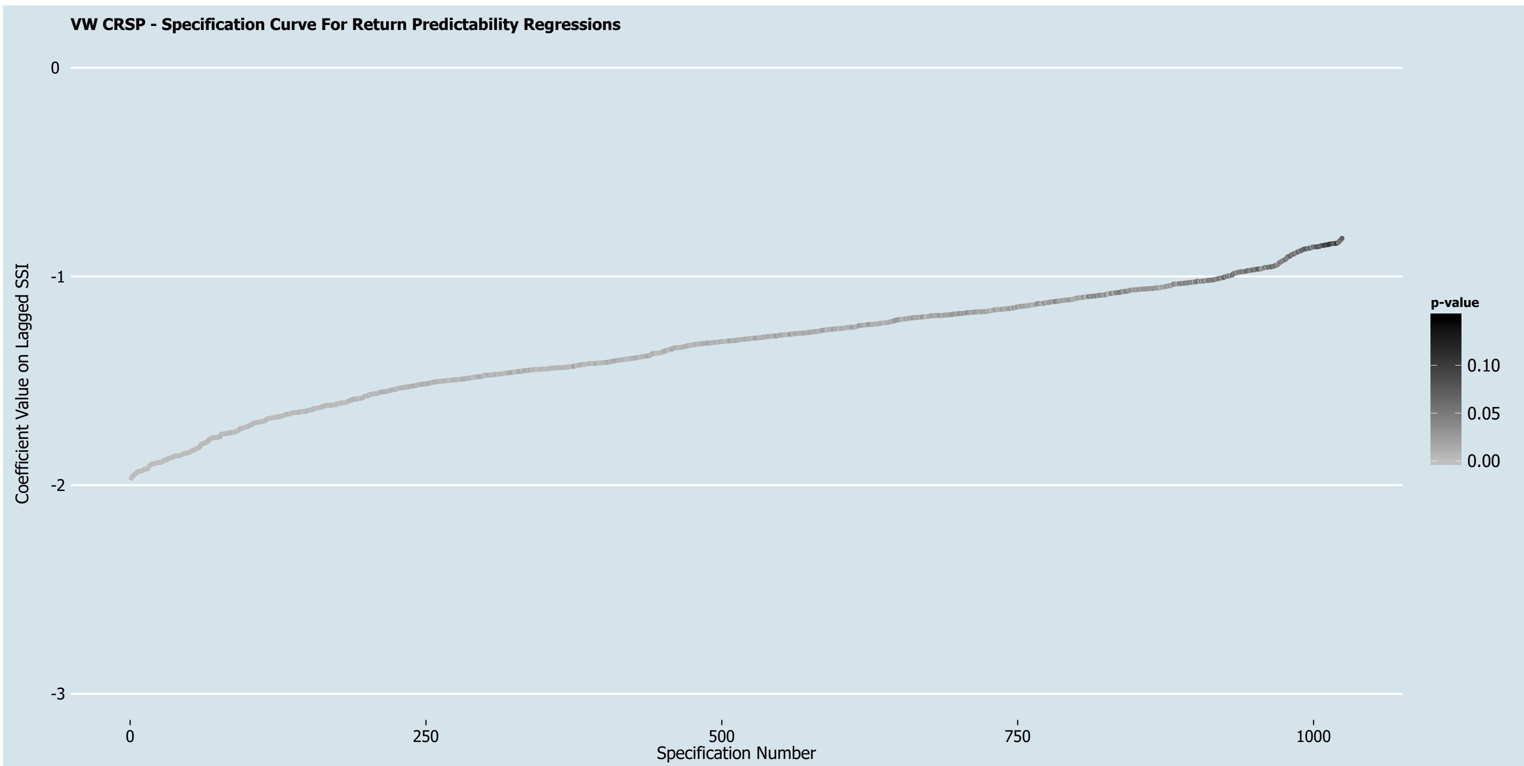


**Figure 8:** Specification curves for return predictability analysis - S&P 500. This figure presents coefficient estimates for $\beta$ across 1,024 subsamples that use different combinations of controls: (i) lagged index return $r_{t-1}$, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$ and change $\Delta sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$ and change $\Delta conf_{t-1}$, (iv) lagged VIX $vix_{t-1}$, (v) lagged innovation to aggregate liquidity $\Delta liq_{t-1}$, (vi) lagged short interest $short_{t-1}$, (vii) lagged intermediary capital risk factor $intc_{t-1}$, (viii) lagged dividend-to-price $dp_{t-1}$ and cyclically adjusted earnings-to-price $caep_{t-1}$, (ix) lagged term spread $term_{t-1}$ and short-rate $rate_{t-1}$, and (x) month of year dummies $D_{mon}$. Each data point is colored according to its associated p-value.

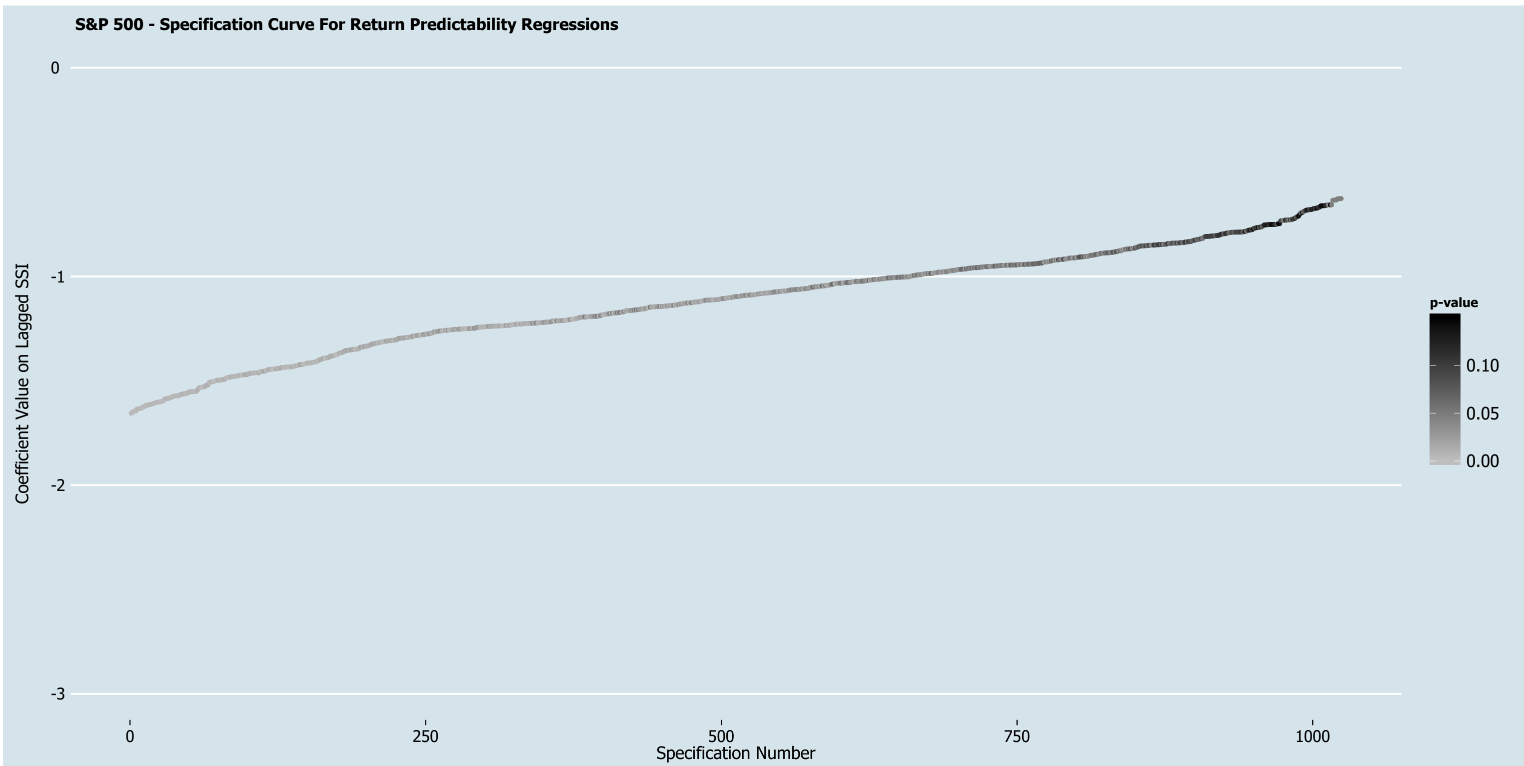
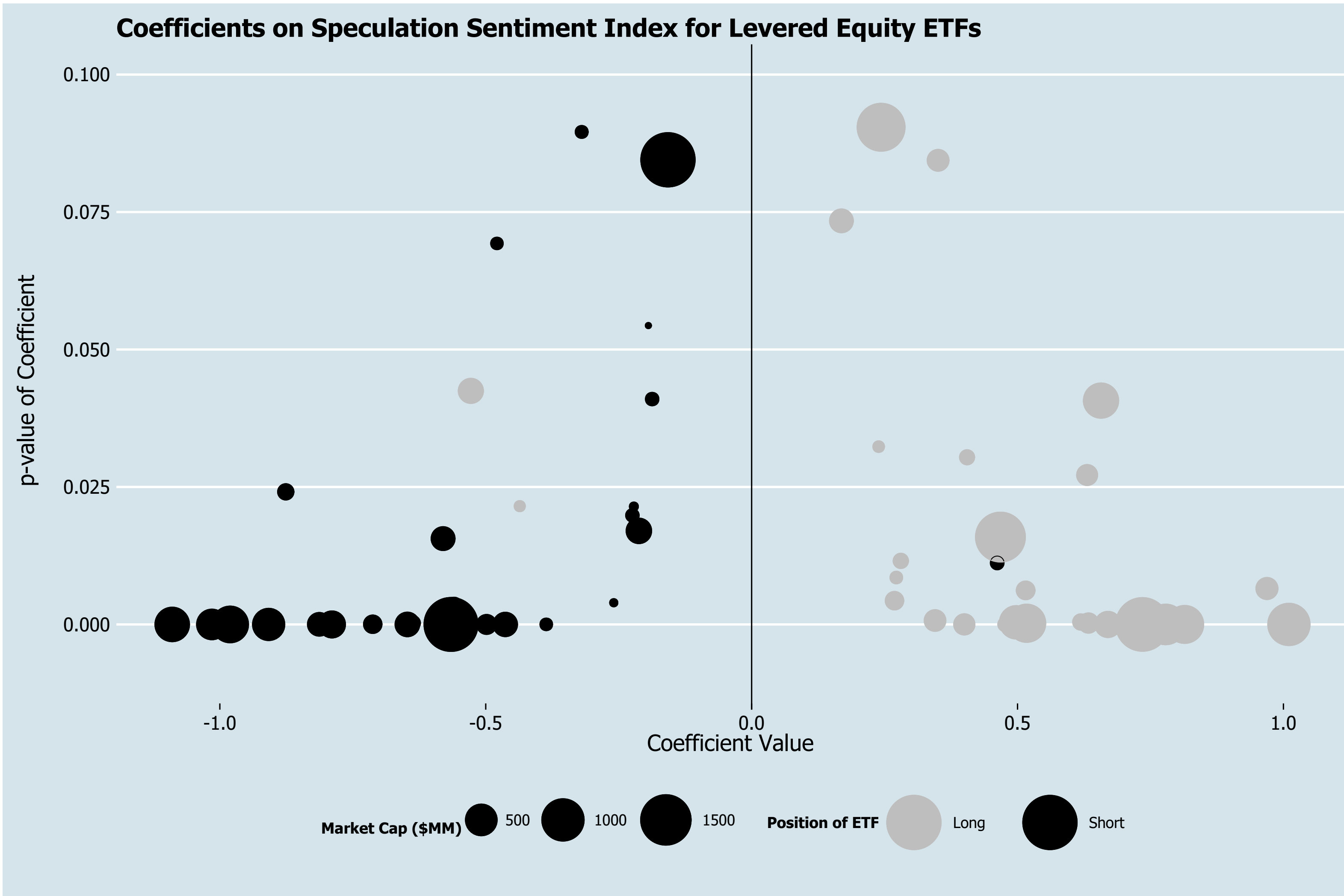


**Figure 9:** The relation of the Speculation Sentiment Index and share creation/redemption activity in leveraged ETFs tracking equity indices. The horizontal axis corresponds to coefficient values $\beta_i^{SSI}$ in the ETF-by-ETF regression, $\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}$, and the vertical axis corresponds to coefficient p-values. Each dot in the scatter plot represents a different leveraged ETF and the size of each dot is determined by its 2016 market capitalization. Leveraged-long ETFs are in gray and leveraged-short ETFs are depicted in black.



# Online Appendix for "Speculation Sentiment"

DAVIES, SHAUN WILLIAM[23]

In this Online Appendix, I consider alternative specifications of $SSI$ and I show that the return predictability analysis is robust to these alternative specifications. Next, I consider an alternative trading strategy to the one proposed in Section 4.1. In the alternative trading strategy, lagged $SSI$ is used as a conditioning variable to determine which leg to enter in a total return swap in which the reference entity is either the CRSP value-weighted index or the CRSP equal-weighted index. Finally, I conclude with a discussion regarding shortcomings in the daily and weekly measure due to stale data and strategic delay by authorized participants in creating ETF shares.

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## OA.1 Alternative $SSI$ Specifications

In this subsection, I examine the robustness of the benchmark return predictability analysis by considering three alternative specifications of $SSI$. The first specification utilizes the raw index computed from taking the difference of percent share change in leveraged-long ETFs and percent share change in leveraged-short ETFs. The second and third specifications compute $SSI$ from only the leveraged-long component or only the leveraged-short component.

### OA.1.1 Raw $net_t$ Index

$SSI$ is constructed from the time series $net_t$ in Eqn. 2. I repeat the regression analysis from Section 4 but use $net_t$ in place of $SSI$. Table OA7 provides the results. The results in Table OA7 are nearly identical to the results in Table 1; The coefficient values and corresponding test statistics are nearly identical for regressions using the CRSP equal-weighted index, CRSP value-weighted index, and the S&P 500 index. The adjusted $R^2$'s are nearly identical as well.

### OA.1.2 Long Component and Short Component Separately

$SSI$ is constructed by taking the difference between leveraged-long ETFs' share change and leveraged-short ETFs' share change, as seen in Eqn. 2. The theoretical underpinning for the index's construction is that it captures the net bullish-bearish speculation sentiment, that is, only when there is consensus among speculators is the index significantly bullish or bearish. The netting in Eqn. 2 does not allow one to examine the predictability coming from *only* leveraged-long ETFs, nor does it allow one to examine the predictability coming from *only* leveraged-short ETFs. It is natural to consider each separately. Define $SSI^L$ as the long-component of $SSI$ and define $SSI^S$ as the short-component. I repeat the regression analysis in Section 4 using the December 2006-December 2016 sample, but use $SSI^L$ and $SSI^S$ in place of $SSI$.

Table OA3 provides the results; Regressions (1)-(3) repeat the three main specifications of Table 1 but using the the long-component of $SSI$. Regressions (4)-(6) repeat the analysis using the short-component of $SSI$. Like the main specification of $SSI$, $SSI^L$ is negatively related to subsequent returns. The coefficients in the regressions using the CRSP equal-weighted index, the CRSP value-weighted index, and the S&P 500 index are statistically significant across all regressions. While $SSI^L$ is statistically meaningful, the economic magnitudes of the coefficients are generally smaller than that of $SSI$ in Table 1.

The coefficient on $SSI^S$ is positive valued, which is consistent with earlier results, that is, when speculators heavily demand leveraged-short exposure, aggregate returns are higher the subsequent month. The coefficients associated with the short-component, however, are economically and statistically weaker than those associated with $SSI^L$ and $SSI$: The coefficient associated with $SSI^S$ is smaller in magnitude than the coefficients associated with $SSI^L$ and $SSI$ across all regressions. Moreover, the coefficient on $SSI^S$ is statistically significant only in the univariate specification. Together, the analysis suggests that both $SSI^L$ and $SSI^S$ provide predictability, but both are weaker predictors than the main specification $SSI$.

## OA.2 Trading Strategy with Total Return Swap

The aggregate return predictability results suggest that one could construct a trading strategy to exploit speculation sentiment by taking positions in the CRSP index. In this subsection, I provide a trading strategy conditioned on $SSI$ that generates excess returns that survive standard risk adjustments. The strategy involves rolling monthly positions in total return swaps in which the CRSP equal-weighted index or the CRSP value-weighted index is the reference entity.

I begin by using the time series $net_t$ prior to January 2010 to estimate the $AR(1)$ process that formulates $SSI$ (see Section 3 for a description of how $SSI$ is formed). By estimating the $AR(1)$ process out of sample I avoid a look ahead bias. The trading strategy is as follows: Each month, a position is established in a one month total return swap with the CRSP equal-weighted or the CRSP value-weighted index as the reference entity. The position and notional exposure are determined by the previous month's realization of $SSI$ ($SSI_{t-1}$). If the previous month's $SSI_{t-1}$ is positive, the strategy calls for entering short-leg of the total return swap so that the position pays the total return on the index and receives the fixed or floating payment (e.g., LIBOR plus a swap spread or the general collateral cost associated with borrowing the reference asset). If instead $SSI_{t-1}$ is negative, the strategy calls for entering the long-leg of the swap so that the position pays the fixed or floating payment and receives the index's total return. Furthermore, the notional value of the swap is determined by the absolute value of the previous month's Speculation Sentiment measure $SSI_{t-1}$. The trading strategy yields 84 months of returns, covering January 2010 through December 2016. $SSI_t$ is normalized so that the average notional exposure, $AVG(|SSI_t|)$, is equal to $1.

Panel A of Table OA8 reports the abnormal returns from the trading strategy using four different risk models: The CAPM, the Fama-French three factor model, the Fama-French three factor model plus momentum and the Fama-French five factor model.[24] Across all four risk models, the intercepts, that is, abnormal returns, for the CRSP equal-weighted index swap strategy are statistically significant at the 5% p-value threshold and abnormal returns are in the range of 1.30%-1.44% monthly (16.7%-18.7% annually). The abnormal returns for the CRSP value-weighted index swap strategy are slightly smaller in economic magnitude (1.00%-1.13% monthly) and statistically significant at the 10% level across three of the risk models but not the five factor model.

Panel B of Table OA8 reports the trading strategy portfolio characteristics compared to the S&P 500. I report the Sharpe Ratio, maximum monthly loss, standard deviation of monthly returns, the semi-standard deviation of monthly returns (i.e., the standard deviation calculated only on negative returns), the maximum notional exposure of the swap, the average notional exposure of the swap and the standard deviation of the notional exposure of the swap. The trading strategy involves more return volatility as compared to the S&P 500; The maximum losses, standard deviation of monthly return and semi standard deviation of return are all larger in the trading strategy as compared to the S&P 500. Nevertheless, the extra return volatility is associated with better returns; The trading strategy using either the equal-weighted or value-weighted CRSP index dominates the S&P 500 with regards to the Sharpe Ratio (1.058 and 0.899 respectively versus 0.826 for the S&P 500).

[24] In the same spirit of long-short portfolio studies that ignore borrowing costs and margin, the trading strategy returns regressed on the risk factors are calculated as the position in the reference entity multiplied by the reference entity's return, net of the risk-free rate. The excess returns are large enough that a reasonable funding cost would be dwarfed.

## OA.3 Potential Pitfalls With Daily and Weekly Share Change Measures

A clear advantage of $SSI$ is the frequency at which it may be calculated. Share changes are reported on a daily basis. One can measure speculation sentiment at the daily or weekly frequency as easily as one measures it at the monthly frequency. However, I provide evidence to caution an empiricist about potential pitfalls using a daily or weekly measure constructed from ETF share changes.

First, Staer (2016) shows that ETFs often report using $T + 1$ accounting meaning that shares outstanding (and share changes) are reported with a one day lag, but that the lag is time-varying and may at times be $T$ accounting. Furthermore, changes in reporting lag are not public. This implies that daily share change data may be one-day stale on some dates and not stale on others.

Second, reported shares outstanding may also differ across data providers. As an example, $SSI$ is computed at the daily, weekly, monthly, and quarterly frequency using data from three different sources: Bloomberg, ProShares, and Compustat. Table OA9 provides the correlations of $SSI$ measures based on ETF shares changes reported by different data sources. At the daily frequency, $SSI$ based on data from Bloomberg and $SSI$ based on data from ProShares are highly correlated (0.745), but the correlation is not perfect. The Bloomberg and ProShares measures become more correlated at a weekly frequency (0.944) and nearly perfectly correlated at the monthly frequency (0.994) and the quarterly frequency (0.999). $SSI$ based on data from Compustat exhibits weak correlations with the Bloomberg and ProShares measures at the daily and weekly frequency. Even at the monthly frequency, the Compustat based measure is only 0.875 correlated with the Bloomberg measure and only 0.869 correlated with the ProShares measure. At the quarterly frequency, the Compustat based measure is 0.959 correlated with both.

Third, Evans, Moussawi, Pagano, and Sedunov (2016) describes how APs can strategically delay the creation of new shares until $T + 6$. By doing so, APs avoid costs associated with short-selling and it also allows APs to strategically time return reversals (since the authorized participants are essentially engaging in a naked short position).

Given the inability to observe reporting lags,the discrepancies across data sources, and strategic creation/redemption activity by APs over short-horizons, one should be cautious in using daily and weekly share-based measures.

**Table OA1:** Autocorrelation in $net_t$ and $SSI_t$. Panel A presents the results of the regression $net_t = a + \beta_1 net_{t-1} + \beta_2 net_{t-2} + \beta_3 net_{t-3} + \beta_4 net_{t-4} + \beta_5 net_{t-5} + \epsilon_t$, in which $net_t$ is defined in Eqn. 2, $a$ is the regression intercept and $\epsilon_t$ is the error term. Panel B presents the estimation of the $AR(1)$ process governing $net_t$. The $AR(1)$ process is estimated using OLS. Panel C presents the results of the regression $SSI_t = a + \beta_1 SSI_{t-1} + \beta_2 SSI_{t-2} + \beta_3 SSI_{t-3} + \beta_4 SSI_{t-4} + \beta_5 SSI_{t-5} + \epsilon_t$, in which $SSI_t$ is the Speculation Sentiment Index on date $t$, $a$ is the regression intercept and $\epsilon_t$ is the error term.

| Panel A: $net_t$ Regression with Lags | |
|---|---|
| Intercept | -0.021 |
| | (-0.302) |
| $net_{t-1}$ | 0.296*** |
| | (3.163) |
| $net_{t-2}$ | -0.088 |
| | (-0.896) |
| $net_{t-3}$ | 0.167* |
| | (1.730) |
| $net_{t-4}$ | -0.023 |
| | (-0.238) |
| $net_{t-5}$ | 0.031 |
| | (0.336) |
| $R^2$ | 0.106 |
| Adjusted $R^2$ | 0.066 |
| $N$ | 118 |

| Panel B: $AR(1)$ Estimation | |
|---|---|
| Intercept | -0.038 |
| | (-0.561) |
| $net_{t-1}$ | 0.280*** |
| | (3.206) |
| $R^2$ | 0.079 |
| Adjusted $R^2$ | 0.071 |
| $N$ | 122 |

| Panel C: $SSI_t$ Regression with Lags | |
|---|---|
| Intercept | 0.013 |
| | (0.191) |
| $SSI_{t-1}$ | 0.013 |
| | (0.137) |
| $SSI_{t-2}$ | -0.091 |
| | (-0.967) |
| $SSI_{t-3}$ | 0.148 |
| | (1.592) |
| $SSI_{t-4}$ | 0.017 |
| | (0.181) |
| $SSI_{t-5}$ | 0.095 |
| | (1.010) |
| $R^2$ | 0.036 |
| Adjusted $R^2$ | -0.008 |
| $N$ | 117 |

*Note:* $^{*}$ $p < 0.1$; $^{**}$ $p < 0.05$; $^{***}$ $p < 0.01$

**Table OA2:** Return predictability and $net_t$. Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged short ETFs: $r_t = a + \beta net_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $net_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged short ETFs, $\beta$ is the estimated coefficient on $net_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta net_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the $net_{t-1}$. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.875*** | -1.638** | | -1.012** | -2.428*** | |
| | (4.201) | (2.397) | | (2.325) | (3.948) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.128 | 0.407 | 0.372 | 0.062 | 0.431 | 0.283 |
| Adjusted $R^2$ | 0.121 | 0.268 | 0.233 | 0.050 | 0.212 | 0.024 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

Panel B: VW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.420*** | -1.288** | | -0.797* | -1.801*** | |
| | (3.607) | (2.189) | | (1.973) | (3.104) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.098 | 0.372 | 0.341 | 0.045 | 0.423 | 0.330 |
| Adjusted $R^2$ | 0.090 | 0.224 | 0.194 | 0.034 | 0.202 | 0.089 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

Panel C: S&P 500

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.261*** | -1.039* | | -0.701* | -1.598*** | |
| | (3.309) | (1.880) | | (1.776) | (2.827) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.084 | 0.378 | 0.356 | 0.037 | 0.425 | 0.348 |
| Adjusted $R^2$ | 0.076 | 0.233 | 0.213 | 0.025 | 0.205 | 0.113 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

*Note:* $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

**Table OA3:** Return predictability with leveraged-long $SSI^L$ and leveraged-short $SSI^S$. Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged leveraged-long Speculation Sentiment Index value: $r_t = a + \beta SSI^L_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $SSI_{t-1}$ is the lagged Speculation Sentiment Index value, $\beta$ is the estimated coefficient on $SSI_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta SSI^L_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the lagged leveraged-long Speculation Sentiment Index value. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on with the leveraged-short Speculation Sentiment Index value. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Leveraged-Long $SSI^L$ | | | Leveraged-Short $SSI^S$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.903*** | -1.422** | | 1.182** | 0.743 | |
| | (4.240) | (2.526) | | 2.520 | 1.278 | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| $R^2$ | 0.131 | 0.410 | 0.371 | 0.051 | 0.382 | 0.371 |
| Adjusted $R^2$ | 0.124 | 0.270 | 0.230 | 0.043 | 0.235 | 0.230 |
| $N$ | 121 | 121 | 121 | 121 | 121 | 121 |

Panel B: VW CRSP

| | Leveraged-Long $SSI^L$ | | | Leveraged-Short $SSI^S$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.373*** | -1.170** | | 0.949** | 0.686 | |
| | (3.447) | (2.312) | | 2.324 | 1.345 | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| $R^2$ | 0.091 | 0.375 | 0.341 | 0.043 | 0.353 | 0.341 |
| Adjusted $R^2$ | 0.083 | 0.227 | 0.193 | 0.035 | 0.199 | 0.193 |
| $N$ | 121 | 121 | 121 | 121 | 121 | 121 |

Panel C: S&P 500

| | Leveraged-Long $SSI^L$ | | | Leveraged-Short $SSI^S$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.204*** | -0.955** | | 0.803** | 0.567 | |
| | (3.121) | (1.987) | | 2.035 | 1.173 | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| $R^2$ | 0.076 | 0.382 | 0.357 | 0.034 | 0.366 | 0.357 |
| Adjusted $R^2$ | 0.068 | 0.236 | 0.213 | 0.026 | 0.216 | 0.213 |
| $N$ | 121 | 121 | 121 | 121 | 121 | 121 |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

**Table OA4:** Return predictability and OPTIMIZED (REVISIT CAPTION). Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged short ETFs: $r_t = a + \beta net_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $net_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged short ETFs, $\beta$ is the estimated coefficient on $net_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a+\beta net_{t-1}+\gamma_c\Gamma_{t-1}+D_{mon}+\epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the $net_{t-1}$. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.875*** | -1.638** | | -1.012** | -2.428*** | |
| | (4.201) | (2.397) | | (2.325) | (3.948) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.128 | 0.407 | 0.372 | 0.062 | 0.431 | 0.283 |
| Adjusted $R^2$ | 0.121 | 0.268 | 0.233 | 0.050 | 0.212 | 0.024 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

Panel B: VW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.420*** | -1.288** | | -0.797* | -1.801*** | |
| | (3.607) | (2.189) | | (1.973) | (3.104) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.098 | 0.372 | 0.341 | 0.045 | 0.423 | 0.330 |
| Adjusted $R^2$ | 0.090 | 0.224 | 0.194 | 0.034 | 0.202 | 0.089 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

Panel C: S&P 500

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $net_{t-1}$ | -1.261*** | -1.039* | | -0.701* | -1.598*** | |
| | (3.309) | (1.880) | | (1.776) | (2.827) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.084 | 0.378 | 0.356 | 0.037 | 0.425 | 0.348 |
| Adjusted $R^2$ | 0.076 | 0.233 | 0.213 | 0.025 | 0.205 | 0.113 |
| $N$ | 122 | 122 | 122 | 84 | 84 | 84 |

*Note:* $^{*}\ p < 0.1$; $^{**}\ p < 0.05$; $^{***}\ p < 0.01$

**Table OA5:** Return predictability and CONTROLLING FOR AGGREGATE FLOWS (REVISIT CAPTION). Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged short ETFs: $r_t = a + \beta net_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $net_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged short ETFs, $\beta$ is the estimated coefficient on $net_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta net_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the $net_{t-1}$. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.389*** | -1.031* | | -0.921** | -2.308*** | |
| | (2.991) | (1.678) | | (2.105) | (3.835) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.070 | 0.389 | 0.371 | 0.051 | 0.424 | 0.283 |
| Adjusted $R^2$ | 0.062 | 0.244 | 0.230 | 0.040 | 0.203 | 0.024 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel B: VW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -0.942** | -0.842 | | -0.705* | -1.778*** | |
| | (2.305) | (1.561) | | (1.737) | (3.149) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.043 | 0.357 | 0.341 | 0.035 | 0.425 | 0.330 |
| Adjusted $R^2$ | 0.035 | 0.204 | 0.193 | 0.024 | 0.205 | 0.089 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel C: S&P 500

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -0.746* | -0.635 | | -0.598 | -1.603*** | |
| | (1.887) | (1.242) | | (1.509) | (2.899) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.029 | 0.367 | 0.357 | 0.027 | 0.428 | 0.348 |
| Adjusted $R^2$ | 0.021 | 0.217 | 0.213 | 0.015 | 0.209 | 0.113 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

*Note:* $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

**Table OA6:** Return predictability and CONTROLLING FOR MARKET CONDITIONS (REVISIT CAPTION). Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged short ETFs: $r_t = a + \beta net_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $net_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged short ETFs, $\beta$ is the estimated coefficient on $net_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta net_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the $net_{t-1}$. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.541$^{***}$ | -1.432$^{**}$ | | -1.199$^{***}$ | -2.510$^{***}$ | |
| | (3.347) | (2.491) | | (2.794) | (4.199) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.086 | 0.409 | 0.371 | 0.087 | 0.446 | 0.283 |
| Adjusted $R^2$ | 0.078 | 0.269 | 0.230 | 0.076 | 0.233 | 0.024 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel B: VW CRSP

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.300$^{***}$ | -1.173$^{**}$ | | -1.082$^{***}$ | -1.890$^{***}$ | |
| | (3.247) | (2.344) | | (2.735) | (3.344) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.081 | 0.376 | 0.341 | 0.084 | 0.435 | 0.330 |
| Adjusted $R^2$ | 0.074 | 0.228 | 0.193 | 0.072 | 0.219 | 0.089 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

Panel C: S&P 500

| | Full Sample | | | Post-2009 Sample | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $SSI_{t-1}$ | -1.147$^{***}$ | -0.963$^{**}$ | | -1.008$^{**}$ | -1.689$^{***}$ | |
| | (2.961) | (2.037) | | (2.610) | (3.062) | |
| CONTROLS | NO | YES | YES | NO | YES | YES |
| POST 2009 SAMPLE | NO | NO | NO | YES | YES | YES |
| $R^2$ | 0.069 | 0.384 | 0.357 | 0.077 | 0.436 | 0.348 |
| Adjusted $R^2$ | 0.061 | 0.237 | 0.213 | 0.065 | 0.220 | 0.113 |
| $N$ | 121 | 121 | 121 | 84 | 84 | 84 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

**Table OA7:** Return predictability and PAIRS (REVISIT CAPTION). Regression (1) regresses the equal-weighted CRSP, value-weighted CRSP, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged short ETFs: $r_t = a + \beta net_{t-1} + \epsilon_t$ in which $r_t$ is the index monthly return, $net_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged short ETFs, $\beta$ is the estimated coefficient on $net_{t-1}$, and $\epsilon_t$ is the error term. Regression (2) includes a set of lagged controls: $r_t = a + \beta net_{t-1} + \gamma_c \Gamma_{t-1} + D_{mon} + \epsilon_t$, in which $\Gamma_{t-1}$ is a set of additional lagged controls and $D_{mon} = \{D_{Jan}, \ldots, D_{Nov}\}$ are dummy variables for the month of the year corresponding to the month of $r_t$. Regression (3) excludes the $net_{t-1}$. The sample runs from December 2006 through December 2016. Regressions (4) - (6) repeat the first three regressions on a sub sample of dates January 2010-December 2016 to exclude the financial crisis. All variables, except for returns, are standardized.

Panel A: EW CRSP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| SP500 PAIR | -0.576 | -1.640*** | | |
| | (0.907) | (3.613) | | |
| NASDAQ PAIR | -1.647** | | -1.925*** | |
| | (2.124) | | (4.331) | |
| DJ PAIR | 0.173 | | | -1.375*** |
| | 0.259 | | | (2.983) |
| $R^2$ | 0.141 | 0.098 | 0.135 | 0.069 |
| Adjusted $R^2$ | 0.120 | 0.091 | 0.128 | 0.061 |
| $N$ | 122 | 122 | 122 | 122 |

Panel B: VW CRSP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| SP500 PAIR | -0.219 | -1.150*** | | |
| | (0.390) | (2.868) | | |
| NASDAQ PAIR | -1.212* | | -1.463*** | |
| | (1.767) | | (3.730) | |
| DJ PAIR | -0.130 | | | -1.153*** |
| | (0.220) | | | (2.878) |
| $R^2$ | 0.106 | 0.064 | 0.104 | 0.065 |
| Adjusted $R^2$ | 0.083 | 0.056 | 0.096 | 0.057 |
| $N$ | 122 | 122 | 122 | 122 |

Panel C: S&P 500

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| SP500 PAIR | -0.207 | -1.017*** | | |
| | (0.380) | (2.627) | | |
| NASDAQ PAIR | -0.968 | | -1.278*** | |
| | (1.455) | | (3.357) | |
| DJ PAIR | -0.220 | | | -1.056*** |
| | (0.384) | | | (2.734) |
| $R^2$ | 0.088 | 0.054 | 0.086 | 0.059 |
| Adjusted $R^2$ | 0.065 | 0.047 | 0.078 | 0.051 |
| $N$ | 122 | 122 | 122 | 122 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

**Table OA8:** Trading strategy abnormal returns from January 2010 through December 2016. Panel A provides the returns from a entering into a one month total return swap based on the sign and magnitude of previous month's level of the Speculation Sentiment Index $SSI_{t-1}$ regressed on priced factors. The reference entity in the total return swap is either the CRSP equal-weighted index or the CRSP value-weighted index. If previous month's $SSI_{t-1}$ is positive, the strategy calls for entering short-leg of the total return swap. The strategy calls for entering the long-leg of the total return swap if $SSI_{t-1}$ is positive. The notional value of the swap is determined by the absolute value of the previous month's $SSI_{t-1}$. Model (1) consists of the market factor. Model (2) consists of the market factor, size factor, and value factor. Model (3) consists of the market factor, size factor, value factor and momentum factor. Model (4) consist of the market factor, size factor, value factor, profitability factor, and investment factor. Panel B provides characteristics of the equal-weighted and value-weighted portfolios during the sample and it also includes the same characteristics for the S&P 500 index as a benchmark.

Panel A: Excess Returns

| | Equal-Weighted | | | | Value-Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (1) | (2) | (3) | (4) |
| Intercept | 1.373** | 1.344** | 1.441** | 1.300** | 1.066* | 1.031* | 1.126* | 1.009 |
| | (2.247) | (2.172) | (2.316) | (2.047) | (1.794) | (1.716) | (1.864) | (1.635) |
| Mkt-Rf | 0.266* | 0.310* | 0.288 | 0.338* | 0.326** | 0.383** | 0.362** | 0.404** |
| | (1.712) | (1.783) | (1.652) | (1.871) | (2.158) | (2.269) | (2.136) | (2.301) |
| SMB | | -0.175 | -0.147 | -0.119 | | -0.191 | -0.164 | -0.154 |
| | | (-0.601) | (-0.504) | (-0.385) | | (-0.674) | (-0.578) | (-0.514) |
| HML | | -0.014 | -0.127 | 0.050 | | -0.104 | -0.214 | -0.025 |
| | | (-0.050) | (-0.435) | (0.137) | | (-0.387) | (-0.758) | (-0.071) |
| MOM | | | -0.249 | | | | -0.243 | |
| | | | (-1.217) | | | | (-1.224) | |
| CMA | | | | -0.082 | | | | -0.124 |
| | | | | (-0.140) | | | | (-0.218) |
| RMW | | | | 0.290 | | | | 0.209 |
| | | | | (0.631) | | | | (0.468) |
| $R^2$ | 0.035 | 0.039 | 0.057 | 0.044 | 0.054 | 0.061 | 0.079 | 0.065 |
| Adjusted $R^2$ | 0.023 | 0.003 | 0.009 | -0.017 | 0.042 | 0.026 | 0.032 | 0.005 |
| N | 84 | 84 | 84 | 84 | 84 | 84 | 84 | 84 |

*Note:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$

Panel B: Portfolio Characteristics

| | Equal-Weighted | Value-Weighted | S&P 500 |
|---|---|---|---|
| SHARPE RATIO | 1.058 | 0.899 | 0.826 |
| MAX MONTHLY LOSS | -9.016% | -8.803% | -8.198% |
| STDEV MONTHLY RETURN | 5.443% | 5.345% | 3.659% |
| SEMI STDEV MONTHLY RETURN | 2.705% | 2.538% | 2.266% |
| MAX NOTIONAL | 2.878x | 2.878x | 1 |
| AVG NOTIONAL | 1.000x | 1.000x | 1 |
| STDEV NOTIONAL | 0.726x | 0.726x | 0 |

**Table OA9:** Correlation of $SSI$ measures based on data from Bloomberg, ProShares, and Compustat. The daily, weekly, monthly, and quarterly series are formulated using data from each respective data source and pairwise correlations are computed.

| | Daily $SSI$ | | |
|---|---|---|---|
| Bloomberg | 1.000 | | |
| ProShares | 0.745 | 1.000 | |
| Compustat | 0.021 | 0.007 | 1.000 |
| | Weekly $SSI$ | | |
| Bloomberg | 1.000 | | |
| ProShares | 0.944 | 1.000 | |
| Compustat | 0.644 | 0.596 | 1.000 |
| | Monthly $SSI$ | | |
| Bloomberg | 1.000 | | |
| ProShares | 0.994 | 1.000 | |
| Compustat | 0.875 | 0.869 | 1.000 |
| | Quarterly $SSI$ | | |
| Bloomberg | 1.000 | | |
| ProShares | 0.999 | 1.000 | |
| Compustat | 0.959 | 0.959 | 1.000 |