Speculation Sentiment[*†]

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Abstract

I exploit a novel setting to measure disagreement between unsophisticated speculators and "smart" money, that is, the leveraged exchange-traded funds' (ETFs) primary market. The leveraged ETFs' primary market provides observable arbitrage activity that originates from unobservable speculative demand shocks that create relative mispricing between a leveraged ETF and its underlying derivative securities. I form the *Speculation Sentiment Index* using the realized arbitrage trades and the index proxies for the direction and magnitude of market-wide speculative demand shocks. The Speculation Sentiment Index predicts aggregate asset returns, anomaly returns, and it is associated with market-wide mispricing and arbitrage activity.

[*]**Keywords:** Investor sentiment, non-fundamental demand, return predictability, leveraged exchange-traded fund

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> ...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]

1 Introduction

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.[2] 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 speculation 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*). The index predicts aggregate asset returns and the relation is economically meaningful: A one standard deviation increase in the monthly index is associated with a 1.2%-1.9% decline in

[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).

[2] My use of the term "non-fundamental" includes beliefs that are uncorrelated with fundamental news and also over- and under-reaction to fundamental news.

broad market indices the following month.[3] 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 Standard & Poor's 500 (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 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: "Dumb" money trades the shares and "smart" money trades 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 the 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.[4] Thus, leveraged ETFs provide a special setting to directly observe a proxy

[3]The Speculation Sentiment Index may be downloaded here: https://www.shaunwdavies.com/research .

[4]In theory, if one had high frequency pricing data, he or she could also measure the realization of demand shocks (and arbitrage activity) via expansions and contractions in mispricing. Using net share change, which proxies for the aggregation of all mispricing corrected via arbitrage, has the advantage that it does not require high frequency data.

of speculative demand shocks. To see this, consider the examples in Figure 1. The first figure depicts the realization of a bullish demand shock and the second figure depicts the realization of a bearish demand shock. In both figures, 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. For the bullish demand shock, observable arbitrage activity is in the form of share creations. For the bearish demand shock, observable arbitrage activity is in the form of share redemptions.

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 effects due to other market frictions that generate relative mispricing between all leveraged ETFs (both long and short) and their underlying derivative securities (e.g., shocks to the cost of arbitrage capital). Importantly, the measure does *not* require that leveraged ETF trading is the source of mispricing in the broad market, that is, this is not a price pressure story from leveraged ETF trading. After all, the broad market mispricing identified later in this paper is substantial relative to the size of the leveraged ETF market. Instead, I argue that leveraged ETFs are a unique setting to identify and measure market-wide speculative demand shocks.

The empirical results are consistent with my identifying assumption and SSI predicts negative asset returns. I focus the main predictive analysis on three benchmark indices: (i) the Center for Research in Security Prices (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 monthly SSI and the sign on the monthly 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 monthly SSI correctly predicts the sign on the monthly 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 rough point of reference, the probabilities of successfully predicting a fair coin flip at that frequency or greater 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 monthly index returns as the dependent variable and lagged monthly SSI along with a set of sentiment proxies and market controls as the independent variables. A one standard deviation increase in lagged SSI is associated with a statistically significant 1.3%-2.0% decline in the CRSP equal weighted index, a 0.9%-1.5% decline in the CRSP value weighted index, and a 0.8%-1.3% 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. Furthermore, the results are robust to alternative constructions of SSI and out-of-sample tests.

While I focus primarily on monthly return predictability, there is no obvious reason why speculative demand shocks should resolve themselves in a month's time and not over longer horizons. As an additional test, I examine SSI's ability to predict cumulative returns over one, two, three, four, five and six month horizons. SSI predicts economically meaningful and statistically significant returns out to six months. However, the vast majority of the predicted return is earned in the first four months and a significant fraction is earned in the first month. Thus, while I focus on monthly return predictability, there is evidence that speculative demand shocks may take several months to fully resolve themselves.

The return predictability results suggest that one could formulate a profitable trading strategy based on lagged realizations of SSI. I construct a trading strategy that entails a long-short equity portfolio in which the long and short legs are determined by the equities' sensitivities (out of sample) to SSI. Each month, the set of all NYSE traded stocks are sorted into quintiles based on their estimated sensitivities to SSI. When lagged speculation sentiment is positive, the strategy calls for going long the stocks comprising the fifth quintile and going short the stocks comprising the first quintile. Conversely, when lagged speculation sentiment is negative, the strategy takes a short position in the stocks comprising the fifth quintile and a long position in the stocks comprising the first quintile. Controlling for standard risk factors, the trading strategy earns statistically significant excess returns in the range of 1.4%-1.6% monthly (17.5%-21.1% annually). The trading strategy results show that SSI has a unique distinction in that it provides cross-sectional return predictability in addition to time-series return predictability.[5]

To conclude the analysis, I provide evidence that SSI is, in fact, measuring non-fundamental demand. I examine the relation between SSI and the returns on anomaly factors and long-short anomaly portfolios (Stambaugh & Yuan, 2017). Stambaugh, Yu, and Yuan (2012) argues that valid measures of investor sentiment should *positively* predict anomaly returns; That is, when sentiment levels are high, there are both greater commonalities in mispricing and higher levels of mispricing. Indeed, I find that SSI has substantial *positive* predictive power of both anomaly factor returns and long-short anomaly portfolio spreads. The predictive evidence suggests that speculation sentiment is an important measure of investor sentiment and also provides evidence that SSI's ability to predict aggregate market returns is not spurious. I also show that, within the long-short anomaly portfolio regressions, the majority of the predicted return comes in the short-leg of the portfolio. The evidence is suggestive that the mispricing generated by SSI may not be exploited by rational agents due to short-selling constraints.

The main contribution of this paper is in providing a clean measure of speculation sentiment

[5] There is little evidence that cross-sectional return predictors make good time-series return predictors, especially out of sample. See Engelberg, Mclean, Pontiff, and Ringgenberg (2019).

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 pushing asset prices away from their fundamental values.[6] 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). Similar to my reliance on leveraged ETFs to measure demand shocks that dislocate asset prices, Pasquariello (2014) relies on hundreds of violations of textbook arbitrage parities to measure market-wide financial dislocation. The measure of financial dislocation is time-varying and carries an economically meaningful risk premium (measured in the cross section). Conversely, I focus on a single dimension of financial dislocation, that is, speculative demand shocks, and I show that these demand shocks are predictive of future returns (measured in both the time series and the cross section). Furthermore, the measure from Pasquariello (2014) is developed from settings in which arbitrage capital is unsuccessful in maintaining parity relations, while my measure is based on settings in which arbitrage capital is successful at restoring efficiency.

Speculation sentiment is one dimension of broader *investor sentiment*.[7] I argue that speculation sentiment is a gambling-like, short-horizon dimension of investor sentiment. In that regard, my measure of speculation sentiment is related to the closed-end fund discount: Zweig (1973), Lee, Shleifer, and Thaler (1991), and Neal and Wheatley (1998) argue that closed-end funds are disproportionately held by individual traders, much like leveraged ETF shares, and that the aggregate discount reflects individual traders' bearish or bullish beliefs. Nevertheless, I show that my results are robust to the inclusion of the aggregate closed-end fund discount.[8] The robustness of

[6]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).

[7]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 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.

[8]The results are also robust to the inclusion of the Baker-Wurgler Investor Sentiment Index (Baker & Wurgler, 2006) which aggregates several market sentiment measures, including the closed-end fund discount. While Baker

the results suggests that the non-fundamental demand identified in leveraged ETF share change is distinct from the non-fundamental demand identified in the closed-end fund discount.

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.[9] 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. Nevertheless, there are reasons why SSI is unique and important. First, the index is arguably the best sentiment proxy to date as it has significant predictive power in both the time series and the cross section. The index is also robust to alternative specifications of SSI and is robust to out-of-sample tests. Second, the index is constructed from the trades of arbitrageurs exploiting relative mispricing between leveraged ETFs' shares and the ETFs' underlying assets. Thus, there is a natural economic interpretation to the measure; SSI proxies for realized disagreement between "dumb" and "smart" traders that leads to mispricing. Third, the measure's input data is widely available, the measure is straightforward to construct, and the measure may easily be constructed at different frequencies. Fourth, the leveraged ETF market is vibrant and it is likely that the index will serve as a powerful sentiment measure in the foreseeable future. These reasons suggest that SSI will serve as an important sentiment proxy in future asset pricing and corporate finance studies.

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

and Wurgler (2006) shows that the Baker-Wurgler Investor Sentiment Index generates predictability in the cross section of returns, I show predictability in aggregate market returns. Huang, Jiang, Tu, and Zhou (2015) provide a modified measure of the Baker-Wurgler Investor Sentiment Index that utilizes a partial least squares (PLS) method to minimize noise in the index's input variables and shows that the modified measure predicts aggregate returns. My results are robust to the inclusion of this measure as a control variable.

[9] See Baker and Wurgler (2007) for a survey of investor sentiment measures and DeVault, Sias, and Starks (2019) for an analysis of existing sentiment measures relation to institutional demand versus individual demand. See also F. Jiang, Lee, Martin, and Zhou (2018) for a measure of corporate manager sentiment based on the tone of financial disclosures and Da, Engelberg, and Gao (2014) for a measure of fear sentiment based on daily Internet search volume.

via the ETF primary market mechanism. In a similar spirit, Brown, Davies, and Ringgenberg (2019) show theoretically and empirically that ETF share changes (i.e., ETF flows) provide informative signals of non-fundamental demand shocks and that conditioning on these signals yields return predictability.[10] Brown et al. (2019) is agnostic regarding the types of the implicit demand shocks and, unlike my analysis, focuses only on the cross section of ETF share creations (both leveraged and unleveraged ETFs). The study shows that those ETFs with the most inflows subsequently underperform those with the most outflows. 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 aggregate returns and anomaly returns.

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. Empirically, however, there is debate to how much excess volatility leveraged ETFs generate: Tuzun (2013) and Shum, Hejazi, Haryanto, and Rodier (2015) 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 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

[10] 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.

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.[11] Furthermore, ETFs are accessible to novice and professional investors alike.[12]

ETFs are a pooled investment vehicle, like a mutual fund, which allows investors to buy a basket of assets at once.[13] 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 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

[11] 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."

[12] 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).

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

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 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.[14] For example, to obtain 2x or -2x exposure to an index, the ETF sponsor enters into total return swaps, which are rolled on a regular 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.

[14] 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, were 1.5 and 1.3 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 1.5 times and all shares in SDS would have transacted 1.3 times during that same period. For the other ProShares leveraged ETFs, the numbers are slightly larger.

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.[15] 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, Guofu Zhou's website, Hao Zhou's website, Robert Stambaugh's website,

[15]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.*

Asaf Manela's website, Matthew Ringgenberg's website, Robert Shiller's website, Kenneth French's website, Turan Bali, 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.[16] From Bloomberg I also get weekly data on ETF institutional ownership and ETF characteristics, that is, expense ratios, stated benchmarks, leverage quantities and directions (for leveraged ETFs), and asset focuses (e.g., bonds, equities, or commodities). From ProShares, Compustat, and CRSP, I get ETF shares outstanding data, which are used to crosscheck the Bloomberg data. From CRSP, I also 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 volumes, and shares outstanding. Finally, I clean the ETF data based on the methodology provided in the data appendix of Brown et al. (2019).

To control for broader investor sentiment, I use the Baker-Wurgler Investor Sentiment Index (Baker & Wurgler, 2006) and the closed-end fund discount, which are both 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. I also use the aligned investor sentiment level (Huang et al., 2015), which exploits information in the Baker-Wurgler Investor Sentiment Index using a partial least squares (PLS) method. The measure is designed to predict aggregate stock returns and the data is obtained from Guofu Zhou's website.

To control for market conditions, I use VIX index data, which is obtained from Bloomberg. I also control for the variance risk premium (Bollerslev, Tauchen, & Zhou, 2009) using data from Hao Zhou's website. 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

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

are obtained from Robert Shiller's website. Term spread and short-rate data are obtained from the U.S. Treasury's website. 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. Finally, I use anomaly factor return data and long-short anomaly portfolio data from Robert Stambaugh's website.

As discussed earlier, leveraged ETFs cater to short-horizon traders that desire amplified exposure to market benchmarks. Moreover, as discussed in Section 2.2, leveraged ETFs are primarily held by individual investors. It is well-established that there is investor demand for lottery-like assets; Kumar (2009) and Han and Kumar (2013) show that speculative individual traders demonstrate a propensity to gamble with lottery-like stocks (e.g., low-priced stocks with high idiosyncratic volatility and idiosyncratic skewness). Motivated by these findings, Bali, Brown, Murray, and Tang (2017) forms a measure of investor lottery demand using stocks largest (smallest) daily return the previous month.[17] The measure, MAX factor, is formed using a strategy that goes short the stocks with the five largest daily returns and goes long the stocks with the five smallest daily return. The MAX factor earns subsequent excess returns that cannot be explained by traditional risk factors and the measure also explains the beta anomaly (Black, Jensen, Scholes, et al., 1972; Frazzini & Pedersen, 2014; Baker, Hoeyer, & Wurgler, 2016). As such, to control for investor lottery demand I use the MAX factor which is obtained from Turan Bali.

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 and the closed-end fund discount, which are only available through September 2015 and November 2015 respectively. In the Online Appendix, I consider the robustness of my results with a data series that extends through December 2018.

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

[17] See also Bali, Cakici, and Whitelaw (2011).

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. However, in the Online Appendix, I consider an alternative construction of SSI that utilizes new leveraged ETFs as they come to market and show that the results are robust. See Table OA7.

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 mitigated. For example, if there is 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.[18]

net_t exhibits autocorrelation.[19] In the Online Appendix, Panel A of Table OA2 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,

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

in which a is a constant, γ is the $AR(1)$ coefficient on net_{t-1}, and SSI_t is the innovation to the series. I use the time series of net_t from October 2006 through December 2016 to estimate the $AR(1)$ process. After estimating the parameters a and γ, 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*.[20] Notably, SSI_t and net_t are highly correlated (correlation coefficient of 0.96). The analysis hereafter is qualitatively the same using the original raw share change series net. SSI is depicted in Figure 4.[21] The index exhibits the

[18]Notably, arbitrage activity is an equilibrium outcome that reflects, among other things, the cost of arbitrage capital. As a robustness check, I construct an alternative specification of SSI that is orthogonal to macro conditions associated with the cost of arbitrage capital. See Table OA6.

[19]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.

[20]In the Online Appendix, Panel B of Table OA2 provides the $AR(1)$ estimation. Panel C of Table OA2 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.

[21]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 Section OA.8 and Table OA20 of 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

most pronounced swings just prior, during, and immediately after the 2008 Financial Crisis. Thus, for robustness, I repeat much of the empirical analysis while excluding all observations before 2010 and I show that the main results hold. Furthermore, in the Online Appendix, I provide several alternative specifications of SSI as robustness tests: (i) The raw net_t series in place of SSI, (ii) SSI formed using a raw net_t series orthogonal to aggregate ETF flows, (iii) SSI formed using a raw net_t series orthogonal to macro economic conditions, (iv) SSI formed using an evolving portfolio of leveraged ETFs rather than just the original ProShares funds, (v) SSI formed from only the three leveraged-long ETFs, (vi) SSI formed from only the three leveraged-short ETFs, (vii) SSI formed using dollar flows into the leveraged ETFs rather than percentage changes in shares outstanding and (viii) SSI formed only from each long-short pair. The results in the main paper are robust to alternative specifications of SSI. Furthermore, in the Online Appendix, Table OA1 provides the correlations between SSI and the other control variables used in the paper.

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

creating new ETF shares. The monthly measure does not suffer from these shortcomings.

force a particular principal component embodies. In this setting, however, the interpretation is straightforward: The net bullish/bearish sentiment measured by the difference between leveraged-long and leveraged-short ETFs' share change is the primary driver of fund-level arbitrage activity.

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 predict subsequent returns.

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 monthly 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 monthly SSI correctly predicts the sign on the index's monthly 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 a fair coin flip at these frequencies or better 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 monthly 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 index monthly return, the CRSP value weighted index monthly return, or the S&P 500 index monthly return in month t, a is the regression intercept, SSI_{t-1} is the one month lagged value of SSI, β is the regression coefficient, and ϵ_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 β may be interpreted as the effect of a one standard deviation increase in SSI on subsequent returns (throughout the paper all control variables, other than returns, are standardized).[22] In regression (1), the coefficient β 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%. Moreover, the adjusted R^2's are substantial for time series return predictability regressions: For the CRSP equal weighted index, the adjusted R^2 is 0.12, for the CRSP value weighted index, the adjusted R^2 is 0.09, and for the S&P 500 index, the adjusted R^2 is 0.07.

To control for other known predictors of returns and sentiment proxies, I perform predictive bivariate regressions,

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

in which Γ_{t-1} is a lagged control variable. The results for the regressions are also reported in Table 1. The additional lagged control variables with the regression number included in parenthesis are: Index return r_{t-1} (2), cyclically adjusted earnings-to-price $caep_{t-1}$ (3), term spread $term_{t-1}$ (4), dividend-to-price dp_{t-1} (5), short-rate $rate_{t-1}$ (6), variance risk premium vrp_{t-1} (7), intermediary capital risk factor $intc_{t-1}$ (8), innovation to aggregate liquidity Δliq_{t-1} (9), short interest $short_{t-1}$ (10), VIX vix_{t-1} (11), Baker-Wurgler investor sentiment level $sent_{t-1}$ (12), aligned investor sentiment level $hjtz_{t-1}$ (13), closed-end fund discount $cefd_{t-1}$ (14), consumer confidence level $conf_{t-1}$ (15), change in consumer confidence level $\Delta conf_{t-1}$ (16), and investor lottery demand

[22] My inference for statistical significance in the return predictability analysis assumes independently and normally distributed residuals. However, in Panel A of Table OA3 located in the Online Appendix, I account for a potential Stambaugh-bias (Stambaugh, 1999) and calculate p-values using a small sample parametric bootstrap and GMM corrected standard errors. β remains statistically significant at a 1% p-value threshold for the CRSP equal weighted index and is statistically significant at a 5% p-value threshold for the CRSP value weighted index and the S&P 500 index.

$fmax_{t-1}$ (17).[23] For the CRSP equal weighted index regressions, the coefficients on SSI_{t-1} are statistically significant at a 1% p-value threshold in regressions (2)-(17) and range in value from -2.00 to -1.30. For the CRSP value weighted index regressions, the coefficients are statistically significant at the 1% p-value threshold for all regressions except for regression (7) which corresponds to the variance risk premium and the coefficient on SSI_{t-1} in that regression carries statistical significance at a 5% p-value threshold. Furthermore, for the CRSP value weighted index regressions, the coefficients range in value from -1.50 to -0.93. For the S&P 500 index regressions, the coefficients are statistically significant at the 1% p-value threshold for all regressions except for regressions (7) and (9). Regression (7) corresponds to the variance risk premium and the coefficient on SSI_{t-1} carries statistical significance at a 10% p-value threshold. Regression (9) corresponds to the innovation to aggregate liquidity and the coefficient on SSI_{t-1} carries statistical significance at a 5% p-value threshold. Furthermore, for the S&P 500 index regressions, the coefficients range in value from -1.26 to -0.78. Together, the bivariate regression results in Table 1 demonstrate an economically meaningful and statistically significant relation between SSI and future market returns, even after controlling for other known predictors of returns and sentiment proxies.

It is worthwhile to focus on one particular control variable, the variance risk premium; In Table 1, the regressions which use the variance risk premium as a control consistently show smaller coefficients on SSI and less statistical significance. Moreover, in subsequent robustness tests, results are consistently weaker when using the variance risk premium as a control. Therefore, special attention is required in exploring the relation between SSI and vrp. vrp is the spread between implied and realized variance and it serves as a proxy for aggregate market risk aversion (Rosenberg & Engle, 2002; Bakshi & Madan, 2006; Bollerslev et al., 2009). Large values of vrp are associated with higher subsequent returns (i.e., a larger risk premium due to greater risk aversion) and lower values of vrp are associated with lower subsequent returns (i.e., a smaller risk premium due to less risk aversion). To that end, in unreported analysis, univariate regressions using vrp as a predictor of the CRSP equal weighted index return, the CRSP value weighted index return and the S&P 500 index return from December 2006 through December 2016 yields coefficient estimates, with t-statistics in

[23]Throughout the paper, I use end-of-month values for the VIX index. End-of-month values are highly correlated with monthly average values (0.95 correlation coefficient during the paper's sample period).

parenthesis, of 2.02 (4.56), 1.60 (4.10), and 1.45 (3.85) respectively. Thus, both SSI and vrp are strong univariate predictors of the aggregate returns. However, in the bivariate regressions using both SSI and vrp in Table 1, the coefficients on both variables are smaller and the t-statistics, while statistically significant, are also attenuated. While slightly weaker, the coefficients on both variables remain economically meaningful and statistically significant. Thus, it appears that SSI and vrp contain both a common component and distinct components. Additionally, in the Online Appendix, Table OA1 presents the correlations of each control variable with SSI. The correlation coefficient for vrp and SSI is -0.46, again highlighting a common component to both variables. Thus, the results suggests that when speculative sentiment is bullish, aggregate risk aversion is lower. Conversely, when speculative sentiment is bearish, aggregate risk aversion is greater. Nevertheless, despite this common component in the two variables, their distinct components remain important (both in economic magnitude and statistical significance) predictors of aggregate returns.

While all coefficients on SSI_{t-1} in Table 1 are statistically significant at a 10% p-value threshold or lower, it is reasonable to consider multivariate regressions that include more than one lagged control. However, choosing a particular multivariate specification is simultaneously defensible and also arbitrary. As such, rather than picking one particular multivariate specification, I consider all combinations available with my set of control variables to demonstrate the robustness of the return predictability analysis. 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. Each figure presents coefficient estimates for β across 65,536 specifications that use different combinations of controls: (i) Lagged index return r_{t-1}, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$, (iv) lagged VIX vix_{t-1}, (v) lagged innovation to aggregate liquidity Δliq_{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}, (ix) lagged cyclically adjusted earnings-to-price $caep_{t-1}$, (x) lagged term spread $term_{t-1}$, (xi) lagged short-rate $rate_{t-1}$, (xii) month of year dummies D_{mon}, (xiii) lagged closed-end fund discount $cefd_{t-1}$, (xiv) lagged variance risk premium (vrp_{t-1}), (xv) lagged aligned investor sentiment level ($hjtz_{t-1}$), and (xvi) lagged investor lottery demand ($fmax_{t-1}$). Furthermore, each data point is colored according to its associated p-value. Out of the 65,536 specifications plotted, β remains relatively stable in the CRSP equal weighted index, CRSP value weighted index, and S&P 500 regressions. Furthermore, β is statistically significant with a 10% p-value threshold for 50,318 of 65,536 (77%) of the CRSP equal weighted index regressions, 44,810 of 65,536 (68%) of the CRSP value weighted index regressions, and 33,638 of 65,536 (51%) of the S&P 500 index regressions. Moreover, β is negative valued in all 65,536 specifications for the CRSP equal weighted index and also in all 65,536 specifications for the CRSP value weighted index. β is positive valued in only five of the 65,536 S&P 500 index specifications.

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 Table 1. As a robustness check, the 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 in Table 2. The CRSP equal weighted index regressions report a coefficient on SSI_{t-1} that is statistically significant at a 10% p-value threshold or smaller in regressions (1)-(17).[24] The coefficient magnitudes on SSI_{t-1}, however, are slightly attenuated and range between -1.33 to -0.75. For the CRSP value weighted index regressions, the coefficient on SSI_{t-1} is statistically significant at a 10% p-value threshold or smaller in all regressions except for regression (7) which corresponds to the specification using the variance risk premium as a control. The coefficients on SSI_{t-1} are also slightly smaller in the CRSP value weighted index regressions, ranging between -1.19 to -0.53. Finally, in the S&P 500 index regressions, the coefficient on SSI_{t-1} is statistically significant at a 10% p-value threshold or smaller in all regressions except for regression (7) which corresponds to the specification using the variance risk premium as a control. Like the CRSP equal weighted and value weighted regressions, the coefficients on SSI_{t-1} are slightly smaller in the S&P 500 index regressions and range between -1.08 to -0.45.

While I focus primarily on monthly return predictability, there is no obvious reason why spec-

[24]In Panel B of Table OA3 located in the Online Appendix, I account for a potential Stambaugh-bias (Stambaugh, 1999) and calculate p-values using a small sample parametric bootstrap and GMM corrected standard errors in the univariate regressions. β is statistically significant at a 5% p-value threshold for both the CRSP equal weighted index and the CRSP value weighted index and β is statistically significant at a 10% p-value threshold for the S&P 500 index.

ulative demand shocks should resolve themselves in a month's time and not over longer horizons. Table 3 provides univariate regression results in which lagged SSI predicts cumulative returns over one, two, three, four, five, and six months in each of the three indices. In the table, 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. Hodrick (1992) standard errors are reported because of the mechanical autocorrelation introduced by the dependent variable's overlapping periods.

SSI largely predicts economically and statistically significant returns out to six months in each of the three indices in Table 3. However, the vast majority of the predicted return is earned in the first four months and a significant fraction is earned the first month. Thus, while I focus on monthly return predictability, there is evidence that speculative demand shocks may take several months to fully resolve themselves. The results of Table 3 also highlight an interesting research question outside of this study: How long does it take for prices to "correct" for different types of non-fundamental demand shocks? Said differently, do different types of non-fundamental shocks take longer to diffuse through markets and reverse? This is a topic of future research.

The results in Table 3 are also depicted in Figure 9. Each panel in Figure 9 depicts the results for either the CRSP equal weighted index, the CRSP equal weighted index, or the S&P 500 index. The vertical axis represents the coefficient β from the univariate regressions and the horizontal axis represents the number of months the cumulative return is calculated over. 90% confidence intervals are depicted with each data point using Hodrick (1992) standard errors. In all three panels, predicted returns are evident in the first month and continue to grow until approximately month four.

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 the monthly regression specifications, the coefficients on SSI with CRSP equal weighted index returns are the largest in magnitude and the coefficients on SSI with S&P 500 index returns are the smallest in magnitude. The rank order of coefficients suggests that speculative demand shocks disproportionately affect smaller capitalization stocks. Collectively, the results of this section are consistent with speculative demand shocks moving asset prices away from fundamentals.

Furthermore, in the Online Appendix, I provide additional evidence and robustness checks in support of SSI having predictive ability. First, I show that the results are robust to alternative specifications of SSI. Specifically, in Table OA4 I repeat the analysis but use the raw series net_t in place of SSI_t and show that the results are robust. In Table OA5, I consider SSI_t orthogonalized to aggregate ETF flows and show that the results are robust. In Table OA6, I consider SSI_t orthogonalized to macro conditions and show that the results are robust. In Table OA7, I form SSI_t using the entire universe of leveraged ETFs as they begin trading. Again, the results are robust. In Table OA8, I form SSI_t using only the three leveraged-long ETFs and show that return predictability remains but it is slightly weaker (statistically and in economic magnitude) as compared to SSI_t formed using both leveraged-long and leveraged-short ETFs. Table OA9 provides the analog to Table OA8 using SSI_t formed using only the three leveraged-short ETFs. Again, the results remain robust but are weaker statistically and in economic magnitude as compared to SSI_t formed using both leveraged-long and leveraged-short ETFs. In Table OA10, I form $SSI^{\$}$ using dollar flows into the leveraged ETFs rather than percentage changes in shares outstanding. The results are robust. Table OA11 considers the return predictability coming from each leveraged ETF pair (e.g., using SSO and SDS which provide leveraged-long and leveraged-short exposure to the S&P 500). Each pair provides return predictability in similar magnitudes and statistical significance to the baseline analysis using SSI_t. Second, in Table OA12, I show that the results are robust to an out-of-sample setting in the same spirit of Campbell and Thompson (2007).

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. Additionally, because the previous section demonstrates aggregate return predictability using SSI, I also provide a trading strategy utilizing total return swaps in the Online Appendix. The reference entity in the total return swaps is a stock market index and the strategy yields better excess returns compared to the long-short equity portfolio studied in this section. The results are located in Table OA13.

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 using data from February 2007 through January 2010.[25] 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 τ 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 τ, 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 τ 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-leg and short-leg are flipped. The economic motivation for the portfolio is that, when SSI is large and positive, stocks which are the most positively related to SSI are relatively overvalued and stocks which are the most negatively related to SSI are relatively undervalued. Conversely, when SSI is large and negative, stocks which are the most positively related to SSI are relatively undervalued and stocks which are the most negatively related to SSI are relatively overvalued.

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

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. Conversely, when the absolute value of SSI is large, the exposure of the portfolio is increased. While long-short portfolios require zero investment by construction, the exposure is determined by how many dollars are invested in one side of the portfolio (i.e., either the long-leg or short-leg). I normalize SSI so that the average exposure of each leg is equal to one dollar. Thus, when SSI is large, each leg of the portfolio invests more than a dollar and when SSI is small, each leg of the portfolio invests less than a dollar.

Equal weighted and value weighted portfolios are formed in which value weights are determined by the stocks' market capitalizations in month τ. The returns from the trading strategy yield abnormal returns that cannot be explained by canonical risk factors. Table 4 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% or lower for value weighted portfolio. Moreover, the intercepts are stable: For the equal weighted portfolio, the intercept equals between 1.46% and 1.61%, and for the value weighted portfolio, the intercept equals between 1.35% and 1.54%. These monthly abnormal returns imply annualized abnormal returns in the range of 19.0%-21.1% for the equal weighted portfolio and 17.5%-20.1% for the value weighted portfolio.

Panel B of Table 4 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 in the equal weighted index; The trading strategy using the equal weighted portfolio dominates the S&P 500 with regards to the Sharpe Ratio (0.93 versus 0.83 for the S&P 500). However, the Sharpe Ratio for the value weighted portfolio falls short of the S&P 500 with regards to the Sharpe Ratio (0.76

versus 0.83 for the S&P 500).

5 Evidence that SSI is Non-Fundamental Demand

In Section 4, SSI was shown to have substantial power in predicting aggregate returns. While that evidence supports the view that SSI measures aggregate speculative demand shocks that distort asset prices, the results could be spurious (e.g., see Novy-Marx, 2014). In this section, I provide evidence that SSI is, in fact, non-fundamental demand. I examine the relation between SSI and future anomaly factor returns and long-short anomaly portfolio spreads. Stambaugh et al. (2012) argues that, given commonality in mispricing, anomaly returns should *increase* with valid measures of sentiment. Thus, positively predicting anomaly returns is an important hurdle for a valid sentiment measure to conquer. Under the null hypothesis, SSI should not predict anomaly returns. However, I find that SSI has substantial *positive* predictive power for both anomaly factor returns and individual long-short anomaly portfolio spreads. As such, to the extent that anomaly portfolios reflect mispricing, speculative demand as measured by SSI is highly predictive of mispricing, consistent with SSI being a strong measurement of sentiment. Furthermore, in the long-short anomaly portfolio spread analysis, the majority of the predicted returns comes from the short-leg of the trading strategy. Greater predictive power in the short-leg is consistent with Miller (1977) and Stambaugh et al. (2012) which argue that mispriced assets in the short-leg of a portfolio are more difficult for rational traders to exploit due to short-selling constraints.

I focus the anomaly predictability analysis on eleven long-short anomaly portfolios and two anomaly factors. The eleven long-short anomaly portfolios examined are (i) the net stock issuance anomaly – NSI – Ritter (1991), (ii) the composite equity issues anomaly – CEI – Daniel and Titman (2006), (iii) the accruals anomaly – ACC – Sloan (1996), (iv) the net operating assets anomaly – NOA – Hirshleifer, Hou, Teoh, and Zhang (2004), (v) the asset growth anomaly – AG – Cooper, Gulen, and Schill (2008), (vi) the investment-to-assets anomaly – ITA – Titman, Wei, and Xie (2004), (vii) the distress anomaly – DIS – Campbell, Hilscher, and Szilagyi (2008), (viii) the O-Score anomaly – OSC – Ohlson (1980), (ix) the momentum anomaly – MOM – Jegadeesh and Titman (1993), (x) the gross profitability anomaly – $GPRO$ – Wang and Yu (2015), and (xi) the return-on-assets anomaly – ROA – Wang and Yu (2015). The two anomaly factors – $MGMT$ and $PERF$ – Stambaugh and Yuan (2017), are generated using the eleven aforementioned anomaly portfolios; $MGMT$ is constructed from NSI, CEI, ACC, NOA, AG, and ITA, while $PERF$ is constructed from DIS, OSC, MOM, $GPRO$, and ROA. $MGMT$ has a flavor of quantities that firms' managements can affect rather directly and $PERF$ relates more to performance (which firms' managements can only indirectly affect).

I begin the analysis of anomaly returns by examining SSI's ability to predict the $MGMT$ and $PERF$ factor returns. Similar to Table 1 and Table 2, I perform a univariate regression,

$$r_t = a + \beta SSI_{t-1} + \epsilon_t, \tag{10}$$

in which r_t is either the $MGMT$ factor monthly return or the $PERF$ factor monthly return in month t, a is the regression intercept, SSI_{t-1} is the one month lagged value of SSI, β is the regression coefficient, and ϵ_t is the regression error term. The results for the regressions are reported in Table 5 as regression (1). Results for the $MGMT$ factor are reported in Panel A and the results for $PERF$ factor are reported in Panel B. The sample's index returns run from December 2006 through December 2016. In regression (1), the coefficient β is statistically significant with a 1% p-value threshold for each of the two factors; For the $MGMT$ factor, a one standard deviation increase in lagged SSI is associated with a 0.6% return on the factor. For the $PERF$ factor, the effect is twice as large with a one standard deviation increase in SSI being associated with a 1.2% return on the factor.[26] The univariate regression results show that SSI is both economically and statistically significant in predicting anomaly factor returns.

It is also interesting to consider SSI's ability to predict the size factor SMB. Specifically, Stambaugh and Yuan (2017) shows that the Baker-Wurgler Investor Sentiment Index predicts the Fama-French three-factor model's SMB (Fama & French, 1993). Stambaugh and Yuan (2017) attributes the predictability as coming from mispriced securities in the short-leg of the long-short portfolio that forms the factor. Consequently, Stambaugh and Yuan (2017) forms a new SMB

[26] In Panel C of Table OA3 located in the Online Appendix, I account for a potential Stambaugh-bias (Stambaugh, 1999) and calculate p-values using a small sample parametric bootstrap and GMM corrected standard errors. Both estimates of β are statistically significant at a 5% p-value threshold.

factor by excluding stocks that have a greater likelihood of being mispriced. The new SMB factor is nearly twice as large on average as compared to the Fama-French SMB factor (46 bps per month versus 25 bps). Moreover, the new SMB factor is not predicted by the Baker-Wurgler Investor Sentiment Index. In Panel C of Table 5, I consider SSI's ability to predict future returns on the Stambaugh-Yuan SMB factor. In regression (1), I perform a univariate predictive regression like those performed on $MGMT$ and $PERF$. The coefficient β on SSI is -0.4 and the coefficient is statistically significant at a 10% p-value threshold.[27] As such, when speculative demand is bullish it predicts a smaller size premium. Conversely, when speculative demand is bearish it predicts a larger size premium.

To conclude the regression analysis using $MGMT$, $PERF$, and SMB, I perform predictive bivariate regressions,

$$r_t = a + \beta SSI_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t, \tag{11}$$

in which Γ_{t-1} is a lagged control variable. The results for the regressions are also reported in Table 5. The additional control variables are the same as those in Table 1 and Table 2. SSI, when combined with an additional lagged control, predicts $MGMT$ with a coefficient ranging between 0.53 and 0.71 and each coefficient being statistically significant at a 1% or 5% p-value threshold. SSI, when combined with an additional lagged control, predicts $PERF$ with a coefficient ranging between 0.70 and 1.22 and each coefficient being statistically significant at a 1%, 5%, or 10% p-value threshold with the exception of the regressions that include the variance risk premium (vrp), changes in aggregate liquidity (Δliq), and investor lottery demand ($fmax$) for which the coefficient is statistically insignificant. Finally, SSI, when combined with an additional lagged control, predicts the Stambaugh-Yuan SMB with a coefficient ranging between -0.26 and -0.47 and each coefficient being statistically significant at a 5% or 10% p-value threshold with the exception of the regressions that include the variance risk premium (vrp) and changes in aggregate liquidity (Δliq) for which the coefficient is statistically insignificant.

The regression results in Table 5 collectively show that SSI is directly related to mispricing

[27] In Panel C of Table OA3 located in the Online Appendix, I account for a potential Stambaugh-bias (Stambaugh, 1999) and calculate p-values using a small sample parametric bootstrap and GMM corrected standard errors. The estimate of β is statistically significant at a 10% p-value threshold.

across a large set of assets. Furthermore, Table 5 also provides evidence that the return predictability results from Section 4 are not spurious. Table 5 also provides additional economic insights regarding SSI. First, given that the coefficient on $PERF$ is nearly twice as large as the coefficient on $MGMT$ in each regression, it appears that speculation sentiment manifests itself more in mispricing related to performance as opposed to mispricing related to managerial choices. Second, because SSI predicts the anomaly factors $MGMT$ and $PERF$ as well as the Stambaugh-Yuan SMB factor, it suggests that the mispricing factors in Stambaugh and Yuan (2017) may be incomplete; The relation between SSI and the factors $MGMT$ and $PERF$ shows that SSI represents mispricing, while the relation between SSI and SMB shows that there may still be mispriced securities in the portfolios used to form the Stambaugh-Yuan SMB factor. This is a topic of future research.

Next, I examine SSI's ability to predict the long-short spreads, the long-leg return, and the short-leg return on the eleven anomaly portfolios outlined above. I perform a univariate regression,

$$r_t = a + \beta SSI_{t-1} + \epsilon_t, \tag{12}$$

in which r_t is either the long-short spread, the long-leg return, or the short-leg return in month t, a is the regression intercept, SSI_{t-1} is the one month lagged value of SSI, β is the regression coefficient, and ϵ_t is the regression error term. The results for the regressions are reported in Table 6. Regression (1) examines the net stock issuance anomaly (NSI_t), regression (2) examines the composite equity issues anomaly (CEI_t), regression (3) examines the accruals anomaly (ACC_t), regression (4) examines the net operating assets anomaly (NOA_t), regression (5) examines the asset growth anomaly (AG_t), regression (6) examines the investment-to-assets anomaly (ITA_t), regression (7) examines the distress anomaly (DIS_t), regression (8) examines the O-Score anomaly (OSC_t), regression (9) examines the momentum anomaly (MOM_t), regression (10) examines the gross profitability anomaly ($GPRO_t$), and regression (11) examines the return-on-assets anomaly (ROA_t). Results for the long-short spread are reported in Panel A, results for the long-leg return are reported in Panel B, and results for the short-leg return are reported in Panel C. The sample's index returns run from December 2006 through December 2016.

First, consider Panel A and the six anomaly portfolios that are used to construct the $MGMT$ factor (these are denoted in Table 6 with the heading "MGMT"). SSI positively predicts the long-short portfolio spreads on the net stock issuance anomaly and the composite equity issues anomaly, statistically significant with a 1% p-value threshold, which can be seen in (1) and (2). However, SSI is negatively related to the accruals anomaly in (3), statistically significant with a 5% p-value threshold and SSI is statistically insignificant in predicting the net operating assets anomaly, the asset growth anomaly, and the investment-to-assets anomaly in (4)-(6). These results further strengthen the earlier insight that SSI is less related to mispricing occurring from managerial decision-making.

Next, consider the five anomaly portfolios that are used to construct the $PERF$ factor (these are denoted in the table with the heading "PERF"). SSI positively predicts each of the long-short portfolio spreads, statistically significant with a 1% or 5% p-value threshold, which can be seen in (7)-(11). The regression results using the $PERF$ anomaly returns further strengthens the earlier insight that SSI is more related to mispricing related to performance.

Panel B and Panel C of Table 6 show that SSI negatively predicts the returns on both the long-legs and short-legs constructing each of the anomaly portfolios. Moreover, the predictability is significant at a 1% p-value threshold in each of the 22 regressions. Notably, the coefficients on SSI in the short-leg predictive regressions are approximately twice as large as the coefficients on SSI in the long-leg predictive regressions. Greater magnitude of the coefficients in the short-leg is consistent with Miller (1977) and Stambaugh et al. (2012) which argue that mispriced assets in the short-leg of a portfolio are more difficult for rational traders to exploit due to short-selling limits. That said, there remains significant predictability in the long-leg as well, albeit smaller. As such, the results suggest that there are mispriced assets that rational agents could take a long position in, but do not.

In the Online Appendix, I provide additional evidence that SSI is non-fundamental demand. The evidence is threefold. First, I examine the contemporaneous affect of SSI on arbitrage activity in the universe of all ETFs. I perform fund-by-fund regressions and show that other ETFs' arbitrage activity (i.e., share change) is highly related to the contemporaneous realization of SSI. Moreover, I show that the effects are stronger in a subset of speculative ETFs, that is, other leveraged ETFs. The results suggest that speculative demand generates non-fundamental demand across the ETF universe. The empirical analysis is outlined and discussed in Section OA.7.1. Second, I characterize the trading motives behind speculative demand shocks via revealed preferences. I find that SSI is contrarian, that is, when markets are doing well, SSI is bearish and when markets are doing poorly, SSI is bullish. I also consider the possibility that SSI is related to rational portfolio rebalancing. Specifically, if an investor is trying to achieve a target leverage ratio using a leveraged ETF, she must rebalance daily to maintain the target leverage. I show analytically that such rebalancing looks like a contrarian trading strategy. Nevertheless, I construct a measure of potential rebalancing as a control variable and I show that the return predictability of SSI is robust to its inclusion. The empirical analysis is outlined and discussed in Section OA.7.2. Third, I examine changes in institutional ownership of leveraged ETF shares. I construct a measure $inst$, similar to the construction of net, using percentage changes in institutional ownership. I find that institutional ownership *positively* predicts aggregate returns, which is in strong contrast to the negative predictability coming from net. That is, institutional ownership of leveraged ETFs appears to be informed demand. In light of this finding, I construct a measure of net demand that strips out changes in institutional ownership. The measure, $netMINUSinst$, negatively predicts aggregate returns (similar to net) and the statistical significance is stronger after controlling for changes in institutional ownership. The findings further support the paper's identifying assumption that the excess demand of individual traders for leveraged ETF shares is a proxy for market wide speculative sentiment. The empirical analysis is outlined and discussed in Section OA.7.3.

6 Conclusion

This paper provides perhaps the most direct and cleanest measure of investor sentiment to date using a novel market setting: The leveraged exchange-traded funds' (ETFs) primary market. Leveraged ETFs are special because a distinct investor clientele trades the ETF shares ("dumb" money, short-horizon traders) and another distinct investor clientele trades the shares' underlying assets (relatively smarter institutions) and (ii) mispricing between the ETF shares and the underlying assets is corrected via *observable* arbitrage trades. Thus, observed arbitrage trades proxy for market-wide latent demand shocks that gave rise to the initial mispricing. In other words, these arbitrage trades signal aggregate disagreement between "dumb" and "smart" money. With exception to this paper, the leveraged ETF primary market has gone largely unnoticed despite its incredibly rich information on investor sentiment.

The paper's sentiment measure (SSI) constructed from observable arbitrage trades is a powerful predictor of both market returns and anomaly portfolio spreads. As such, there is strong evidence that the measure is, in fact, measuring non-fundamental demand. It is likely that the measure will serve as an important sentiment proxy in future asset pricing and corporate finance studies. Moreover, this paper provides a blueprint for future studies on how to use the information in ETF arbitrage trades to measure other dimensions of non-fundamental demand and the tests one should run on such measures.

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Table 1: Return predictability and SSI. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, 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, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI_{t-1}	-1.89***	-1.73***	-1.85***	-1.89***	-1.88***	-1.87***	-1.30***	-1.78***	-1.61***	-1.88***	-2.00***	-1.71***	-1.85***	-1.85***	-1.91***	-1.89***	-1.66***
	(4.21)	(3.05)	(4.22)	(4.20)	(4.26)	(4.18)	(2.76)	(3.57)	(3.48)	(4.19)	(4.34)	(3.70)	(4.02)	(4.02)	(4.22)	(4.18)	(3.37)
Γ_{t-1}		0.05	1.16***	0.28	1.02**	-0.59	1.51***	0.25	1.12**	-0.60	0.49	-1.18**	-0.24	0.96**	-0.24	0.19	0.56
		0.46	2.63	0.62	2.30	(1.27)	3.23	0.51	2.15	(1.33)	1.06	(2.41)	(0.51)	1.98	(0.52)	0.42	1.13
R^2	0.13	0.13	0.18	0.13	0.17	0.14	0.20	0.13	0.16	0.14	0.14	0.17	0.13	0.16	0.13	0.13	0.14
Adj R^2	0.12	0.12	0.16	0.12	0.15	0.13	0.19	0.12	0.15	0.13	0.12	0.15	0.12	0.14	0.12	0.12	0.12
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	-1.42***	-1.50***	-1.40***	-1.42***	-1.41***	-1.41***	-0.93**	-1.45***	-1.13***	-1.42***	-1.46***	-1.32***	-1.30***	-1.39***	-1.41***	-1.42***	-1.39***
	(3.57)	(3.06)	(3.54)	(3.56)	(3.56)	(3.54)	(2.23)	(3.27)	(2.80)	(3.55)	(3.58)	(3.16)	(3.24)	(3.35)	(3.54)	(3.56)	(3.17)
Γ_{t-1}		-0.03	0.48	0.08	0.31	-0.37	1.23***	-0.06	1.13**	-0.06	0.20	-0.54	-0.59	0.42	0.09	-0.07	0.08
		(0.29)	1.21	0.18	0.78	(0.89)	2.95	(0.14)	2.46	(0.16)	0.48	(1.23)	(1.48)	0.96	0.21	(0.17)	0.18
R^2	0.10	0.10	0.11	0.10	0.10	0.10	0.16	0.10	0.14	0.10	0.10	0.11	0.11	0.10	0.10	0.10	0.10
Adj R^2	0.09	0.08	0.09	0.08	0.09	0.09	0.14	0.08	0.13	0.08	0.08	0.09	0.10	0.08	0.08	0.08	0.08
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	-1.23***	-1.25***	-1.22***	-1.23***	-1.23***	-1.22***	-0.78*	-1.25***	-0.95**	-1.24***	-1.26***	-1.15***	-1.10***	-1.21***	-1.22***	-1.24***	-1.22***
	(3.20)	(2.66)	(3.17)	(3.19)	(3.19)	(3.17)	(1.92)	(2.91)	(2.41)	(3.19)	(3.17)	(2.83)	(2.83)	(3.01)	(3.16)	(3.20)	(2.86)
Γ_{t-1}		-0.01	0.37	0.09	0.20	-0.41	1.14***	-0.04	1.14**	0.05	0.10	-0.48	-0.70*	0.41	0.14	-0.09	0.04
		(0.06)	0.95	0.23	0.51	(1.02)	2.82	(0.08)	2.57	0.13	0.25	(1.12)	(1.79)	0.97	0.37	(0.23)	0.10
R^2	0.08	0.08	0.09	0.08	0.08	0.09	0.14	0.08	0.13	0.08	0.08	0.09	0.10	0.08	0.08	0.08	0.08
Adj R^2	0.07	0.06	0.07	0.06	0.07	0.07	0.12	0.06	0.11	0.06	0.06	0.07	0.09	0.07	0.06	0.06	0.06
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

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

Table 2: Return predictability and SSI post-2009. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, 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, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from January 2010 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI_{t-1}	-1.16***	-1.32***	-1.14***	-1.14**	-1.10**	-1.16***	-0.75*	-1.32***	-1.13***	-1.16***	-1.18***	-0.95**	-1.17***	-1.01**	-1.16***	-1.20***	-1.33***
	(2.69)	(2.93)	(2.69)	(2.62)	(2.61)	(2.68)	(1.80)	(2.97)	(2.66)	(2.70)	(2.75)	(2.04)	(2.70)	(2.20)	(2.68)	(2.79)	(3.01)
Γ_{t-1}		-0.13	0.72	-0.28	0.90**	0.35	1.53***	-0.61	0.79*	-0.40	0.57	-0.38	0.23	0.40	-0.18	0.55	-0.67
		(1.20)	1.66	(0.65)	2.12	0.74	3.67	(1.35)	1.80	(0.92)	1.33	(0.77)	0.53	0.84	(0.40)	1.27	(1.52)
R^2	0.08	0.10	0.11	0.09	0.13	0.09	0.21	0.10	0.12	0.09	0.10	0.07	0.08	0.07	0.08	0.10	0.11
Adj R^2	0.07	0.07	0.09	0.06	0.11	0.06	0.19	0.08	0.09	0.07	0.08	0.04	0.06	0.05	0.06	0.08	0.08
N	84	84	84	84	84	84	84	84	84	84	84	70	84	72	84	84	84

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	-0.93**	-1.19***	-0.92**	-0.90**	-0.88**	-0.93**	-0.53	-1.12***	-0.90**	-0.93**	-0.96**	-0.82*	-0.93**	-0.85*	-0.93**	-0.96**	-1.13***
	(2.32)	(2.86)	(2.31)	(2.24)	(2.24)	(2.31)	(1.37)	(2.72)	(2.28)	(2.31)	(2.43)	(1.85)	(2.32)	(1.95)	(2.32)	(2.39)	(2.76)
Γ_{t-1}		-0.22*	0.60	-0.33	0.84**	0.09	1.51***	-0.71*	0.76*	-0.16	0.75*	-0.01	0.09	0.31	-0.21	0.42	-0.76*
		(1.96)	1.50	(0.82)	2.14	0.20	3.94	(1.70)	1.86	(0.39)	1.89	(0.03)	0.22	0.69	(0.51)	1.03	(1.87)
R^2	0.06	0.10	0.09	0.07	0.11	0.06	0.21	0.09	0.10	0.06	0.10	0.05	0.06	0.06	0.06	0.07	0.10
Adj R^2	0.05	0.08	0.06	0.05	0.09	0.04	0.19	0.07	0.08	0.04	0.08	0.02	0.04	0.03	0.04	0.05	0.08
N	84	84	84	84	84	84	84	84	84	84	84	70	84	72	84	84	84

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	-0.82**	-1.08***	-0.81**	-0.79**	-0.77**	-0.82**	-0.45	-1.01**	-0.79**	-0.82**	-0.85**	-0.74*	-0.82**	-0.76*	-0.82**	-0.85**	-1.02**
	(2.09)	(2.67)	(2.08)	(2.01)	(2.00)	(2.08)	(1.18)	(2.52)	(2.05)	(2.08)	(2.21)	(1.70)	(2.08)	(1.79)	(2.09)	(2.16)	(2.56)
Γ_{t-1}		-0.23**	0.55	-0.35	0.84**	-0.03	1.39***	-0.72*	0.70*	-0.07	0.75*	0.07	0.00	0.36	-0.22	0.37	-0.77*
		(2.02)	1.39	(0.88)	2.18	(0.08)	3.68	(1.76)	1.76	(0.18)	1.93	0.15	0.00	0.81	(0.54)	0.94	(1.93)
R^2	0.05	0.10	0.07	0.06	0.10	0.05	0.19	0.09	0.09	0.05	0.09	0.04	0.05	0.05	0.05	0.06	0.09
Adj R^2	0.04	0.07	0.05	0.04	0.08	0.03	0.17	0.06	0.06	0.03	0.07	0.01	0.03	0.02	0.03	0.04	0.07
N	84	84	84	84	84	84	84	84	84	84	84	70	84	72	84	84	84

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

Table 3: Return predictability horizons and SSI. Each column represents a regression in which the CRSP equal weighted, CRSP value weighted, or S&P 500 index cumulative returns are regressed on the lagged Speculation Sentiment Index value: $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which r_t is the index cumulative return, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. r_t is the one month forward cumulative return, r_{t+1} is the two month forward cumulative return, r_{t+2} is the three month forward cumulative return, r_{t+3} is the four month forward cumulative return, r_{t+4} is the five month forward cumulative return, and r_{t+5} is the six month forward cumulative return. Standard errors are based on Hodrick (1992), using code from Alexander Chinco's website. The sample runs from December 2006 through December 2016. All variables, except for returns, are standardized.

Panel A: EW CRSP

	r_t	r_{t+1}	r_{t+2}	r_{t+3}	r_{t+4}	r_{t+5}
SSI_{t-1}	-1.89***	-1.83	-2.38**	-3.10*	-3.61*	-2.75
	(4.21)	(1.62)	(2.01)	(1.89)	(1.97)	(1.47)
R^2	0.13	0.05	0.05	0.06	0.06	0.03
Adj R^2	0.12	0.04	0.04	0.05	0.05	0.02
N	121	121	121	121	121	121

Panel B: VW CRSP

	r_t	r_{t+1}	r_{t+2}	r_{t+3}	r_{t+4}	r_{t+5}
SSI_{t-1}	-1.42***	-1.32	-2.06**	-2.68*	-3.05**	-2.70*
	(3.57)	(1.59)	(2.08)	(1.83)	(2.00)	(1.76)
R^2	0.10	0.04	0.06	0.07	0.07	0.04
Adj R^2	0.09	0.03	0.05	0.06	0.06	0.03
N	121	121	121	121	121	121

Panel C: S&P 500

	r_t	r_{t+1}	r_{t+2}	r_{t+3}	r_{t+4}	r_{t+5}
SSI_{t-1}	-1.23***	-1.19	-2.03**	-2.61*	-3.02**	-2.75*
	(3.20)	(1.59)	(2.22)	(1.88)	(2.06)	(1.86)
R^2	0.08	0.03	0.06	0.07	0.07	0.05
Adj R^2	0.07	0.02	0.05	0.07	0.07	0.04
N	121	121	121	121	121	121

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 4: 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	1.46**	1.46**	1.61**	1.54**	1.35*	1.37*	1.54**	1.49*
	(2.09)	(2.06)	(2.27)	(2.11)	(1.83)	(1.83)	(2.05)	(1.94)
Mkt-Rf	0.22	0.21	0.18	0.19	0.15	0.12	0.08	0.09
	(1.23)	(1.05)	(0.90)	(0.91)	(0.78)	(0.56)	(0.40)	(0.40)
SMB		0.06	0.10	0.03		0.12	0.16	0.08
		(0.17)	(0.29)	(0.09)		(0.34)	(0.47)	(0.22)
HML		-0.06	-0.22	0.03		-0.01	-0.20	0.12
		(-0.18)	(-0.67)	(0.07)		(-0.04)	(-0.58)	(0.26)
MOM			-0.36				-0.41*	
			(-1.56)				(-1.68)	
CMA				-0.25				-0.40
				(-0.38)				(-0.56)
RMW				-0.15				-0.24
				(-0.30)				(-0.45)
R^2	0.02	0.02	0.05	0.02	0.01	0.01	0.04	0.02
Adjusted R^2	0.01	-0.02	0.00	-0.04	0.00	-0.03	-0.01	-0.05
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	0.93	0.76	0.83
MAX MONTHLY LOSS	-11.42%	-9.38%	-8.20%
STDEV MONTHLY RETURN	6.17%	6.50%	3.66%
SEMI STDEV MONTHLY RETURN	2.64%	2.79%	2.27%
MAX LEVERAGE	1.88x	1.88x	NA
AVG LEVERAGE	0.00x	0.00x	NA
STDEV LEVERAGE	0.73x	0.73x	NA

Table 5: Anomaly factor predictability and SSI. Regression (1) regresses the MGMT factor, PERF factor, or SMB factor on the lagged Speculation Sentiment Index value: $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which r_t is the monthly factor, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the MGMT factor, PERF factor, or SMB factor on the lagged Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the monthly factor, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns and factors, are standardized.

Panel A: MGMT

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI_{t-1}	0.62***	0.54***	0.62***	0.62***	0.62***	0.63***	0.66***	0.60***	0.71***	0.62***	0.67***	0.62***	0.66***	0.60***	0.62***	0.62***	0.53**
	3.25	2.70	3.21	3.23	3.23	3.30	3.19	2.84	3.60	3.22	3.36	3.16	3.37	3.09	3.22	3.22	2.51
Γ_{t-1}		0.13	-0.12	0.09	-0.11	-0.28	0.11	-0.04	0.37	0.15	-0.15	-0.21	-0.19	0.22	0.00	-0.15	-0.23
		1.45	(0.63)	0.44	(0.59)	(1.42)	0.53	(0.17)	1.64	0.80	(0.76)	(1.02)	(0.97)	1.07	(0.02)	(0.77)	(1.08)
R^2	0.08	0.10	0.08	0.08	0.08	0.10	0.08	0.08	0.10	0.09	0.09	0.09	0.09	0.09	0.08	0.09	0.09
Adj R^2	0.07	0.08	0.07	0.07	0.07	0.08	0.07	0.07	0.09	0.07	0.07	0.07	0.07	0.08	0.07	0.07	0.08
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel B: PERF

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	1.20***	1.00**	1.17**	1.20***	1.19***	1.18**	0.70	0.77	0.92*	1.19**	1.22**	0.88**	1.11**	1.06**	1.21***	1.18**	0.80
	2.63	2.12	2.59	2.63	2.65	2.60	1.46	1.55	1.96	2.60	2.55	1.98	2.40	2.41	2.64	2.60	1.62
Γ_{t-1}		0.14	-0.97**	-0.21	-0.98**	0.81*	-1.26**	-0.99*	-1.12**	0.40	-0.05	1.40***	0.45	-1.34***	0.18	-0.62	-0.97*
		1.48	(2.16)	(0.45)	(2.18)	1.74	(2.61)	(1.96)	(2.11)	0.88	(0.10)	2.97	0.96	(2.87)	0.40	(1.33)	(1.96)
R^2	0.06	0.07	0.09	0.06	0.09	0.08	0.11	0.08	0.09	0.06	0.05	0.12	0.06	0.11	0.06	0.07	0.08
Adj R^2	0.05	0.06	0.08	0.04	0.08	0.06	0.09	0.07	0.07	0.05	0.04	0.10	0.05	0.10	0.04	0.05	0.07
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel C: SMB

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI_{t-1}	-0.39*	-0.47**	-0.38*	-0.39*	-0.39*	-0.38*	-0.26	-0.41*	-0.29	-0.39*	-0.40*	-0.33*	-0.43**	-0.37*	-0.41**	-0.39*	-0.45**
	(1.94)	(2.37)	(1.90)	(1.93)	(1.93)	(1.91)	(1.18)	(1.84)	(1.39)	(1.92)	(1.94)	(1.68)	(2.10)	(1.86)	(2.03)	(1.92)	(2.03)
Γ_{t-1}		-0.21**	0.30	0.07	0.32	-0.18	0.34	-0.05	0.40*	-0.15	0.20	-0.22	0.21	0.18	-0.26	0.10	-0.15
		(2.34)	1.51	0.34	1.61	(0.89)	1.55	(0.23)	1.68	(0.76)	0.94	(1.04)	1.00	0.83	(1.26)	0.51	(0.66)
R^2	0.03	0.07	0.05	0.03	0.05	0.04	0.05	0.03	0.05	0.04	0.03	0.04	0.04	0.04	0.04	0.03	0.03
Adj R^2	0.02	0.06	0.03	0.02	0.04	0.02	0.03	0.01	0.04	0.02	0.02	0.02	0.02	0.02	0.03	0.02	0.02
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

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

Table 6: Anomaly portfolio predictability and SSI. Regressions (1)-(11) regresses either the long-short portfolio spread, the long portfolio return, or the short portfolio return of eleven different anomalies on the lagged Speculation Sentiment Index value: $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which r_t is either the long-short portfolio spread, the long portfolio return, or the short portfolio return, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. Regression (1) examines the net stock issuance anomaly (NSI_t), Regression (2) examines the composite equity issues anomaly (CEI_t), Regression (3) examines the accruals anomaly ACC_t, Regression (4) examines the net operating assets anomaly (NOA_t), Regression (5) examines the asset growth anomaly (AG_t), Regression (6) examines the investment-to-assets anomaly (ITA_t), Regression (7) examines the distress anomaly (DIS_t), Regression (8) examines the O-Score anomaly (OSC_t), Regression (9) examines the momentum anomaly (MOM_t), Regression (10) examines the gross profitability anomaly ($GPRO_t$), and Regression (11) examines the return-on-assets anomaly (ROA_t). Panel A reports the results of the regressions using the long-short portfolio spread, Panel B reports the results of the regressions using the long portfolio return, and Panel C reports the results of the regressions using the short portfolio return. Above each anomaly regression, the headers "MGMT" and "PERF" indicate which of the two anomaly factors that the particular anomaly is used in constructing. The sample runs from December 2006 through December 2016. SSI is standardized.

Panel A: Spread

	MGMT						PERF				
	(1) NSI_t	(2) CEI_t	(3) ACC_t	(4) NOA_t	(5) AG_t	(6) ITA_t	(7) DIS_t	(8) OSC_t	(9) MOM_t	(10) $GPRO_t$	(11) ROA_t
SSI_{t-1}	0.92***	0.68***	-0.55**	0.00	-0.01	0.42	1.85***	0.92***	1.32**	1.04**	0.96**
	3.46	2.64	(2.27)	(0.00)	(0.06)	1.51	2.76	3.20	2.01	2.44	2.50
R^2	0.09	0.06	0.04	0.00	0.00	0.02	0.06	0.08	0.03	0.05	0.05
Adj R^2	0.08	0.05	0.03	-0.01	-0.01	0.01	0.05	0.07	0.02	0.04	0.04
N	121	121	121	121	121	121	121	121	121	121	121

Panel B: Long

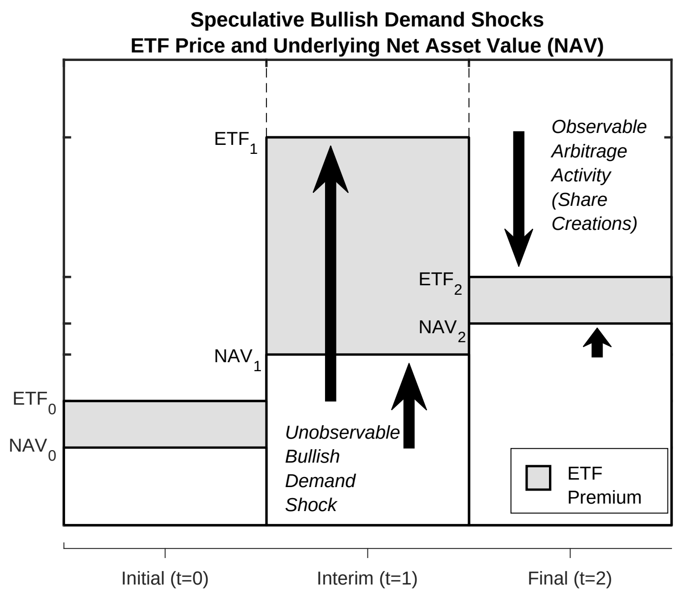
	MGMT						PERF				
	NSI_t	CEI_t	ACC_t	NOA_t	AG_t	ITA_t	DIS_t	OSC_t	MOM_t	$GPRO_t$	ROA_t
SSI_{t-1}	-1.12***	-1.26***	-2.05***	-1.67***	-1.64***	-1.59***	-0.99***	-1.04***	-1.39***	-1.15***	-1.10***
	(3.01)	(3.19)	(4.25)	(3.47)	(3.69)	(3.62)	(2.78)	(2.71)	(2.71)	(3.19)	(2.92)
R^2	0.07	0.08	0.13	0.09	0.10	0.10	0.06	0.06	0.06	0.08	0.07
Adj R^2	0.06	0.07	0.12	0.08	0.10	0.09	0.05	0.05	0.05	0.07	0.06
N	121	121	121	121	121	121	121	121	121	121	121

Panel C: Short

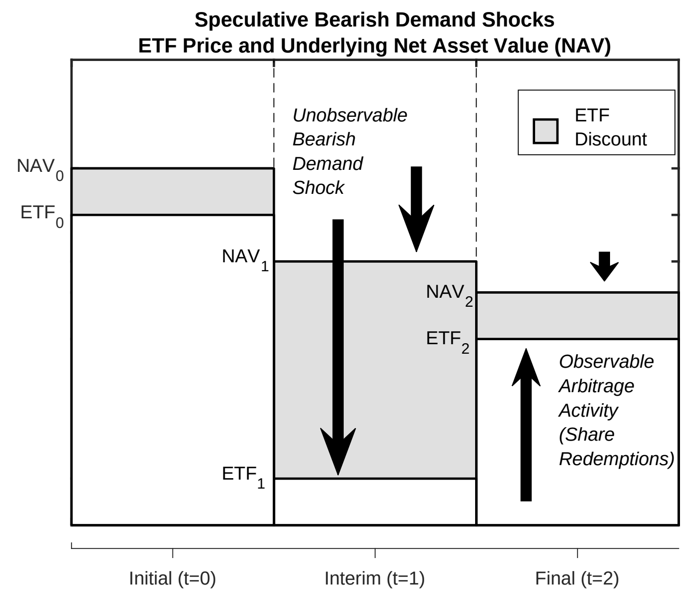
	MGMT						PERF				
	NSI_t	CEI_t	ACC_t	NOA_t	AG_t	ITA_t	DIS_t	OSC_t	MOM_t	$GPRO_t$	ROA_t
SSI_{t-1}	-2.04***	-1.94***	-1.51***	-1.67***	-1.63***	-2.02***	-2.84***	-1.97***	-2.71***	-2.19***	-2.05***
	(3.93)	(3.87)	(3.42)	(3.79)	(3.64)	(4.02)	(3.29)	(3.66)	(3.52)	(3.42)	(3.30)
R^2	0.11	0.11	0.09	0.11	0.10	0.12	0.08	0.10	0.09	0.09	0.08
Adj R^2	0.11	0.10	0.08	0.10	0.09	0.11	0.08	0.09	0.09	0.08	0.08
N	121	121	121	121	121	121	121	121	121	121	121

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Figure 1: Speculative demand shocks on the leveraged ETF shares and the leveraged ETF underlying derivative securities. The first figure portrays a setting in which a speculative bullish demand shock leads to an ETF premium that is exploited via share creations. The second figure portrays a setting in which a speculative bearish demand shock leads to an ETF discount that is exploited via share redemptions.



(a)



(b)

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 provides 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 monthly share turnover, institutional ownership, and end-of-month assets under management. Monthly turnover is calculated as monthly volume divided by end-of-month shares outstanding. Data for percent of fund shares held by institutions comes from Bloomberg and is available beginning in 2010.

Comparable ETF	SPY		QQQ		DIA		IJH	
Leveraged ETF	SSO	SDS	QLD	QID	DDM	DXD	MVV	MZZ
Average Percent of Monthly Turnover in Leveraged to Non-leveraged	149.0%	133.7%	272.6%	322.9%	171.6%	189.9%	1161.9%	1418.9%
January 31, 2007 - December 31, 2016								
Average Percent of Institutional Ownership in Leveraged to Non-leveraged	39.9%	17.4%	36.5%	33.5%	24.7%	20.2%	42.0%	28.7%
March 28, 2010 - December 25, 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.

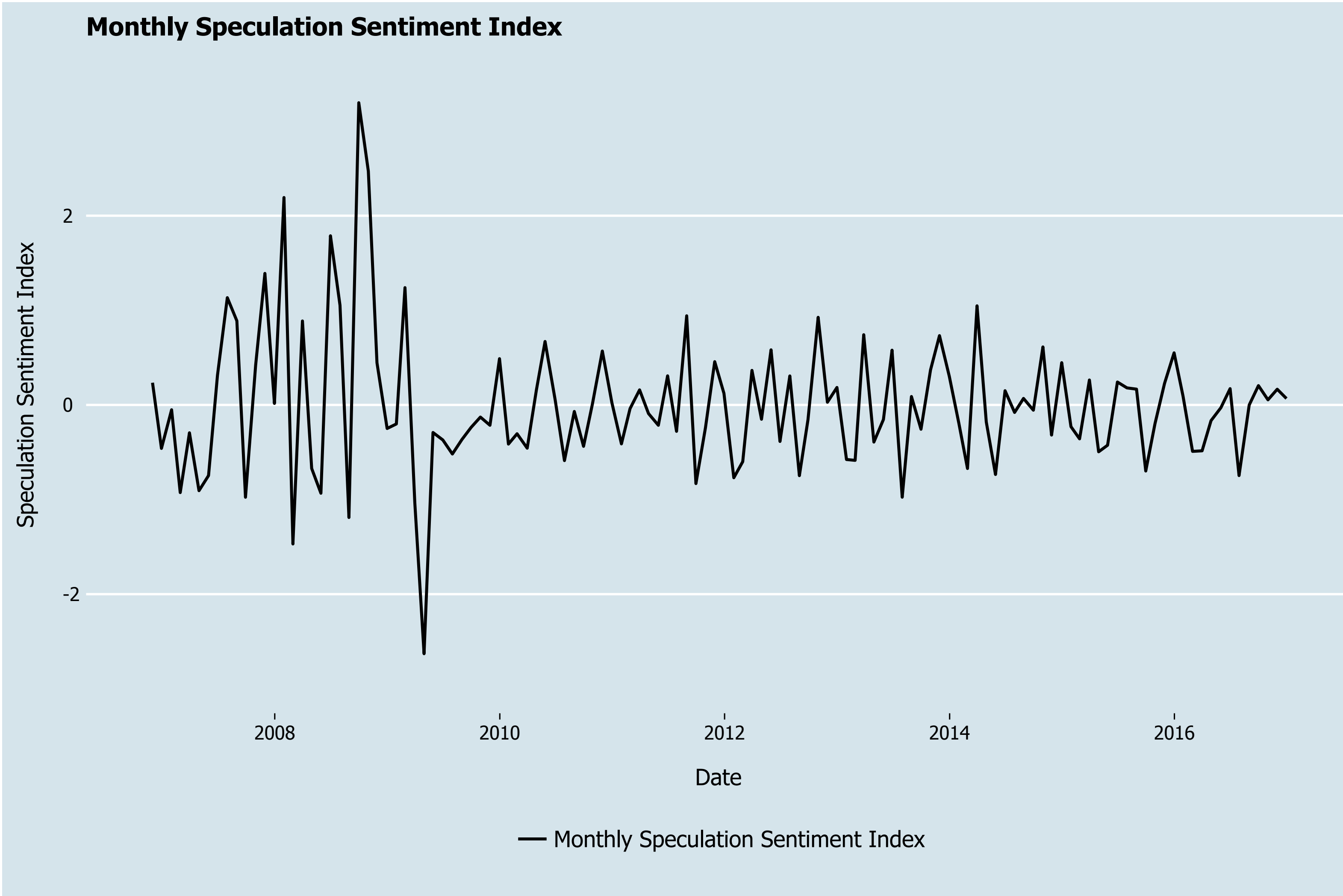
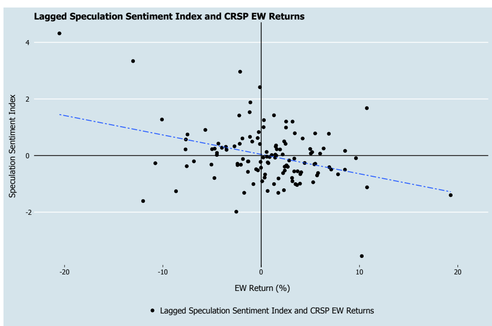
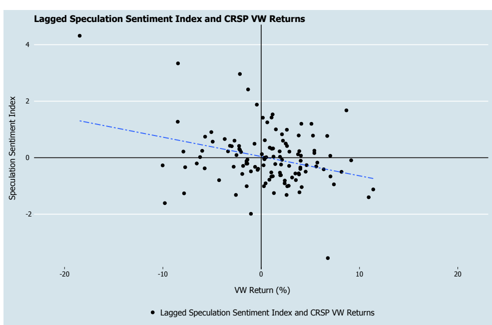


Figure 5: Scatter plots and the ability of the sign on SSI_{t-1} to predict the sign on r_t. In each panel, a scatter plot of r_t versus SSI_{t-1} is presented in which Panel A depicts the CRSP equal weighted index, Panel B depicts the CRSP value weighted index, and Panel C depicts the S&P 500 index. 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.



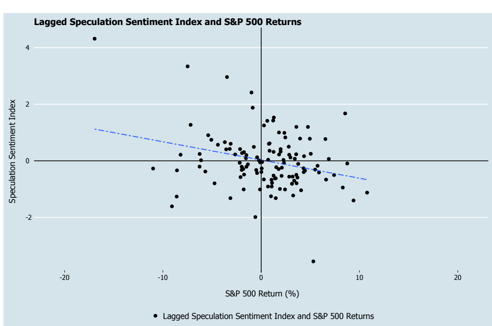
	EW CRSP	
	Extreme Quartiles	Full Sample
Percent of Sample Sign on SSI_{t-1} Predicts Sign on r_t	68.33%	60.33%
$\Pr(x \geq \text{Observed})$ Using Binomial Dist. Characterized by $p = .5$	0.31%	1.44%
Bayes Factor for Prior Distributed by $2\tilde{p}$ compared to $p = 0.5$	12.52	1.80
N	60	121

(a) CRSP Equal Weighted Index Returns versus Lagged SSI



	VW CRSP	
	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 - CRSP equal weighted. This figure presents coefficient estimates for β across 65,536 subsamples that use different combinations of controls: (i) Lagged index return r_{t-1}, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$, (iv) lagged VIX vix_{t-1}, (v) lagged innovation to aggregate liquidity Δliq_{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}, (ix) lagged cyclically adjusted earnings-to-price $caep_{t-1}$, (x) lagged term spread $term_{t-1}$, (xi) lagged short-rate $rate_{t-1}$, (xii) month of year dummies D_{mon}, (xiii) lagged closed-end fund discount $cefd_{t-1}$, (xiv) lagged variance risk premium vrp_{t-1}, (xv) lagged aligned investor sentiment level $hjtz_{t-1}$, and (xvi) lagged investor lottery demand $fmax_{t-1}$. Each data point is colored according to its associated p-value.

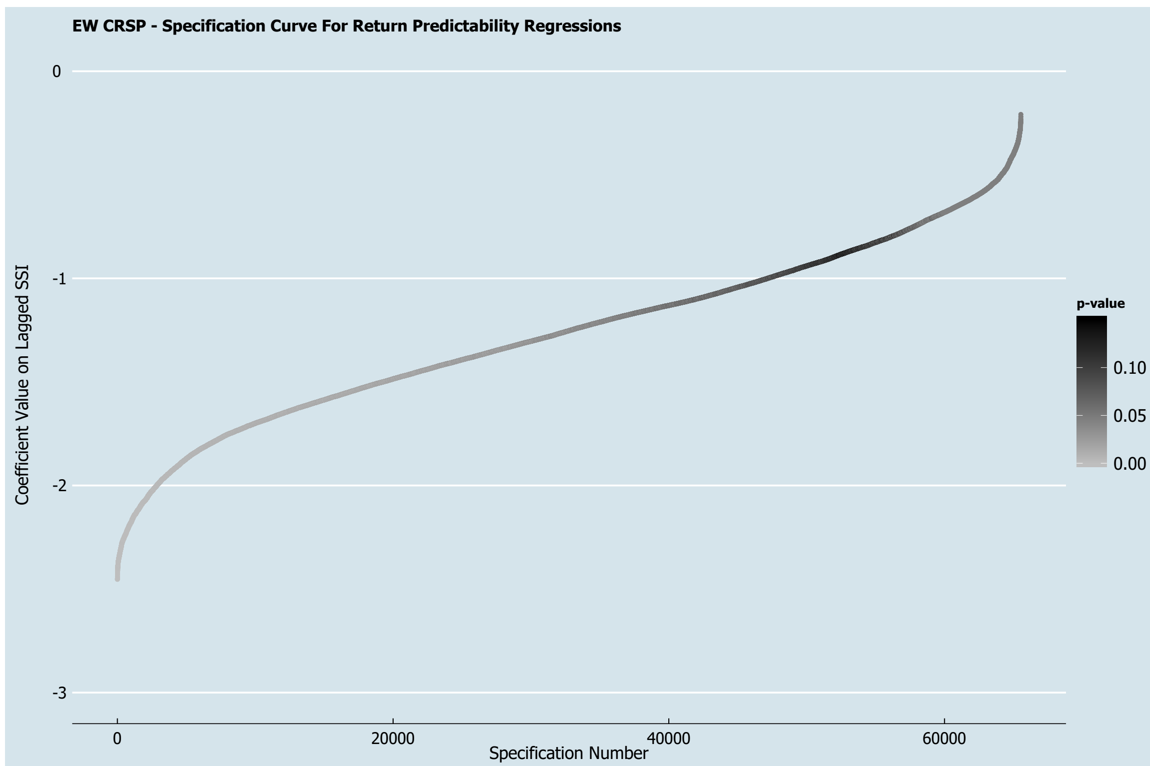


Figure 7: Specification curves for return predictability analysis - CRSP value weighted. This figure presents coefficient estimates for β across 65,536 subsamples that use different combinations of controls: (i) Lagged index return r_{t-1}, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$, (iv) lagged VIX vix_{t-1}, (v) lagged innovation to aggregate liquidity Δliq_{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}, (ix) lagged cyclically adjusted earnings-to-price $caep_{t-1}$, (x) lagged term spread $term_{t-1}$, (xi) lagged short-rate $rate_{t-1}$, (xii) month of year dummies D_{mon}, (xiii) lagged closed-end fund discount $cefd_{t-1}$, (xiv) lagged variance risk premium vrp_{t-1}, (xv) lagged aligned investor sentiment level $hjtz_{t-1}$, and (xvi) lagged investor lottery demand $fmax_{t-1}$. Each data point is colored according to its associated p-value.

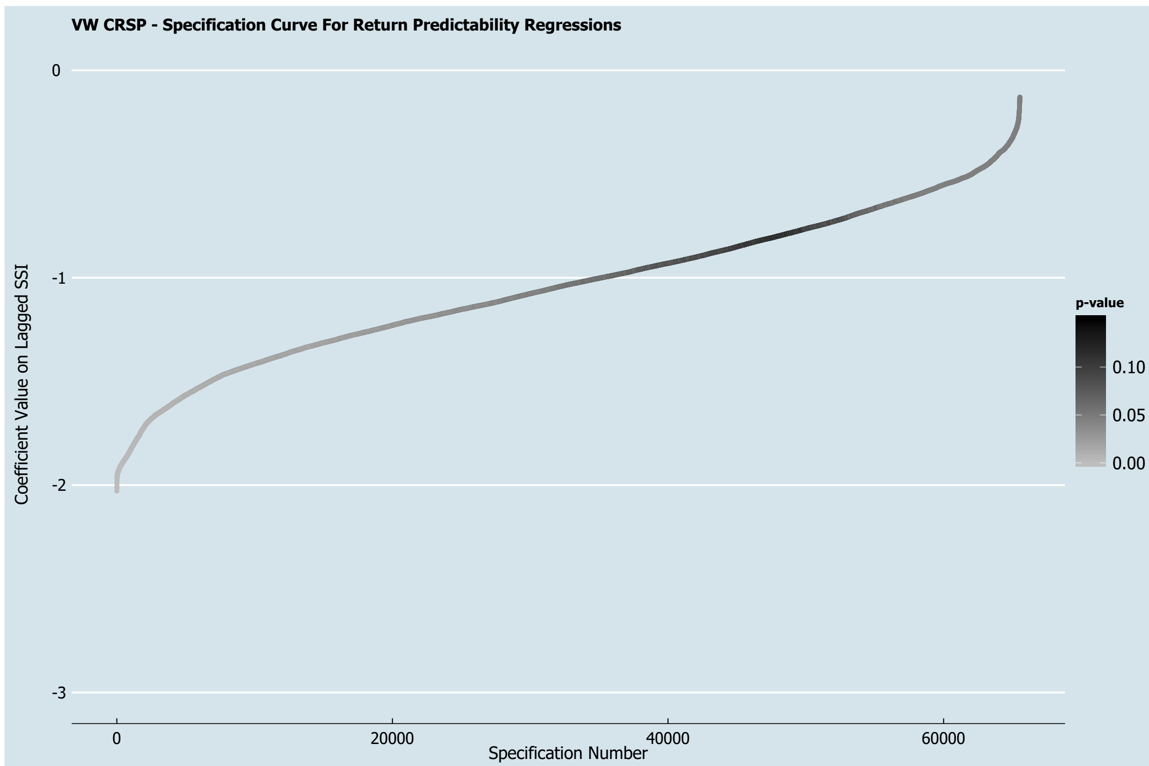


Figure 8: Specification curves for return predictability analysis - S&P 500. This figure presents coefficient estimates for β across 65,536 subsamples that use different combinations of controls: (i) Lagged index return r_{t-1}, (ii) lagged Baker-Wurgler sentiment level $sent_{t-1}$, (iii) lagged consumer confidence level $conf_{t-1}$, (iv) lagged VIX vix_{t-1}, (v) lagged innovation to aggregate liquidity Δliq_{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}, (ix) lagged cyclically adjusted earnings-to-price $caep_{t-1}$, (x) lagged term spread $term_{t-1}$, (xi) lagged short-rate $rate_{t-1}$, (xii) month of year dummies D_{mon}, (xiii) lagged closed-end fund discount $cefd_{t-1}$, (xiv) lagged variance risk premium vrp_{t-1}, (xv) lagged aligned investor sentiment level $hjtz_{t-1}$, and (xvi) lagged investor lottery demand $fmax_{t-1}$. Each data point is colored according to its associated p-value.

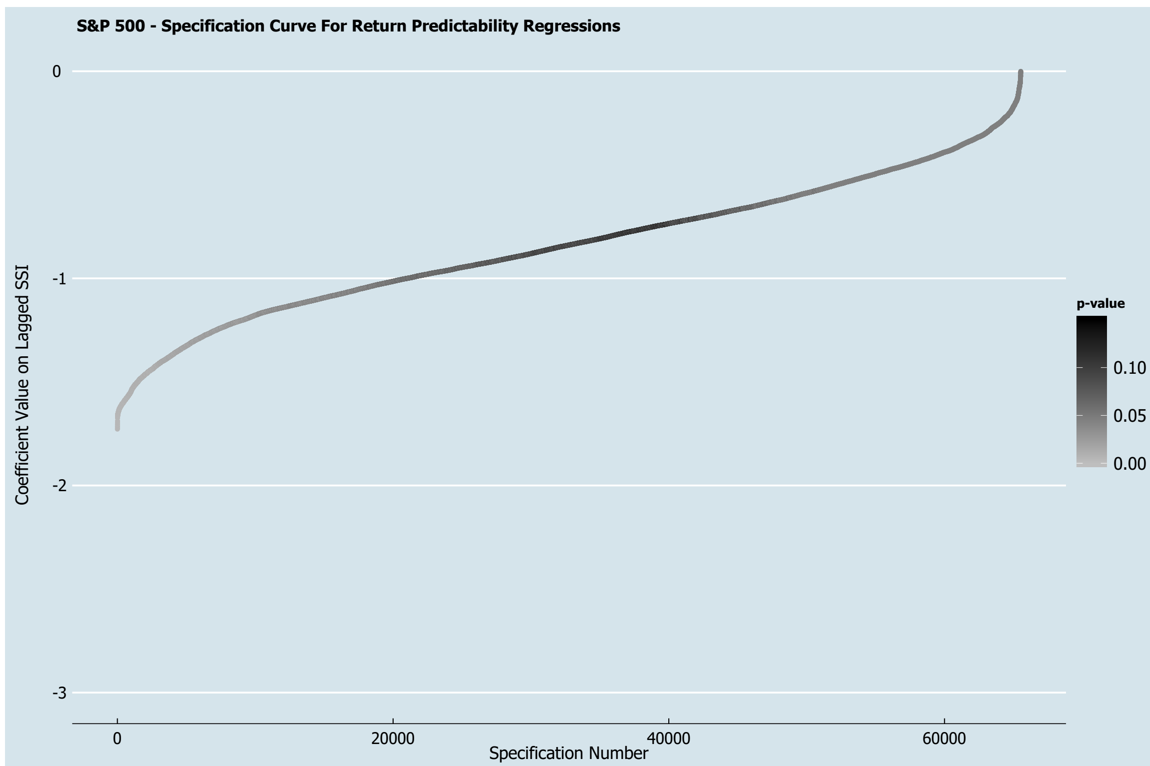
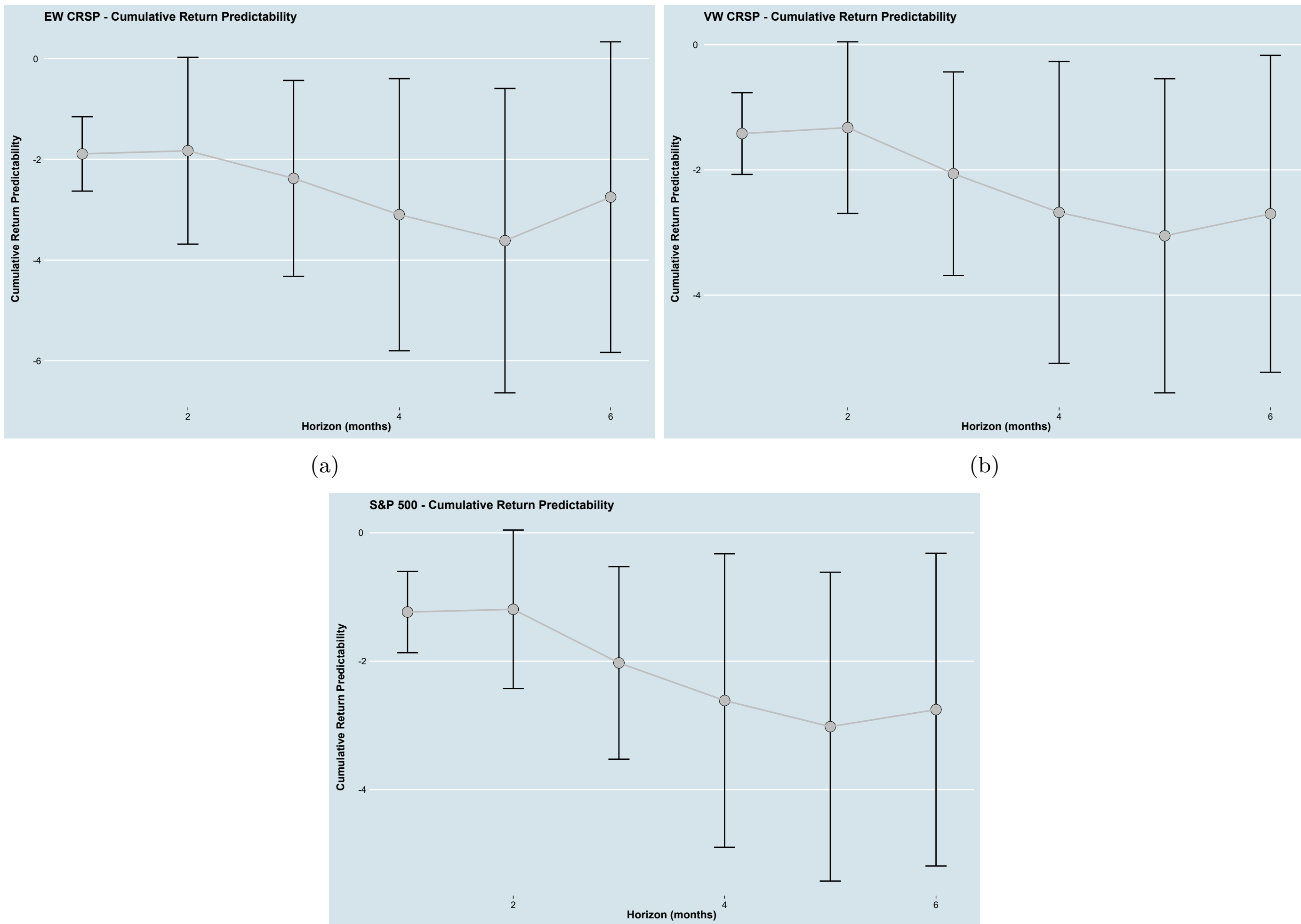


Figure 9: Return predictability horizons and SSI. Each figure depicts the regression coefficients β from the regression $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which r_t is either the CRSP equal weighted index cumulative return, the CRSP value weighted index cumulative return, or the S&P 500 index cumulative return, SSI_{t-1} is the lagged Speculation Sentiment Index value, and ϵ_t is the error term. The cumulative return r_t is measured at one, two, three, four, five, and six month horizons. 90% confidence intervals are depicted as the error bars. Standard errors are based on Hodrick (1992), using code from Alexander Chinco's website. The sample runs from December 2006 through December 2016.



(a) (b)

(c)

Online Appendix for "Speculation Sentiment"

DAVIES, SHAUN WILLIAM[28]

In this Online Appendix, I provide support for the results in the main text. First, I provide supporting empirical work for the return predictability results in the main text. I provide the correlations between SSI and the control variables used in the analysis and I present empirical analysis on the autocorrelation of net_t and SSI_t. Next, I evaluate the robustness of the standard errors and p-values in the univariate return predictability analysis in Column (1) of Table 1, Table 2, and Table 5. Specifically, I compute p-values using a small sample parametric boostrap analysis and compute standard errors using GMM. Next, I consider alternative specifications of SSI and I show that the return predictability analysis is robust to these alternative specifications. I also conduct an out-of-sample analysis with a data series that extends through December 2018 and I show that the return predictability results improve with the added data. With the out-of-sample data, I also calculate out-of-sample R^2_{OS}'s in the spirit of Campbell and Thompson (2007). The out-of-sample R^2_{OS}'s are positive valued for the CRSP equal weighted index return regression, the CRSP value weighted index return regression, and the S&P 500 index return regression. Next, I consider an alternative trading strategy to the one proposed in Section 4.1. In the alternative trading strategy, lagged SSI_t 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.

In addition to support for the return predictability results, I also provide additional evidence that SSI is non-fundamental demand. The evidence is threefold. First, I study the relation between SSI and contemporaneous arbitrage activity across a universe of over 1,000 ETFs.[29] 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

[28] Citation format: Davies, Shaun William Davies, Online Appendix for "Speculation Sentiment," 2019, Working Paper.

[29] 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).

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 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 147 leveraged ETFs, the results are stronger: On a value weighted (equal weighted) basis, 36%-50% (22%-33%) 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.[30] 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.

Second, I study the trading motives behind speculative demand shocks via revealed preferences. I document a strong contrarian trading tendency; When markets are performing well, speculation sentiment is bearish and when markets are performing poorly, speculation sentiment is bullish. The contrarian-type trading can be partially explained by rational portfolio rebalancing. That is, I show analytically that maintaining a target leverage ratio with leveraged ETFs requires daily rebalancing in the opposite direction of a day's market moves. As such, is natural to think that SSI may simply be picking up daily rebalancing activities. I show that this is not the case; Even

[30]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: $28.8\% \times 7.65\% \times 225B = 5B$.

after controlling for potential rebalancing, SSI exhibits statistically significant and economically meaningful predictive power.

Third, I examine changes in institutional ownership of leveraged ETF shares. I use monthly ownership data from Bloomberg and I construct a measure of monthly changes in institutional ownership. The measure, *inst*, is constructed similarly to *net* and it also has a similar interpretation. When *inst* is large and positive, it suggests that institutional investors demanded long exposure via leveraged ETFs. When *inst* is large and negative, it suggests that insitutional investors demanded short exposure via leveraged ETFs. I find that institutional ownership *positively* predicts aggregate returns, which is in strong contrast to *net* negatively predicting returns. The finding suggests that changes in institutional ownership of leveraged ETFs appears is informed. In light of this finding, I construct a measure of net demand that strips out changes in institutional ownership. The measure, $netMINUSinst$, negatively predicts aggregate returns (similar to *net*) and the statistical significance is stronger after controlling for changes in institutional ownership. The findings further support the paper's identifying assumption that the excess demand of individual traders for leveraged ETF shares is a proxy market wide speculative sentiment.

Finally, I conclude the Online Appendix 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.

OA.1 Correlation between SSI and Control Variables

In Table OA1, I present the correlations between SSI and the control variables used throughout the paper. Specifically, I calculate pairwise correlations between SSI and index monthly returns (r_{ew}, r_{vw}, and r_{sp}), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). SSI is strongly negatively correlated with contemporaneous returns, the variance risk premium, the intermediary capital risk factor, innovations to aggregate liquidity and investor lottery demand. Furthermore, SSI is strongly positively correlated with monthly VIX and the aligned investor sentiment index.

OA.2 Autocorrelation in net_t and SSI_t

In Section 3.2, I discuss the autocorrelation in net_t and reference Panel A of Table OA2. The table is located in this Online Appendix. Furthermore, to correct for the autocorrelation, as discussed in the main prose, I estimate net_t as an $AR(1)$ process and I use the resulting innovations to form SSI_t. The estimated coefficients for the $AR(1)$ process are located in Panel B of Table OA2. Finally, as also discussed, I test for autocorrelation in SSI_t. The results are reported in Panel C of Table OA2.

OA.3 Small Sample Parametric Bootstrap

Stambaugh (1999) highlights potential biases in predictive regressions, that is, the OLS estimator's small sample properties violate standard regression assumptions. As such, t-statistics that do not account for this bias may be inflated and give a false sense of statistical significance. Therefore, to ensure that the coefficients on SSI_{t-1} in the univariate regressions reported in Column (1) of Table 1, Table 2, and Table 5 are statistically significant, I correct for a potential Stambaugh bias in this subsection. Specifically, I compute p-values using a small sample parametric bootstrap detailed below.

Let r_t be the return on the benchmark index in period t and SSI_t be the value of the Speculation Sentiment Index at the end of period t. The univariate predictive regressions reported in Column (1) of Table 1, Table 2, and Table 5 are of the form,

$$r_t = a + \beta SSI_{t-1} + \epsilon_t. \tag{OA1}$$

I estimate the coefficients using OLS and the t-statistics are computed as GMM corrected standard errors (with equal weighting). Denote the t-statistic for β as τ. After obtaining the coefficient estimates and t-statistics, I estimate the small-sample distribution of the t-statistics under the null hypothesis of no predictability. To obtain the distribution, I perform the following bootstrap procedure:

(i) I estimate the restricted VAR,

$$\begin{bmatrix} r_{t+1} \\ SSI_{t+1} \end{bmatrix} = A + \begin{bmatrix} 0 & 0 \\ 0 & \phi \end{bmatrix} \begin{bmatrix} r_t \\ SSI_t \end{bmatrix} + \epsilon_{t+1}, \tag{OA2}$$

and keep the residuals ϵ.

(ii) For each bootstrap simulation I,

(a) Initialize $\begin{bmatrix} r_0 \\ SSI_0 \end{bmatrix}$ to their unconditional means.

(b) For $t = 1$ through $t = \overline{T}$, let,

$$\begin{bmatrix} r_{t+1} \\ SSI_{t+1} \end{bmatrix} = A + \begin{bmatrix} 0 & 0 \\ 0 & \phi \end{bmatrix} \begin{bmatrix} r_t \\ SSI_t \end{bmatrix} + e_{t+1}, \tag{OA3}$$

in which e_{t+1} is a random draw (with replacement) from the residuals ϵ recovered in step (i).

(c) I throw away the "burn-in" initial data and keep the last T observations corresponding to the length of the original data sample. I then estimate a coefficient $\hat{\beta}$ and corresponding t-statistic $\hat{\tau}$ using the simulated data.

(iii) I use the bootstrap distribution of the $\hat{\tau}$ to get a p-value for the actual t-statistic τ.

In total, I use 1,000,000 bootstrap simulations and in each simulation $\overline{T}$ is equal to 400.[31]

I report the small sample parametric bootstrap results in Table OA3. Panel A reports the regression results using the full sample of data. In that panel, the coefficient on SSI_{t-1} in the CRSP equal weighted index return predicability analysis is statistically significant at a 1% p-value

[31] To compute the GMM corrected standard errors I use John Cochrane's olsgmm.m Matlab function. Furthermore, I am indebted to Shri Santosh for his comments on this analysis.

threshold and the coefficients on SSI_{t-1} in the CRSP value weighted index return and S&P 500 index return analysis are statistically significant at a 5% p-value threshold. Panel B reports the regression results using data that begins post-2009. The coefficients on SSI_{t-1} in the CRSP equal weighted index return and the CRSP value weighted index return analysis are significant at a 5% p-value threshold. The coefficient on SSI_{t-1} in the S&P 500 index return analysis is significant at a 10% p-value threshold. In Panel C, I report the regression results predicting the anomaly factor returns. The coefficients on SSI_{t-1} in the $MGMT$ factor return and $PERF$ factor return analysis are statistically significant at a 5% p-value threshold and the coefficient in the SMB factor return analysis is statistically significant at a 10% p-value threshold.

OA.4 Alternative SSI Specifications

In this subsection, I examine the robustness of the benchmark return predictability analysis by considering several alternative specifications of SSI: (i) The raw *net* series in place of SSI, (ii) SSI formed using a raw *net* series orthogonal to aggregate ETF flows, (iii) SSI formed using a raw *net* series orthogonal to macro economic conditions, (iv) SSI formed using an evolving portfolio of leveraged ETFs rather than just the original ProShares funds, (v) SSI formed from only the three leveraged-long ETFs, (vi) SSI formed from only the three leveraged-short ETFs, and (vii) SSI formed only from each long-short pair.

OA.4.1 Raw *net* Index

SSI is constructed from the time series *net* in Eqn. 2. I repeat the full sample regression analysis from Section 4 but use *net* in place of SSI. Table OA4 provides the results. The results in Table OA4 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.4.2 *net* Orthogonal to Aggregate ETF Flows

ETF arbitrage activity (i.e., ETF flows) exhibits time trends across all funds. For example, since the mid 2000s, ETFs have exploded in popularity and the ETF industry as a whole has been characterized by ETF inflows. As a robustness test, I control for aggregate ETF flows in generating the time series of SSI. Specifically, instead of using the formulation in Eqn. 4, I use,

$$net_t = a + \gamma net_{t-1} + \chi ETFPCA1_t + SSI_t^{flows}, \tag{OA4}$$

in which $ETFPCA1_t$ is the first principal component that explains aggregate ETF flows. To form $ETFPCA1_t$, I take the largest 100 ETFs (based on June 2006 end-of-month market capitalizations) and form the first principal component that explains the joint variation in the covariance matrix of ETF share change (in which share change is measured as monthly percent change). SSI_t^{flows} forms the Speculation Sentiment Index orthogonal to aggregate ETF flows. I repeat the full sample regression analysis from Section 4 but use SSI_t^{flows} in place of SSI_t. Table OA5 provides the results. The results in Table OA5 are both statistically and economically meaningful. Moreover, the results are qualitatively the same as compared to those in Table 1.

OA.4.3 *net* Orthogonal to Aggregate Macro Conditions

ETF arbitrage activity (i.e., ETF flows) is an equilibrium outcome and reflects, among other market conditions, the cost of arbitrage capital. As a robustness test, I control for several macro variables in generating the time series of SSI. Specifically, instead of using the formulation in Eqn. 4, I use,

$$net_t = a + \gamma net_{t-1} + \chi controls_t + SSI_t^{\perp}, \tag{OA5}$$

in which $controls_t$ consists of lagged short interest ($short_{t-1}$), lagged VIX (vix_{t-1}), and the lagged intermediary capital risk factor ($intc_{t-1}$). $SSI_t^{\perp}$ forms the Speculation Sentiment Index orthogonal to macro conditions. I repeat the full sample regression analysis from Section 4 but use $SSI_t^{\perp}$ in place of SSI_t. Table OA6 provides the results. The results in Table OA6 are both statistically and economically meaningful. Moreover, the results are qualitatively the same as compared to those in

Table 1.

OA.4.4 Evolving SSI

The baseline specification of SSI is restricted to the original set of leveraged ETFs. Since the introduction of the ProShares funds in 2006, there have been many -3x, -2x, 2x, and 3x leveraged ETFs launched. As a robustness test, I form an evolving version of SSI. Specifically, I include any leveraged ETF pair that follows either the Dow Jones Industrial Average, NASDAQ-100 index, and the S&P 500 index. In total, there are 14 ETF pairs (28 funds in total). Each month, a leveraged-long, index-level ETF share change is computed by taking a weighted average of each leveraged-long ETF's share change (in which weights are determined by monthly ETF market capitalizations) for each of the three indices (i.e, the Dow Jones Industrial Average, NASDAQ-100 index, and the S&P 500 index). Similarly, a leveraged-short, index-level ETF share change is computed by taking a weighted average of each leveraged-short ETF's share change. Then, as in Eqn. 2, the net change is computed by taking the difference between the leveraged-long and the leveraged-short index changes (forming net^*). I then form SSI^* from net^* using Eqn. 4. The evolving SSI^* allows for the index to reflect the introduction of new leveraged ETFs. Furthermore, by weighting share change within benchmark index category by market capitalization, investor preferences are also reflected in the evolving SSI (i.e., the more popular and larger ETFs exhibit greater representation in the index).

I repeat the regression analysis from Section 4 but use SSI^* in place of SSI. Table OA7 provides the results. The full sample results in Table OA7 are similar to the full sample results in Table 1, and generally stronger. The results suggest that accounting for new leveraged ETFs improves measurements of speculative demand shocks.

OA.4.5 Long Component and Short Component Separated

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 full sample regression analysis in Section 4, but use SSI^L and SSI^S in place of SSI.

Table OA8 provides the long results. 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, except for the S&P 500 index regressions with the variance risk premium as a control. While SSI^L is statistically meaningful in almost all regressions, the economic magnitudes of the coefficients are generally smaller than that of SSI in Table 1.

Table OA9 provides the short results. The coefficients on SSI^S are 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: In general, the coefficient associated with SSI^S is smaller in magnitude than the coefficients associated with SSI^L and SSI across all regressions. Together, the analysis in Table OA8 and Table OA9 suggests that both SSI^L and SSI^S provide predictability, but both are weaker predictors than the main specification SSI.

OA.4.6 Dollar Flow SSI

The main specification of SSI is based on percentage changes in shares outstanding for the leveraged ETFs, rather than dollar changes. Using percentage changes in shares outstanding has the attractive feature that it is liklely more stationary than a dollar changes. However, in this robustness check, I compute a dollar flow measure. Specifically, instead of using the formulation in Eqn. 4, I use,

$$net_t^{\$} = a + \gamma net_{t-1}^{\$} + SSI_t^{\$}, \tag{OA6}$$

in which $net_t^{\$}$ is calculated as,

$$net_t^{\$} = \sum_{i \in J} (SO_{i,t} - SO_{i,t-1}) \left(\frac{P_{i,t} + P_{i,t-1}}{2} \right) - \sum_{i \in K} (SO_{i,t} - SO_{i,t-1}) \left(\frac{P_{i,t} + P_{i,t-1}}{2} \right). \qquad \text{(OA7)}$$

Eqn. OA7 represents the difference in dollar flows into the leveraged-long ETFs and leveraged-short ETFs, in which changes in shares outstanding are weighted by the average price. I repeat the full sample regression analysis from Section 4 but use $SSI^{\$}$ in place of SSI. Table OA10 provides the results. In general, the magnitudes of the coefficients are slightly smaller in comparing the results in Table OA10 to those in Table 1. Moreover, the results in Table OA10, while statistically significant across all specifications,except for the S&P 500 regression using the variance risk premium, are slightly weaker statistically as compared to Table 1. Despite being slightly weaker in economic magnitude and statistical significance, the results in Table OA10 using $SSI^{\$}$ are qualitatively similar to those in Table 1 using the main specification of SSI.

OA.4.7 Long-Short Pairs Separated

Similar to examining the long component and short component separately, it is also natural to consider each long-short ETF pair individually. Specifically, rather than calculating net using three leveraged-long ETFs and three leveraged-short ETFs, I analyze the return predictability arising from the S&P 500 index pair (SSO and SDS), the NASDAQ-100 index pair (QLD and QID), and the Dow Jones Industrial Average pair (DDM and DXD). I repeat the univariate regression analysis from Section 4 but use each pair in place of SSI. Table OA11 provides the results.

The results in Table OA11 show that each index pair exhibits strong predictability in the univariate regressions; All three univariate regression coefficients are significant with a 1% p-value threshold in each panel. Furthermore, the NASDAQ-100 index pair outperforms both the S&P 500 index pair and Dow Jones Industrial Average index pair in a horse race regression in which all three are included as independent variables.

OA.5 Out-of-Sample Analysis

The first draft of this paper was made public on August 7, 2017. Since then, two additional years of return data have been published on CRSP (January 2017 through December 2018). While the new data series consist of only 24 months, the series provide an out-of-sample environment to further test the paper's findings. I begin by repeating the univariate predictive regressions over three horizons: December 2006 through December 2018, January 2010 through December 2018, and January 2017 through December 2018. I examine the predictability of both SSI and the raw share change series net. The results are reported in Table OA12. The results for the CRSP equal weighted index are reported in Panel A, the results for the CRSP value weighted index are reported in Panel B, and the results for the S&P 500 index are reported in Panel C. In each of the three panels, the first three columns of results are for SSI and the second three columns of results are for net. Each column is labeled with the regression's sample dates. The standardization is performed using the entire data series of December 2006 through December 2018. Furthermore, I only use data prior to January 2017 to estimate the $AR(1)$ process that formulates SSI (see Section 3 for a description of how SSI is formed). By estimating the $AR(1)$ with data prior to January 2017, I avoid a look ahead bias.

First, consider SSI. The first column of Table OA12 is best appreciated by comparing it to column (1) of Table 1. For all three indices, the economic magnitudes of the coefficients are slightly smaller, but the statistical significance of the coefficients are stronger in the December 2006 through December 2018 sample. Similarly, the second column of Table OA12 is best appreciated by comparing it to column (1) of Table 2. For all three indices, the economic magnitudes of the coefficients are larger and the statistical significance of the coefficients are stronger in the December 2010 through December 2018 sample. Finally, the third column of Table OA12 shows the ability of SSI to predict returns entirely out-of-sample. While the coefficients are not statistically significant, perhaps due to only 24 observations, the sign and magnitude of the coefficients are consistent with earlier results.

Next, consider net. The results in the fourth column are best appreciated by comparing them to column (1) of Table OA4. While the economic magnitudes of the coefficients are slightly attenuated over the whole sample (December 2006 through December 2018), the statistical significance improves as compared to Table OA4. The results in the fifth column are included for completeness; In the post-2009 period through 2018, *net* has significant return predictability in all three indices. Finally, the sixth column of Table OA12 shows the ability of *net* to predict returns entirely out-of-sample. While the coefficients are not statistically significant, the sign and magnitude of the coefficients are consistent with earlier results.

In addition to performing out-of-sample regressions, I also compute out-of-sample R^2_{OS}'s for SSI in the spirit of Campbell and Thompson (2007) and Welch and Goyal (2007). R^2_{OS} measures whether or not a variable is a better predictor of returns than the historical average return. R^2_{OS} is computed as,

$$R^2_{OS} = 1 - \frac{\sum_{t=1}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=1}^{T}(r_t - \overline{r}_t)^2}, \tag{OA8}$$

over the horizon January 2017 through December 2018 and in which $\hat{r}_t$ is the fitted value of the CRSP equal weighted index return, the CRSP value weighted index return, or the S&P 500 index return using the coefficients from univariate predictive regressions from December 2006 through December 2016, $\overline{r}_t$ is the historical average return through $t-1$, and r_t is the realized index return. Note, while Campbell and Thompson (2007) uses at least 20 years of data to obtain initial coefficient estimates, I am restricted to using only ten years (121 months).

I report R^2_{OS} in Panel D of Table OA12. For each index, I report two values of R^2_{OS}: One using the historical average return starting in December 2006 and one using the historical average return starting in January 1927. For all three indices, both values of R^2_{OS} are positive valued. Thus, there does appear to be out-of-sample predictive power from SSI that outperforms the historical average, albeit using a small sub sample of data.

OA.6 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 a market 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 SSI_{t-1} is positive, the strategy calls for entering the 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 OA13 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.[32] 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 (1.01%-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 OA13 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

[32]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.

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 CRSP equal weighted index or CRSP value weighted index dominates the S&P 500 with regards to the Sharpe Ratio (1.060 and 0.900 versus 0.826 for the S&P 500).

OA.7 Additional Evidence that SSI is Non-Fundamental Demand

In this section, I provide additional evidence that SSI is, in fact, non-fundamental demand. The evidence is threefold. First, I examine the relation between SSI and contemporaneous mispricing in other assets. I focus the analysis on the universe of other ETFs which have vibrant primary markets that allow the empiricist to observe arbitrage activity (i.e., exploitations of relative mispricing). Under the null hypothesis, SSI should not be related to contemporaneous mispricing in other assets (i.e, ETFs). However, I find that SSI has substantial explanatory power, which is consistent with SSI being a proxy for aggregate speculative demand shocks.

Second, I examine the trading motivates behind speculative demand shocks by revealed preferences. I find that speculation sentiment is contrarian (at least in the short-run). That is, when markets are performing well, speculative traders demand leveraged-short exposure and when markets are performing poorly, speculative traders demand leveraged-long exposure. I also consider the possibility that speculation sentiment is rational. Specifically, if traders use leveraged ETFs to attain a particular portfolio on the capital market line (CML), portfolios must be rebalanced daily to maintain a target leverage quantity. I show analytically that this daily rebalancing resembles contrarian trading. Subsequently, I use the analytic results and the observed data to compute the implied demand that could arise for rebalancing purposes. While I show that the implied rebalancing demand is positively related to the Speculation Sentiment Index, SSI continues to be a strong predictor of returns even after including implied rebalancing demand as a control. Thus, while some of the demand embodied in SSI may be attributed to rational rebalancing, the residual demand appears to be irrational and a significant proxy for aggregate speculative demand shocks that push asset prices away from fundamentals.

Third, I examine changes in institutional ownership of leveraged ETF shares. I construct a measure *inst*, similar to the construction of *net*, using percentage changes in institutional ownership. I find that *inst positively* predicts aggregate returns. That is, institutional ownership of leveraged ETFs appears to be informed. In light of this finding, I construct a measure of net demand that strips out changes in institutional ownership. The measure, $netMINUSinst$, negatively predicts aggregate returns (similar to *net*) and the statistical significance is stronger after controlling for changes in institutional ownership. The findings further support the paper's identifying assumption that the excess demand of individual traders for leveraged ETF shares is a proxy market wide speculative sentiment.

OA.7.1 Contemporaneous Mispricing and Speculation Sentiment

In this section, I 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.[33] 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,

$$\Delta_{i,t} = a_i + \beta_i^{SSI} SSI_t + \epsilon_{i,t}, \tag{OA9}$$

[33]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.

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, β_i^{SSI} is fund i's loading on SSI_t, and $\epsilon_{i,t}$ is an error term. The univariate regression in Eqn. OA9 relates SSI_t to contemporaneous arbitrage activity in ETF i. In addition to the regression outlined in Eqn. OA9, 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 ($r_{i,t}$).

To provide a snapshot of the results, Table OA14 provides the regression results for two representative ETFs: SPY and VXX. 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.

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, 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 loads negatively on SSI; A one standard deviation 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 β_i^{SSI}, Table OA15 provides a summary regarding the coefficients' p-values. First, Panel A summarizes the p-values for β_i^{SSI} in all 1,006 ETFs used in the monthly regressions. β_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, β_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 OA15 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%-33% 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 OA16 provides the percentile breaks across the estimates of β_i^{SSI}.[34] Beginning with Panel A, the threshold values of β_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 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 -0.386 and 20% have coefficient estimates larger than 0.310. The results in Panel A show that variation in SSI is related to sizable changes in

[34] The number of leveraged ETFs in Table OA15 and in Table OA16 differ by four (147 versus 151). 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 OA15.

arbitrage activity across other ETFs. Furthermore, the economic magnitudes are more pronounced in leveraged ETFs.

Panel B of Table OA16 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. Leveraged ETFs, again, are more pronounced having a median effect of 0.286.

Table OA17 provides a breakdown of the coefficient signs for leveraged *equity* ETFs only. Focusing on leveraged equity ETFs, as opposed to other asset categories, allows one to easily characterize whether or not a given ETF is a bearish or bullish bet on stock market performance. For instance, it is straightforward that a leveraged-short technology fund is a bearish stock market bet while it is unclear if a leveraged-short oil fund is a bet on the stock market at all. 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 OA17 are illustrated in Figure OA1: The coefficient estimates of β_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 equity ETFs are drawn to the lower left-hand corner of the graph and leveraged-long equity 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 contemporaneous, 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.

OA.7.2 Speculation Sentiment As Contrarian Demand

As previously discussed, leveraged ETFs cater to short-horizon traders that desire amplified exposure to market benchmarks. Moreover, as discussed in Section 2.2, leveraged ETFs are primarily held by individual investors. I argue that these features make leveraged ETFs a uniquely tailored product for short-horizon, gambling-like bets on market movements. However, it has not yet been established what motivates a trader to take a bullish bet as opposed to a bearish bet. In this section, I characterize the trading behavior of speculation sentiment in the context of contemporaneous market movements and show that it is generally contrarian.

There is no consensus among researchers regarding whether individual investors in aggregate are short-horizon contrarians or short-horizon momentum traders. Choe, Kho, and Stulz (1999), Grinblatt and Keloharju (2000), Grinblatt and Keloharju (2001), Jackson (2003), and Richards (2005) examine micro-level investor data in several foreign countries and show that investors exhibit contrarian trading patterns, buying stocks after downward price movements and selling stocks after upward price movements. Goetzmann and Massa (2002) also finds contrarian-like trading among index fund investors in the United States and Griffin, Harris, and Topaloglu (2003) documents a short-horizon contrarian tendency among individuals that execute trades through retail brokers. Conversely, a recent study, Da, Huang, and Jin (2019), utilizes a novel data set and documents that individual investors extrapolate from stocks' recent returns, giving them a short-term momentum trading behavior. In a similar spirit, Jiang and Yan (2016) studies both leveraged and non-leveraged ETFs. The study documents a short-term momentum strategy among non-leveraged ETF traders and, conversely, a short-term contrarian strategy among leveraged ETF traders.

In Panel A of Table OA14, I confirm the results from Jiang and Yan (2016); I perform the regression,

$$r_t = a + \beta SSI_t + \epsilon_t, \tag{OA10}$$

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 is the contemporaneous value of SSI, β is the regression coefficient, and ϵ_t is the regression error term. Results for the CRSP equal weighted index are reported as regression (1), results for the CRSP value weighted index are reported as regression (2), and results for the S&P 500 index are reported as regression (3). The sample's index returns run from December 2006 through December 2016. In all three regressions, β is negative valued and significant both statistically and economically. A one standard deviation increase in SSI is associated with between a -2.5% to -3.2% decline in broad market indices. In other words, SSI is more bearish when markets are performing well and more bullish when markets are performing poorly. The results suggest that speculative demand is largely contrarian.

At first blush, a statistically significant negative relation between SSI and *both* contemporaneous and future returns may seem surprising. However, if speculative traders bet against fundamental news (e.g., becoming bearish after the release of good economic data), one can expect a negative relation between SSI and both contemporaneous and future returns. For example, bearish speculative sentiment can prevent prices from fully incorporating good fundamental news and bullish speculative sentiment can prevent prices from fully incorporating bad fundamental news. As long as speculative sentiment does not fully eliminate the fundamental news, there is a negative contemporaneous relation between returns and speculative demand. Furthermore, if prices subsequently reach their fundamental value, there is a negative future relation between returns and speculative demand. Thus, a negative relation between SSI and both contemporaneous and future returns is consistent with contrarian demand that stalls the incorporation of fundamental news.

It is possible that the contrarian trading in leveraged ETFs is rational. To see this, consider an investor that desires a particular portfolio on the CML and requires leverage to achieve the portfolio. Because leveraged ETFs provide daily magnified exposure that does not compound, the investor must rebalance her portfolio daily to retain the target leverage quantity. Specifically, suppose the investor begins with one dollar of wealth and she desires a leverage quantity $m \in \{-3, -2, 2, 3\}$ and uses a leveraged ETF that provides daily $m\times$ exposure. Over any two consecutive days, the investor's objective is to achieve,

$$m \prod_{i=1}^{2} (1 + r_i), \tag{OA11}$$

however, a buy-and-hold strategy with a leveraged ETF share yields,

$$\prod_{i=1}^{2} (1 + mr_i). \tag{OA12}$$

This implies that the investor must rebalance to have notional exposure ω_1 at the end of day 1 such that the following equation is satisfied,

$$m\left((1 + r_1)(1 + E[r_2]) - 1\right) = \left((1 + mr_1)\omega_1(1 + mE[r_2]) + (1 - \omega_1)(1 + mr_1) - 1\right). \tag{OA13}$$

If $\omega_1 < 1$, the investor holds a fraction $(1 - \omega_1)$ of her wealth $(1 + 2r_1)$ in cash (and earns a rate of return equal to zero). Conversely, if $\omega_1 > 1$, the investor borrows a fraction $(1 - \omega_1)$ of her wealth $(1 + 2r_1)$ (at a cost equal to zero). Using Eqn. OA13, ω_1 (the daily rebalancing value) is given explicitly by,

$$\omega_1 \equiv \frac{1 + r_1}{1 + mr_1}. \tag{OA14}$$

Note, that the change in ω_1 with respect to a change in r_1 is given by,

$$\frac{\mathrm{d}\omega_1}{\mathrm{d}r_1} \equiv \frac{1 - m}{(1 + mr_1)^2}, \tag{OA15}$$

which is negative valued if m is positive and is positive valued if m is negative. In other words, if an investor purchases a leveraged-long ETF ($m > 0$), she must sell shares if market returns are positive and buy shares if market returns are negative. Conversely, if an investor purchases a leveraged-short ETF ($m < 0$), she must buy shares if market returns are positive and sell shares if market returns are negative. This implies that rational rebalancing is mechanically contrarian.[35]

If one assumes that all rebalancing is accomplished via share creations, this implies that the daily share change is linear in ω_1. As such, I construct implied rebalancing demand as a control. Specifically, I calculate the daily implied rebalancing demand using the expression in Eqn. OA14 and the realized leveraged ETF returns. For a leveraged-long ETF, the daily implied rebalancing demand is equal to,

$$\Delta_t^{L,\text{imp}} \equiv \frac{1 + \frac{r_t^L}{m}}{1 + r_t^L}, \tag{OA16}$$

in which r_t^L is the leveraged-long ETF's daily return. For a leveraged-short ETF, the daily implied rebalancing demand is equal to,

$$\Delta_t^{S,\text{imp}} \equiv \frac{1 + \frac{r_t^S}{m}}{1 + r_t^S}, \tag{OA17}$$

in which r_t^S is the leveraged-short ETF's daily return. I then aggregate monthly net implied rebalancing demand $rebal_t$ as,

$$rebal_t = \sum_{i \in J} \prod_{\tau=1}^{T} \Delta_{i,\tau}^{L,\text{imp}} - \sum_{i \in K} \prod_{\tau=1}^{T} \Delta_{i,\tau}^{S,\text{imp}}, \tag{OA18}$$

in which J is the set of leveraged-long ETFs and K is the set of leveraged-short ETFs. The products of $\Delta_{i,\tau}^{L,\text{imp}}$ and $\Delta_{i,\tau}^{S,\text{imp}}$ from $\tau = 1$ to $t = T$ reflect the compounding of share change over month t's T days.

In Panel B of Table OA14, I present results from the regression,

$$SSI_t = a + \beta rebal_t + \epsilon_t, \tag{OA19}$$

in which SSI_t is the value of the Speculation Sentiment Index, a is the regression intercept, $rebal_t$ is the contemporaneous value of the implied rebalancing demand, β is the regression coefficient, and ϵ_t is the regression error term. The sample's index returns run from November 2006 through

[35] For a similar discussion, see Ivanov and Lenkey (2014).

November 2016. The coefficient β is both statistically significant and economically meaningful; A one standard deviation increase in implied rebalancing demand is associated with a 0.58 standard deviation increase in SSI and the coefficient is statistically significant at a 1% p-value threshold. Moreover $rebal$ explains 34% of the variation in SSI. The analysis suggests that a significant portion of SSI may be explained by rational rebalancing.

Given that SSI may be driven, in part, by rational rebalancing, it is important to evaluate the predictive ability of SSI in light of $rebal$. In Panel C of Table OA14, I present results from the regression,

$$r_t = a + \beta SSI_{t-1} + \gamma rebal_{t-1} + \epsilon_t, \tag{OA20}$$

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, β is the regression coefficient on SSI, $rebal_{t-1}$ is the one month lagged value of $rebal$, γ is the regression coefficient on $rebal$, and ϵ_t is the regression error term. Results for the CRSP equal weighted index are reported as regression (1), results for the CRSP value weighted index are reported as regression (2), and results for the S&P 500 index are reported as regression (3). The sample's index returns run from December 2006 through December 2016. In each regression, the coefficient β is statistically significant with a 1% p-value threshold. Furthermore, in comparing the magnitude of the coefficients on β to those in Table 1, β is slightly smaller after controlling for implied rebalancing for the CRSP equal weighted index regressions. Conversely, β is slightly larger for the CRSP value weighted index regressions and the S&P 500 index regressions. Moreover, γ is not statistically significant in any of the regressions. Collectively, the results in Panel A, Panel B, and Panel C of Table OA14 show that (i) gambling-like speculative demand favors a contrarian trading strategy, (ii) speculative demand is positively related to potential rational portfolio rebalancing, and (iii) despite being positively related to rational rebalancing, the information in SSI is distinct and remains to be a strong predictor of returns after controlling for implied rebalancing.

OA.7.3 Institutional Ownership

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. The assumption, as discussed in the Introduction, is predicated on the observation that ETF shares are traded almost exclusively by individuals and the underlying assets (i.e., derivative securities) are traded by institutions. Notably, however, institutional ownership of leveraged ETF shares is not zero (see Figure 3). Thus, by revealed preferences, institutions do trade levered ETF shares at times.

To further strengthen the case that SSI proxies for non-fundamental demand, I examine changes in institutional ownership of leveraged ETF shares in this section. Specifically, I utilize monthly changes in institutional ownership of leveraged ETFs using data from Bloomberg. Bloomberg reports the percentage of shares held by institutions and 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.* Similar to constructing net_t in Eqn. 2, I construct net changes in institutional ownership as,

$$inst_t = \sum_{i \in J} \Delta_{i,t}^{inst} - \sum_{i \in K} \Delta_{i,t}^{inst}, \tag{OA21}$$

in which J is the set of leveraged-long ETFs (QLD, SSO, DDM) and K is the set of leveraged-short ETFs (QID, SDS, DXD) and $\Delta_{i,t}^{inst}$ is,

$$\Delta_{i,t}^{inst} = \%\ Ownership_{i,t} - \%\ Ownership_{i,t-1}. \tag{OA22}$$

Similar to net_t, $inst_t$ proxies for the net demand shock for leveraged ETF shares among institutions. If the number is large and positive, institutional investors heavily demanded leveraged long exposure via leveraged ETF shares. If the number is large and negative, institutional investors heavily demanded leveraged short exposure.

The Bloomberg institutional ownership data is not available until early 2010. As such, I consider the ability of $inst_{t-1}$ to predict the CRSP equal weighted index return the CRSP value weighted index return, and the S&P 500 index return over the period May 2010 through December 2018 (yielding 104 monthly observations). I perform univariate regressions of the form,

$$r_t = a\beta inst_{t-1} + \epsilon_t, \tag{OA23}$$

in which r_t is either the CRSP equal weighted index monthly return, the CRSP value weighted index monthly return, or the S&P 500 index month return in month t, a is the regression intercept, $inst_{t-1}$ is the one month lagged value of $inst$, β is the regression ocefficient, and ϵ_t is the regression error term. For completeness, I also run univariate regressions using net_{t-1} as the predictor. The results are located in Table OA19; Panel A reports the results using net_{t-1} as the predictor and Panel B reports the results using $ints_{t-1}$ as the predictor.

The results using *net* in Panel A are consistent with earlier analysis; speculative demand negatively predicts subsequent returns. The results using *inst* in Panel B show that institutional demand *positively* predicts subsequent returns. Thus, the results in Panel A and Panel B further strengthen my identifying assumption: the speculative demand shocks reflected in *net* are uninformed, however when isolating institutional ownership, those demand shocks are informed.

Naturally, the results in Panel A and Panel B suggest that stripping out institutional demand from *net* may improve return predictability. To that end, I construct $netMINUSinst$ as,

$$netMINUSinst_t = net_t - inst_t. \tag{OA24}$$

$netMINUSinst$ reflects the net demand shock among individual investors after stripping out institutional ownership changes. Panel C of Table OA19 reports the univariate return predictability regressions using $netMINUSinst_{t-1}$ as the predictor. Notably, as compared to the regression results in Panel A and Panel B, the results using $netMINUSinst_{t-1}$ have stronger statistical significance and greater adjusted R^2's. Collectively, the results in Table OA19 provide additional evidence that the excess demand from individual traders in leveraged ETFs, relative to institutions, proxies for uninformed, non-fundamental demand shocks.

OA.8 Potential Pitfalls

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. Furthermore, I show that one should exhibit caution in which data sources they use to obtain ETF share changes and they should verify results using multiple sources.

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 four different sources: Bloomberg, ProShares, Compustat, and CRSP. (Compustat and CRSP shares outstanding data is not updated daily.) Table OA20 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-based and ProShares-based 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 or CRSP exhibits weak correlations with the Bloomberg-based and ProShares-based measures at the daily and weekly frequency. Even at the monthly frequency, the Compustat-based and CRSP-based measures are only 0.875 and 0.862 correlated with the Bloomberg-based measure and only 0.869 and 0.854 correlated with the ProShares-based measure. At the quarterly frequency, the Compustat-based measure is 0.959 and correlated with both the Bloomberg-based and ProShares-based measures and the CRSP-based measure is 0.961 correlated with the Bloomberg-based and ProShares-based measures.

Third, Evans, Moussawi, Pagano, and Sedunov (2019) 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. Furthermore, given the discrepancies across data providers even at the monthly and quarterly frequencies, one should rely on multiple data sources as a precaution.

Table OA1: Correlations of SSI and control variables. The table presents the correlation coefficients for SSI and the controls used throughout the analysis: index monthly returns (r_{ew}, r_{vw}, and r_{sp}), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). The t-statistics are calculated as $t = r\sqrt{\frac{n-2}{1-r^2}}$, in which r is the sample correlation and n is the number of paired observations. Statistical significance is determined using a Student's t-distribution with degrees of freedom of $n-2$.

	SSI
r_{ew}	-0.69***
r_{vw}	-0.65***
r_{sp}	-0.63***
$caep$	0.01
$term$	0.00
dp	0.05
$rate$	0.02
vrp	-0.46***
$intc$	-0.51***
Δliq	-0.30***
$short$	0.01
vix	0.32***
$sent$	0.10
$hjtz$	0.26***
$cefd$	0.06
$conf$	-0.12
$\Delta conf$	-0.08
$fmax$	-0.48***

Note:
* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA2: 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 ϵ_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 ϵ_t is the error term.

Panel A: net_t Regression with Lags	
Intercept	-0.02
	(-0.30)
net_{t-1}	0.30***
	(3.17)
net_{t-2}	-0.09
	(-0.90)
net_{t-3}	0.17*
	(1.73)
net_{t-4}	-0.02
	(-0.24)
net_{t-5}	0.03
	(0.34)
R^2	0.11
Adj R^2	0.07
N	118

Panel B: $AR(1)$ Estimation	
Intercept	-0.04
	(-0.56)
net_{t-1}	0.28***
	(3.21)
R^2	0.08
Adj R^2	0.07
N	122

Panel C: SSI_t Regression with Lags	
Intercept	0.01
	(0.19)
SSI_{t-1}	0.01
	(0.14)
SSI_{t-2}	-0.09
	(-0.97)
SSI_{t-3}	0.15
	(1.59)
SSI_{t-4}	0.02
	(0.18)
SSI_{t-5}	0.09
	(1.01)
R^2	0.04
Adj R^2	-0.01
N	117

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA3: Return predictability and SSI with GMM corrected standard errors and small sample parametric bootstrap calculated p-values. In Panel A and Panel B, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, 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, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. Panel A reports regressions using the whole sample and Panel A reports regressions using the post-2009 sample. In Panel C, Regressions (1)-(3) regresses the MGMT factor, PERF factor, or SMB factor on the lagged Speculation Sentiment Index value: $r_t = a + \beta SSI_{t-1} + \epsilon_t$ in which r_t is the monthly factor, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, and ϵ_t is the error term. The regressions in Panel C using the entire sample of data. Reported t-statistics are computed using GMM corrected standard errors with even weighting. Reported p-values are computed using a small sample parametric bootstrap. SSI_{t-1} is standardized.

	Panel A: Full Sample		
	(1) EW CRSP r_t	(2) VW CRSP r_t	(3) S&P 500 r_t
SSI_{t-1}	-1.89***	-1.42**	-1.23**
	(2.79)	(2.38)	(2.22)
R^2	0.13	0.10	0.08
Adj R^2	0.12	0.09	0.07
N	121	121	121

	Panel B: Post-2009		
	S&P 500 r_t	S&P 500 r_t	S&P 500 r_t
SSI_{t-1}	-1.16**	-0.93**	-0.82*
	(2.60)	(2.12)	(1.92)
R^2	0.08	0.06	0.05
Adj R^2	0.07	0.05	0.04
N	84	84	84

	Panel C: Anomaly Factors		
	MGMT r_t	PERF r_t	SMB r_t
SSI_{t-1}	0.62**	1.20**	-0.39*
	2.64	2.15	(1.98)
R^2	0.08	0.06	0.03
Adj R^2	0.07	0.05	0.02
N	121	121	121

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA4: Return predictability and net_t. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, 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 ETF, β is the estimated coefficient on net_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged-short ETFs and a lagged control variable: $r_t = a + \beta net_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ 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, β is the estimated coefficient on net_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
net_{t-1}	-1.87***	-1.83***	-1.89***	-1.88***	-1.94***	-1.88***	-1.21**	-1.82***	-1.58***	-1.87***	-2.11***	-1.71***	-1.84***	-1.89***	-1.92***	-1.86***	-1.66***
	(4.20)	(2.96)	(4.35)	(4.20)	(4.43)	(4.22)	(2.49)	(3.50)	(3.42)	(4.21)	(4.48)	(3.73)	(3.96)	(4.13)	(4.25)	(4.14)	(3.25)
Γ_{t-1}		0.01	1.22***	0.26	1.12**	-0.56	1.46***	0.10	1.11**	-0.62	0.71	-1.14**	-0.12	0.99**	-0.33	0.11	0.45
		0.11	2.81	0.58	2.57	(1.26)	3.02	0.19	2.13	(1.39)	1.50	(2.36)	(0.25)	2.08	(0.73)	0.25	0.88
R^2	0.13	0.13	0.18	0.13	0.17	0.14	0.19	0.13	0.16	0.14	0.14	0.17	0.13	0.16	0.13	0.13	0.13
Adj R^2	0.12	0.11	0.17	0.12	0.16	0.13	0.18	0.11	0.15	0.13	0.13	0.15	0.11	0.14	0.12	0.11	0.12
N	122	122	122	122	122	122	122	122	122	122	122	108	122	110	122	122	122

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
net_{t-1}	-1.42***	-1.62***	-1.43***	-1.42***	-1.44***	-1.42***	-0.88**	-1.53***	-1.12***	-1.42***	-1.54***	-1.34***	-1.28***	-1.42***	-1.42***	-1.43***	-1.44***
	(3.60)	(3.13)	(3.63)	(3.59)	(3.65)	(3.61)	(2.04)	(3.33)	(2.77)	(3.59)	(3.68)	(3.23)	(3.15)	(3.45)	(3.55)	(3.61)	(3.18)
Γ_{t-1}		-0.07	0.54	0.07	0.39	-0.35	1.19***	-0.22	1.12**	-0.08	0.36	-0.52	-0.51	0.45	0.01	-0.13	-0.04
		(0.61)	1.36	0.17	1.00	(0.89)	2.77	(0.47)	2.43	(0.21)	0.86	(1.20)	(1.26)	1.05	0.03	(0.33)	(0.09)
R^2	0.10	0.10	0.11	0.10	0.11	0.10	0.15	0.10	0.14	0.10	0.10	0.11	0.11	0.10	0.10	0.10	0.10
Adj R^2	0.09	0.09	0.10	0.08	0.09	0.09	0.14	0.08	0.13	0.08	0.09	0.09	0.09	0.09	0.08	0.08	0.08
N	122	122	122	122	122	122	122	122	122	122	122	108	122	110	122	122	122

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
net_{t-1}	-1.26***	-1.37***	-1.27***	-1.26***	-1.28***	-1.26***	-0.76*	-1.35***	-0.96**	-1.26***	-1.34***	-1.20***	-1.10***	-1.27***	-1.25***	-1.27***	-1.30***
	(3.31)	(2.79)	(3.32)	(3.30)	(3.34)	(3.32)	(1.82)	(3.05)	(2.46)	(3.29)	(3.32)	(2.97)	(2.79)	(3.18)	(3.24)	(3.32)	(2.97)
Γ_{t-1}		-0.04	0.42	0.09	0.27	-0.40	1.10***	-0.19	1.12**	0.03	0.25	-0.46	-0.62	0.45	0.07	-0.15	-0.08
		(0.36)	1.09	0.24	0.71	(1.04)	2.64	(0.42)	2.53	0.07	0.61	(1.09)	(1.58)	1.08	0.18	(0.39)	(0.18)
R^2	0.08	0.08	0.09	0.08	0.09	0.09	0.13	0.08	0.13	0.08	0.09	0.09	0.10	0.09	0.08	0.08	0.08
Adj R^2	0.08	0.07	0.08	0.07	0.07	0.08	0.12	0.07	0.12	0.07	0.07	0.08	0.09	0.07	0.07	0.07	0.07
N	122	122	122	122	122	122	122	122	122	122	122	108	122	110	122	122	122

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

Table OA5: Return predictability and SSI^{flow} orthogonal to aggregate ETF flows. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value orthogonal to aggregate ETF flows: $r_t = a + \beta SSI^{flow}_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^{flow}_{t-1} is the lagged Speculation Sentiment Index value orthogonal to aggregate ETF flows, β is the estimated coefficient on SSI^{flow}_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value orthogonal to aggregate ETF flows and a lagged control variable: $r_t = a + \beta SSI^{flow}_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^{flow}_{t-1} is the lagged Speculation Sentiment Index value orthogonal to aggregate ETF flows, β is the estimated coefficient on SSI^{flow}_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Panel A: EW CRSP																	
		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^{flow}_{t-1}	-1.83***	-1.64***	-1.80***	-1.84***	-1.82***	-1.82***	-1.24***	-1.71***	-1.54***	-1.81***	-1.93***	-1.67***	-1.78***	-1.80***	-1.85***	-1.82***	-1.59***
	(4.05)	(2.85)	(4.09)	(4.06)	(4.11)	(4.06)	(2.64)	(3.39)	(3.31)	(4.03)	(4.11)	(3.61)	(3.86)	(3.91)	(4.07)	(4.02)	(3.18)
Γ_{t-1}		0.06	1.18***	0.32	1.03**	-0.63	1.55***	0.27	1.14**	-0.60	0.56	-1.21**	-0.25	0.98**	-0.25	0.19	0.57
		0.52	2.68	0.68	2.33	(1.37)	3.33	0.54	2.17	(1.33)	1.19	(2.47)	(0.55)	2.02	(0.55)	0.41	1.14
R^2	0.12	0.12	0.17	0.12	0.16	0.13	0.20	0.12	0.15	0.13	0.13	0.17	0.12	0.15	0.12	0.12	0.13
Adj R^2	0.11	0.11	0.16	0.11	0.15	0.12	0.18	0.11	0.14	0.12	0.11	0.15	0.11	0.13	0.11	0.11	0.12
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121
Panel B: VW CRSP																	
		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^{flow}_{t-1}	-1.35***	-1.42***	-1.34***	-1.35***	-1.35***	-1.35***	-0.87**	-1.37***	-1.06**	-1.35***	-1.39***	-1.27***	-1.23***	-1.33***	-1.34***	-1.35***	-1.31***
	(3.39)	(2.84)	(3.36)	(3.38)	(3.38)	(3.38)	(2.09)	(3.07)	(2.59)	(3.37)	(3.34)	(3.02)	(3.05)	(3.20)	(3.35)	(3.38)	(2.96)
Γ_{t-1}		-0.02	0.50	0.10	0.32	-0.40	1.27***	-0.04	1.15**	-0.07	0.26	-0.57	-0.61	0.43	0.08	-0.07	0.09
		(0.22)	1.25	0.24	0.81	(0.97)	3.06	(0.09)	2.49	(0.17)	0.63	(1.29)	(1.51)	0.99	0.19	(0.18)	0.20
R^2	0.09	0.09	0.10	0.09	0.09	0.10	0.15	0.09	0.13	0.09	0.09	0.10	0.11	0.09	0.09	0.09	0.09
Adj R^2	0.08	0.07	0.08	0.07	0.08	0.08	0.14	0.07	0.12	0.07	0.07	0.08	0.09	0.08	0.07	0.07	0.07
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121
Panel C: S&P 500																	
		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^{flow}_{t-1}	-1.17***	-1.16**	-1.16***	-1.17***	-1.17***	-1.16***	-0.72*	-1.17***	-0.87**	-1.17***	-1.19***	-1.10***	-1.03***	-1.16***	-1.16***	-1.17***	-1.14***
	(3.02)	(2.44)	(3.00)	(3.01)	(3.01)	(3.02)	(1.78)	(2.71)	(2.21)	(3.01)	(2.94)	(2.69)	(2.64)	(2.86)	(2.97)	(3.01)	(2.66)
Γ_{t-1}		0.00	0.38	0.11	0.21	-0.43	1.18***	-0.01	1.16**	0.05	0.17	-0.51	-0.71*	0.42	0.14	-0.10	0.06
		0.01	0.99	0.28	0.53	(1.09)	2.92	(0.03)	2.61	0.12	0.41	(1.17)	(1.82)	0.99	0.35	(0.24)	0.13
R^2	0.07	0.07	0.08	0.07	0.07	0.08	0.13	0.07	0.12	0.07	0.07	0.08	0.10	0.08	0.07	0.07	0.07
Adj R^2	0.06	0.06	0.06	0.06	0.06	0.06	0.12	0.06	0.11	0.06	0.05	0.06	0.08	0.06	0.06	0.06	0.06
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA6: Return predictability and $SSI^{\perp}$ orthogonal to macro conditions. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value orthogonal to macro conditions: $r_t = a + \beta SSI^{\perp}_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $SSI^{\perp}_{t-1}$ is the lagged Speculation Sentiment Index value orthogonal to macro conditions, β is the estimated coefficient on $SSI^{\perp}_{t-1}$, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value orthogonal to macro conditions and a lagged control variable: $r_t = a + \beta SSI^{\perp}_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $SSI^{\perp}_{t-1}$ is the lagged Speculation Sentiment Index value orthogonal to macro conditions, β is the estimated coefficient on $SSI^{\perp}_{t-1}$, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
$SSI^{\perp}_{t-1}$	-1.64***	-1.37***	-1.56***	-1.68***	-1.57***	-1.67***	-1.03**	-1.63***	-1.38***	-1.65***	-1.64***	-1.52***	-1.59***	-1.64***	-1.64***	-1.67***	-1.47***
	(3.58)	(2.90)	(3.46)	(3.65)	(3.44)	(3.65)	(2.18)	(3.61)	(2.98)	(3.60)	(3.53)	(3.21)	(3.44)	(3.41)	(3.57)	(3.62)	(3.19)
Γ_{t-1}		0.18*	1.11**	0.44	0.91**	-0.72	1.64***	1.01**	1.28**	-0.66	0.12	-1.33***	-0.40	1.06**	-0.15	0.37	0.98**
		1.95	2.46	0.93	2.01	(1.52)	3.50	2.24	2.46	(1.44)	0.25	(2.70)	(0.88)	2.13	(0.31)	0.79	2.15
R^2	0.10	0.13	0.14	0.10	0.13	0.11	0.18	0.13	0.14	0.11	0.10	0.15	0.10	0.12	0.10	0.10	0.13
Adj R^2	0.09	0.11	0.13	0.09	0.11	0.10	0.17	0.12	0.13	0.10	0.08	0.13	0.09	0.11	0.08	0.09	0.12
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
$SSI^{\perp}_{t-1}$	-1.37***	-1.26***	-1.33***	-1.38***	-1.35***	-1.38***	-0.89**	-1.36***	-1.12***	-1.37***	-1.37***	-1.31***	-1.28***	-1.36***	-1.36***	-1.37***	-1.29***
	(3.42)	(3.05)	(3.33)	(3.44)	(3.35)	(3.46)	(2.15)	(3.42)	(2.79)	(3.41)	(3.40)	(3.08)	(3.21)	(3.20)	(3.39)	(3.41)	(3.18)
Γ_{t-1}		0.09	0.44	0.20	0.22	-0.47	1.27***	0.55	1.20***	-0.11	-0.05	-0.66	-0.70*	0.50	0.15	0.07	0.42
		1.02	1.09	0.49	0.54	(1.13)	3.07	1.38	2.66	(0.28)	(0.13)	(1.50)	(1.75)	1.14	0.37	0.17	1.05
R^2	0.09	0.10	0.10	0.09	0.09	0.10	0.16	0.10	0.14	0.09	0.09	0.10	0.11	0.09	0.09	0.09	0.10
Adj R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.14	0.09	0.13	0.07	0.08	0.08	0.10	0.08	0.07	0.07	0.08
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
$SSI^{\perp}_{t-1}$	-1.21***	-1.11***	-1.18***	-1.23***	-1.20***	-1.23***	-0.77*	-1.20***	-0.96**	-1.21***	-1.22***	-1.16***	-1.12***	-1.21***	-1.20***	-1.21***	-1.15***
	(3.12)	(2.79)	(3.05)	(3.15)	(3.08)	(3.18)	(1.92)	(3.12)	(2.49)	(3.11)	(3.12)	(2.82)	(2.90)	(2.95)	(3.10)	(3.11)	(2.91)
Γ_{t-1}		0.10	0.33	0.20	0.11	-0.49	1.17***	0.50	1.20***	0.01	-0.10	-0.58	-0.78**	0.49	0.20	0.03	0.34
		1.08	0.84	0.51	0.29	(1.24)	2.91	1.28	2.74	0.02	(0.26)	(1.36)	(2.02)	1.14	0.51	0.08	0.88
R^2	0.08	0.08	0.08	0.08	0.08	0.09	0.14	0.09	0.13	0.08	0.08	0.09	0.11	0.08	0.08	0.08	0.08
Adj R^2	0.07	0.07	0.07	0.06	0.06	0.07	0.12	0.07	0.12	0.06	0.06	0.07	0.09	0.06	0.06	0.06	0.07
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

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

Table OA7: Return predictability and evolving SSI^*. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged evolving 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 evolving Speculation Sentiment Index value, β is the estimated coefficient on SSI^*_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged evolving Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI^*_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^*_{t-1} is the lagged evolving Speculation Sentiment Index value, β is the estimated coefficient on SSI^*_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI^*_{t-1}	-1.90***	-1.84***	-1.88***	-1.91***	-1.90***	-1.88***	-1.34***	-1.85***	-1.63***	-1.89***	-2.04***	-1.80***	-1.86***	-1.92***	-1.92***	-1.90***	-1.69***
	(4.37)	(3.22)	(4.43)	(4.37)	(4.44)	(4.33)	(2.94)	(3.72)	(3.62)	(4.36)	(4.55)	(3.89)	(4.17)	(4.20)	(4.39)	(4.34)	(3.51)
Γ_{t-1}		0.02	1.20***	0.30	1.01**	-0.56	1.45***	0.12	1.08**	-0.63	0.57	-1.16**	-0.19	0.95*	-0.25	0.19	0.48
		0.18	2.71	0.66	2.35	(1.24)	3.19	0.23	2.07	(1.37)	1.23	(2.40)	(0.42)	1.96	(0.54)	0.43	1.00
R^2	0.14	0.14	0.19	0.14	0.18	0.15	0.21	0.14	0.17	0.15	0.15	0.18	0.14	0.17	0.14	0.14	0.15
Adj R^2	0.13	0.12	0.18	0.13	0.16	0.14	0.19	0.12	0.15	0.14	0.13	0.17	0.13	0.15	0.13	0.13	0.13
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^*_{t-1}	-1.41***	-1.59***	-1.40***	-1.41***	-1.41***	-1.40***	-0.94**	-1.49***	-1.13***	-1.41***	-1.47***	-1.39***	-1.29***	-1.44***	-1.40***	-1.41***	-1.39***
	(3.65)	(3.19)	(3.63)	(3.64)	(3.64)	(3.61)	(2.33)	(3.37)	(2.85)	(3.63)	(3.68)	(3.31)	(3.29)	(3.49)	(3.62)	(3.64)	(3.25)
Γ_{t-1}		-0.06	0.51	0.09	0.31	-0.34	1.19***	-0.17	1.11**	-0.08	0.25	-0.54	-0.57	0.41	0.09	-0.07	0.03
		(0.57)	1.26	0.22	0.81	(0.86)	2.94	(0.37)	2.41	(0.19)	0.61	(1.22)	(1.42)	0.93	0.21	(0.17)	0.07
R^2	0.10	0.10	0.11	0.10	0.11	0.11	0.16	0.10	0.14	0.10	0.10	0.11	0.12	0.11	0.10	0.10	0.10
Adj R^2	0.09	0.09	0.10	0.09	0.09	0.09	0.15	0.09	0.13	0.09	0.09	0.10	0.10	0.09	0.09	0.09	0.09
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^*_{t-1}	-1.22***	-1.31***	-1.21***	-1.22***	-1.22***	-1.20***	-0.78**	-1.27***	-0.93**	-1.22***	-1.25***	-1.21***	-1.08***	-1.25***	-1.21***	-1.22***	-1.21***
	(3.25)	(2.73)	(3.23)	(3.24)	(3.24)	(3.21)	(1.99)	(2.98)	(2.43)	(3.24)	(3.23)	(2.96)	(2.85)	(3.12)	(3.21)	(3.25)	(2.91)
Γ_{t-1}		-0.03	0.39	0.10	0.20	-0.39	1.11***	-0.12	1.13**	0.04	0.14	-0.47	-0.68*	0.40	0.15	-0.09	0.01
		(0.31)	1.00	0.26	0.53	(1.00)	2.81	(0.27)	2.53	0.10	0.36	(1.11)	(1.74)	0.94	0.36	(0.23)	0.02
R^2	0.08	0.08	0.09	0.08	0.08	0.09	0.14	0.08	0.13	0.08	0.08	0.09	0.10	0.09	0.08	0.08	0.08
Adj R^2	0.07	0.07	0.07	0.07	0.07	0.07	0.12	0.07	0.11	0.07	0.07	0.08	0.09	0.07	0.07	0.07	0.07
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

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

Table OA8: Return predictability and leveraged-long SSI^L. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, 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^L_{t-1} is the lagged leveraged-long Speculation Sentiment Index value, β is the estimated coefficient on SSI^L_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged leveraged-long Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI^L_{t-1} + \gamma\Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^L_{t-1} is the lagged leveraged-long Speculation Sentiment Index value, β is the estimated coefficient on SSI^L_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI^L_{t-1}	-1.90***	-1.68***	-1.86***	-1.90***	-1.91***	-1.85***	-1.19**	-1.76***	-1.60***	-1.88***	-2.03***	-1.65***	-1.86***	-1.76***	-1.92***	-1.90***	-1.68***
	(4.24)	(3.15)	(4.25)	(4.18)	(4.34)	(4.04)	(2.38)	(3.66)	(3.43)	(4.20)	(4.40)	(3.54)	(4.06)	(3.81)	(4.25)	(4.19)	(3.56)
Γ_{t-1}		0.08	1.16***	0.07	1.05**	-0.30	1.43***	0.40	1.06**	-0.58	0.53	-1.02**	-0.25	0.71	-0.22	0.10	0.71
		0.77	2.63	0.16	2.38	(0.63)	2.87	0.82	2.01	(1.29)	1.15	(2.04)	(0.55)	1.45	(0.48)	0.21	1.52
R^2	0.13	0.14	0.18	0.13	0.17	0.13	0.19	0.14	0.16	0.14	0.14	0.16	0.13	0.14	0.13	0.13	0.15
Adj R^2	0.12	0.12	0.17	0.12	0.16	0.12	0.17	0.12	0.15	0.13	0.13	0.15	0.12	0.13	0.12	0.12	0.13
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^L_{t-1}	-1.37***	-1.37***	-1.36***	-1.38***	-1.37***	-1.35***	-0.77*	-1.34***	-1.06**	-1.37***	-1.42***	-1.25***	-1.26***	-1.30***	-1.37***	-1.38***	-1.30***
	(3.45)	(2.90)	(3.41)	(3.43)	(3.45)	(3.31)	(1.73)	(3.14)	(2.57)	(3.43)	(3.46)	(2.95)	(3.13)	(3.12)	(3.41)	(3.45)	(3.08)
Γ_{t-1}		0.00	0.48	-0.08	0.34	-0.16	1.22***	0.08	1.11**	-0.05	0.21	-0.43	-0.62	0.23	0.10	-0.14	0.24
		0.01	1.21	(0.19)	0.84	(0.37)	2.74	0.19	2.39	(0.13)	0.52	(0.95)	(1.53)	0.53	0.25	(0.35)	0.57
R^2	0.09	0.09	0.10	0.09	0.10	0.09	0.15	0.09	0.13	0.09	0.09	0.10	0.11	0.09	0.09	0.09	0.09
Adj R^2	0.08	0.08	0.09	0.08	0.08	0.08	0.13	0.08	0.12	0.08	0.08	0.08	0.09	0.07	0.08	0.08	0.08
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^L_{t-1}	-1.20***	-1.17**	-1.19***	-1.21***	-1.21***	-1.16***	-0.64	-1.17***	-0.89**	-1.21***	-1.23***	-1.10***	-1.07***	-1.14***	-1.19***	-1.22***	-1.15***
	(3.12)	(2.57)	(3.08)	(3.10)	(3.11)	(2.96)	(1.48)	(2.83)	(2.23)	(3.11)	(3.09)	(2.67)	(2.76)	(2.82)	(3.08)	(3.13)	(2.81)
Γ_{t-1}		0.02	0.37	-0.04	0.22	-0.22	1.14***	0.08	1.13**	0.06	0.12	-0.38	-0.71*	0.25	0.16	-0.15	0.18
		0.16	0.95	(0.11)	0.56	(0.55)	2.63	0.20	2.51	0.15	0.29	(0.86)	(1.83)	0.58	0.40	(0.39)	0.45
R^2	0.08	0.08	0.08	0.08	0.08	0.08	0.13	0.08	0.12	0.08	0.08	0.08	0.10	0.08	0.08	0.08	0.08
Adj R^2	0.07	0.06	0.07	0.06	0.06	0.06	0.11	0.06	0.11	0.06	0.06	0.06	0.09	0.06	0.06	0.06	0.06
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA9: Return predictability and leveraged-short SSI^S. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged leveraged-short Speculation Sentiment Index value: $r_t = a + \beta SSI^S_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^S_{t-1} is the lagged leveraged-short Speculation Sentiment Index value, β is the estimated coefficient on SSI^S_{t-1}, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged leveraged-short Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI^S_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI^S_{t-1} is the lagged leveraged-short Speculation Sentiment Index value, β is the estimated coefficient on SSI^S_{t-1}, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
SSI^S_{t-1}	1.18**	0.73	1.14**	1.26***	1.13**	1.36***	0.99**	0.94*	1.00**	1.17**	1.19**	1.23**	1.13**	1.37***	1.19**	1.20**	0.83*
	2.52	1.40	2.49	2.64	2.45	2.87	2.27	1.88	2.17	2.51	2.52	2.54	2.38	2.77	2.52	2.55	1.67
Γ_{t-1}		0.19*	1.19**	0.48	0.98**	-0.93*	1.92***	0.70	1.48***	-0.64	0.15	-1.45***	-0.46	1.19**	-0.16	0.33	0.93*
		1.88	2.58	0.99	2.13	(1.90)	4.40	1.40	2.85	(1.35)	0.31	(2.88)	(0.98)	2.32	(0.33)	0.69	1.87
R^2	0.05	0.08	0.10	0.06	0.09	0.08	0.18	0.07	0.11	0.06	0.05	0.12	0.06	0.09	0.05	0.05	0.08
Adj R^2	0.04	0.06	0.09	0.04	0.07	0.06	0.17	0.05	0.10	0.05	0.04	0.10	0.04	0.08	0.04	0.04	0.06
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^S_{t-1}	0.95**	0.78*	0.93**	0.98**	0.93**	1.07**	0.80**	0.86*	0.78*	0.95**	0.94**	0.98**	0.86**	1.05**	0.94**	0.95**	0.82*
	2.32	1.72	2.28	2.37	2.28	2.58	2.07	1.96	1.95	2.31	2.29	2.25	2.11	2.38	2.29	2.31	1.86
Γ_{t-1}		0.09	0.50	0.23	0.28	-0.63	1.52***	0.27	1.37***	-0.09	-0.05	-0.76*	-0.75*	0.60	0.14	0.03	0.35
		0.91	1.23	0.54	0.69	(1.47)	3.94	0.61	3.04	(0.22)	(0.11)	(1.68)	(1.83)	1.30	0.35	0.08	0.79
R^2	0.04	0.05	0.06	0.05	0.05	0.06	0.15	0.05	0.11	0.04	0.04	0.07	0.07	0.06	0.04	0.04	0.05
Adj R^2	0.04	0.03	0.04	0.03	0.03	0.04	0.14	0.03	0.10	0.03	0.03	0.05	0.05	0.04	0.03	0.03	0.03
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
SSI^S_{t-1}	0.80**	0.63	0.79**	0.84**	0.79**	0.92**	0.67*	0.71*	0.64	0.80**	0.79**	0.83*	0.71*	0.90**	0.79**	0.80**	0.69
	2.03	1.46	2.00	2.09	2.00	2.31	1.77	1.69	1.65	2.02	1.99	1.98	1.80	2.12	2.00	2.02	1.63
Γ_{t-1}		0.10	0.39	0.22	0.17	-0.63	1.39***	0.26	1.35***	0.03	-0.11	-0.67	-0.83**	0.56	0.20	0.00	0.29
		1.00	0.98	0.54	0.44	(1.53)	3.69	0.61	3.10	0.06	(0.28)	(1.52)	(2.11)	1.27	0.49	(0.01)	0.68
R^2	0.03	0.04	0.04	0.04	0.04	0.05	0.13	0.04	0.11	0.03	0.03	0.05	0.07	0.05	0.04	0.03	0.04
Adj R^2	0.03	0.03	0.03	0.02	0.02	0.04	0.12	0.02	0.09	0.02	0.02	0.03	0.05	0.03	0.02	0.02	0.02
N	121	121	121	121	121	121	121	121	121	121	121	107	121	109	121	121	121

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

Table OA10: Return predictability and dollar flow $SSI^{\$}$. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the dollar flow 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 dollar flow Speculation Sentiment Index value, β is the estimated coefficient on $SSI^{\$}_{t-1}$, and ϵ_t is the error term. Regressions (2)-(17) regress the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged dollar flow Speculation Sentiment Index value and a lagged control variable: $r_t = a + \beta SSI\$_{t-1} + \gamma \Gamma_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $SSI\$_{t-1}$ is the lagged dollar flow Speculation Sentiment Index value, β is the estimated coefficient on $SSI^{\$}_{t-1}$, Γ_{t-1} is a lagged control variable, γ is the estimated coefficient on Γ_{t-1}, and ϵ_t is the error term. The lagged control variables are index monthly return (r), cyclically adjusted earnings-to-price ($caep$), term spread ($term$), dividend-to-price (dp), short-rate ($rate$), variance risk premium (vrp), intermediary capital risk factor ($intc$), innovation to aggregate liquidity (Δliq), short interest ($short$), VIX (vix), Baker-Wurgler sentiment level ($sent$), aligned investor sentiment level ($hjtz$), closed-end fund discount ($cefd$), consumer confidence level ($conf$), change in consumer confidence ($\Delta conf$), and investor lottery demand ($fmax$). The sample runs from December 2006 through December 2016 (if the control variable is available through 2016). All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2) r	(3) $caep$	(4) $term$	(5) dp	(6) $rate$	(7) vrp	(8) $intc$	(9) Δliq	(10) $short$	(11) vix	(12) $sent$	(13) $hjtz$	(14) $cefd$	(15) $conf$	(16) $\Delta conf$	(17) $fmax$
$SSI^{\$}_{t-1}$	-1.73***	-1.49**	-1.68***	-1.73***	-1.71***	-1.73***	-1.17**	-1.60***	-1.48***	-1.71***	-1.82***	-1.56***	-1.68***	-1.72***	-1.75***	-1.72***	-1.48***
	(3.81)	(2.56)	(3.78)	(3.80)	(3.83)	(3.81)	(2.53)	(3.12)	(3.24)	(3.78)	(3.85)	(3.35)	(3.62)	(3.71)	(3.82)	(3.77)	(2.84)
$Cont_{t-1}$		0.07	1.15**	0.27	1.00**	-0.63	1.61***	0.30	1.27**	-0.59	0.49	-1.19**	-0.28	0.98**	-0.22	0.15	0.52
		0.67	2.58	0.58	2.25	(1.34)	3.50	0.58	2.45	(1.31)	1.04	(2.40)	(0.60)	2.00	(0.47)	0.33	1.01
R^2	0.11	0.11	0.16	0.11	0.15	0.12	0.19	0.11	0.15	0.12	0.11	0.15	0.11	0.14	0.11	0.11	0.12
Adj R^2	0.10	0.10	0.14	0.10	0.13	0.11	0.18	0.10	0.14	0.11	0.10	0.14	0.10	0.12	0.10	0.09	0.10
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel B: VW CRSP

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
$SSI^{\$}_{t-1}$	-1.21***	-1.19**	-1.19***	-1.21***	-1.20***	-1.21***	-0.74*	-1.20***	-0.96**	-1.21***	-1.24***	-1.13***	-1.09***	-1.20***	-1.20***	-1.22***	-1.17**
	(3.01)	(2.38)	(2.95)	(2.99)	(2.98)	(2.99)	(1.80)	(2.65)	(2.39)	(2.99)	(2.95)	(2.65)	(2.67)	(2.86)	(2.97)	(3.00)	(2.53)
$Cont_{t-1}$		0.01	0.48	0.06	0.30	-0.40	1.34***	0.02	1.25***	-0.06	0.20	-0.56	-0.64	0.43	0.11	-0.09	0.08
		0.08	1.19	0.16	0.75	(0.95)	3.25	0.04	2.75	(0.16)	0.47	(1.25)	(1.58)	0.97	0.26	(0.23)	0.17
R^2	0.07	0.07	0.08	0.07	0.07	0.08	0.15	0.07	0.13	0.07	0.07	0.08	0.09	0.08	0.07	0.07	0.07
Adj R^2	0.06	0.05	0.07	0.05	0.06	0.06	0.13	0.05	0.11	0.05	0.05	0.06	0.07	0.06	0.06	0.06	0.06
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

Panel C: S&P 500

		r	$caep$	$term$	dp	$rate$	vrp	$intc$	Δliq	$short$	vix	$sent$	$hjtz$	$cefd$	$conf$	$\Delta conf$	$fmax$
$SSI^{\$}_{t-1}$	-1.01**	-0.92*	-0.99**	-1.01**	-1.01**	-1.01**	-0.58	-0.98**	-0.76*	-1.01**	-1.02**	-0.94**	-0.87**	-1.01**	-1.00**	-1.02**	-0.98**
	(2.59)	(1.93)	(2.54)	(2.58)	(2.57)	(2.58)	(1.43)	(2.24)	(1.96)	(2.58)	(2.50)	(2.28)	(2.22)	(2.47)	(2.55)	(2.59)	(2.18)
$Cont_{t-1}$		0.04	0.37	0.08	0.19	-0.43	1.25***	0.06	1.25***	0.05	0.10	-0.50	-0.74*	0.42	0.17	-0.11	0.07
		0.34	0.94	0.20	0.49	(1.07)	3.13	0.13	2.85	0.12	0.25	(1.15)	(1.89)	0.97	0.41	(0.28)	0.15
R^2	0.05	0.05	0.06	0.05	0.06	0.06	0.13	0.05	0.11	0.05	0.05	0.06	0.08	0.06	0.05	0.05	0.05
Adj R^2	0.05	0.04	0.04	0.04	0.04	0.05	0.11	0.04	0.10	0.04	0.04	0.05	0.07	0.04	0.04	0.04	0.04
N	121	121	121	121	121	121	121	121	121	121	119	107	121	109	121	121	121

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

Table OA11: Return predictability and ETF index pairs. Regression (1) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged net difference in each of the three ETF index pairs: $r_t = a + \beta_{SP500}SP500_{t-1} + \beta_{NASDAQ}NASDAQ_{t-1} + \beta_{DJIA}DJIA_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $SP500_{t-1}$ is the lagged net difference in share changes from SSO and SDS, β_{SP500} is the estimated coefficient on $SP500_{t-1}$, $NASDAQ_{t-1}$ is the lagged net difference in share changes from QLD and QID, β_{NASDAQ} is the estimated coefficient on $NASDAQ_{t-1}$, $DJIA_{t-1}$ is the lagged net difference in share changes from DDM and DXD, β_{DJIA} is the estimated coefficient on $DJIA_{t-1}$, and ϵ_t is the error term. Regression (2) is a univariate regression using $SP500_{t-1}$: $r_t = a + \beta_{SP500}SP500_{t-1} + \epsilon_t$. Regression (3) is a univariate regression using $NASDAQ_{t-1}$: $r_t = a+\beta_{NASDAQ}NASDAQ_{t-1}+\epsilon_t$. Regression (4) is a univariate regression using $DJIA_{t-1}$: $r_t = a+\beta_{DJIA}DJIA_{t-1}+\epsilon_t$. The sample runs from December 2006 through December 2016. All variables, except for returns, are standardized.

Panel A: EW CRSP

	(1)	(2)	(3)	(4)
SP500 PAIR	-0.58	-1.64***		
	(0.91)	(3.61)		
NASDAQ PAIR	-1.64**		-1.92***	
	(2.11)		(4.32)	
DJ PAIR	0.17			-1.38***
	0.26			(2.98)
R^2	0.14	0.10	0.13	0.07
Adj R^2	0.12	0.09	0.13	0.06
N	122	122	122	122

Panel B: VW CRSP

	(1)	(2)	(3)	(4)
SP500 PAIR	-0.22	-1.15***		
	(0.40)	(2.87)		
NASDAQ PAIR	-1.21*		-1.46***	
	(1.76)		(3.72)	
DJ PAIR	-0.13			-1.15***
	(0.22)			(2.88)
R^2	0.11	0.06	0.10	0.06
Adj R^2	0.08	0.06	0.10	0.06
N	122	122	122	122

Panel C: S&P 500

	(1)	(2)	(3)	(4)
SP500 PAIR	-0.21	-1.02***		
	(0.39)	(2.63)		
NASDAQ PAIR	-0.96		-1.28***	
	(1.45)		(3.35)	
DJ PAIR	-0.22			-1.06***
	(0.38)			(2.73)
R^2	0.09	0.05	0.09	0.06
Adj R^2	0.06	0.05	0.08	0.05
N	122	122	122	122

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

Table OA12: Out-of-sample return predictability for SSI_t and net_t. In Panel A (CRSP equal weighted), Panel B (CRSP value weighted), and Panel C (S&P 500), the first three columns report the results of the regression $r_t = a + \beta SSI_t + \epsilon_t$ in which r_t is the index monthly return, SSI_t is the lagged Speculation Sentiment Index, β is the estimated coefficient on SSI_t, and ϵ_t is the error term. The first column's sample runs from December 2006 through December 2018, the second column's sample runs from January 2010 through December 2018 and the third column's sample runs from January 2017 through December 2018. The second three columns report results for a similar regression, except that net_t is used in place of SSI_t. All variables, except for returns, are standardized. Panel D reports the out-of-sample R^2_{OS} for SSI_t based on the calculation from Campbell and Thompson (2007). Fitted values of returns are obtained by using coefficients estimated on the December 2006 through December 2016 sample. Panel D reports out-of-sample R^2_{OS} utilizing the average returns over December 2006 through December 2016 and the long-term average returns (January 1926 through December 2016).

Panel A: EW CRSP

	SSI			net		
	12/06—12/18	1/10—12/18	1/17—12/18	12/06—12/18	1/10—12/18	1/17—12/18
SSI_{t-1} or net_{t-1}	-1.74***	-1.82***	-2.54	-1.73***	-1.78***	-3.09
	(4.48)	(2.95)	(0.96)	(4.44)	(2.64)	(1.12)
R^2	0.12	0.08	0.04	0.12	0.06	0.05
Adj R^2	0.12	0.07	(0.00)	0.11	0.05	0.01
N	145	108	24	145	108	24

Panel B: VW CRSP

	SSI			net		
	12/06—12/18	1/10—12/18	1/17—12/18	12/06—12/18	1/10—12/18	1/17—12/18
SSI_{t-1} or net_{t-1}	-1.31***	-1.46**	-2.11	-1.31***	-1.40**	-2.64
	(3.77)	(2.52)	(0.81)	(3.78)	(2.22)	(0.98)
R^2	0.09	0.06	0.03	0.09	0.04	0.04
Adj R^2	0.08	0.05	(0.02)	0.08	0.04	(0.00)
N	145	108	24	145	108	24

Panel C: S&P 500

	SSI			net		
	12/06—12/18	1/10—12/18	1/17—12/18	12/06—12/18	1/10—12/18	1/17—12/18
SSI_{t-1} or net_{t-1}	-1.14***	-1.30**	-2.28	-1.17***	-1.25**	-2.89
	(3.38)	(2.29)	(0.87)	(3.48)	(2.03)	(1.06)
R^2	0.07	0.05	0.03	0.08	0.04	0.05
Adj R^2	0.07	0.04	(0.01)	0.07	0.03	0.00
N	145	108	24	145	108	24

Panel D: Out-of-Sample R^2

	EW CRSP	VW CRSP	S&P 500
12/06 Start Date Avg	0.05	0.03	0.03
Long-Term Avg	0.12	0.04	0.03

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA13: 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	1.37**	1.34**	1.44**	1.30**	1.07*	1.03*	1.13*	1.01
	(2.25)	(2.17)	(2.32)	(2.05)	(1.80)	(1.72)	(1.86)	(1.64)
Mkt-Rf	0.27*	0.31*	0.29	0.34*	0.33**	0.39**	0.36**	0.41**
	(1.72)	(1.79)	(1.66)	(1.88)	(2.17)	(2.28)	(2.15)	(2.31)
SMB		-0.17	-0.15	-0.12		-0.19	-0.16	-0.15
		(-0.60)	(-0.50)	(-0.38)		(-0.67)	(-0.58)	(-0.51)
HML		-0.01	-0.13	0.05		-0.10	-0.21	-0.03
		(-0.05)	(-0.44)	(0.13)		(-0.39)	(-0.76)	(-0.07)
MOM			-0.25				-0.24	
			(-1.22)				(-1.22)	
CMA				-0.08				-0.12
				(-0.14)				(-0.22)
RMW				0.29				0.21
				(0.63)				(0.47)
R^2	0.03	0.04	0.06	0.04	0.05	0.06	0.08	0.07
Adj R^2	0.02	0.00	0.01	-0.02	0.04	0.03	0.03	0.01
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	1.06	0.90	0.84
MAX MONTHLY LOSS	-9.01%	-8.80%	-8.20%
STDEV MONTHLY RETURN	5.44%	5.35%	3.66%
SEMI STDEV MONTHLY RETURN	2.70%	2.54%	2.27%
MAX NOTIONAL	2.88x	2.88x	1.00
AVG NOTIONAL	1.00x	1.00x	1.00
STDEV NOTIONAL	0.73x	0.73x	0.00

Table OA14: 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	-0.01	0.00	0.00	-0.01	-0.05	-0.06	-0.06	-0.04
	(-0.15)	(-0.02)	0.00	(-0.13)	(-0.58)	(-0.62)	(-0.70)	(-0.42)
SSI_t	0.29***	0.35***	0.28***	0.48***	-0.75***	-0.79***	-0.90***	-0.50***
	(3.32)	(3.95)	(3.24)	(4.72)	(-4.68)	(-5.18)	(-5.76)	(-3.16)
$\Delta_{i,t-1}$		-0.23***				0.29***		
		(-2.63)				(3.21)		
$r_{i,t-1}$			-0.13				-0.31***	
			(-1.44)				(-3.32)	
$r_{i,t}$				0.34***				-0.40***
				(3.29)				(-4.34)
R^2	0.08	0.13	0.10	0.16	0.20	0.29	0.29	0.34
Adj R^2	0.08	0.12	0.08	0.15	0.19	0.27	0.28	0.32
N	122	122	122	122	92	91	91	92

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

Table OA15: 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 β_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			
$p < 0.01$	8.75%	10.24%	9.74%	6.96%
$p < 0.05$	17.20%	19.98%	17.99%	13.72%
	Value Weighted Analysis			
$p < 0.01$	17.39%	16.63%	17.02%	22.47%
$p < 0.05$	28.07%	28.84%	29.49%	28.40%
N=1,006				
Panel B: Leveraged ETFs				
	Equal Weighted Analysis			
$p < 0.01$	27.89%	30.61%	33.33%	21.77%
$p < 0.05$	44.22%	42.18%	42.18%	30.61%
	Value Weighted Analysis			
$p < 0.01$	39.82%	50.16%	47.47%	35.92%
$p < 0.05$	58.86%	54.06%	54.05%	48.15%
N=147				

Table OA16: Percentile breaks for coefficient estimates of β_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 β_i^{SSI}

	Percentile									
	10^{th}	20^{th}	30^{th}	40^{th}	50^{th}	60^{th}	70^{th}	80^{th}	90^{th}	Observations
Unlevered Equity	-0.26	-0.18	-0.12	-0.08	-0.04	0.01	0.06	0.13	0.24	637
Unlevered Fixed Income	-0.31	-0.21	-0.14	-0.09	-0.04	-0.02	0.06	0.15	0.22	145
Unlevered Commodity	-0.27	-0.21	-0.18	-0.12	-0.06	-0.01	0.05	0.10	0.19	55
Levered	-0.58	-0.39	-0.22	-0.12	-0.03	0.04	0.19	0.31	0.52	151

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
Unlevered Equity	0.03	0.05	0.07	0.10	0.13	0.16	0.20	0.25	0.33	637
Unlevered Fixed Income	0.03	0.05	0.08	0.11	0.14	0.17	0.22	0.29	0.35	145
Unlevered Commodity	0.03	0.06	0.08	0.11	0.13	0.19	0.21	0.24	0.30	55
Levered	0.03	0.08	0.14	0.21	0.29	0.36	0.46	0.56	0.71	151

Table OA17: 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	25.49%	74.51%	51
Short	87.76%	12.24%	49

	Value Weighted Analysis		
Leveraged ETF Type	% Negative Coefficient	% Positive Coefficient	N
Long	15.99%	84.01%	51
Short	95.24%	4.76%	49

Table OA18: Contemporaneous effects of SSI on market returns and the relation between SSI and potential investor rebalancing. In Panel A, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the contemporaneous Speculation Sentiment Index value: $r_t = a + \beta SSI_t^S + \epsilon_t$ in which r_t is the index monthly return, SSI_t is the contemporaneous Speculation Sentiment Index value, β is the estimated coefficient on SSI_t, and ϵ_t is the error term. In Panel B, Regression (1) regresses the Speculation Sentiment Index value on the pseudo investor rebalancing value: $SSI_t = a + \beta rebal_t + \epsilon_t$ in which SSI_t is the Speculation Sentiment Index value, $rebal_t$ is the pseudo investor rebalancing value, β is the estimated coefficient on $rebal_t$, and ϵ_t is the error term. In Panel C, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged Speculation Sentiment Index value and the lagged pseudo investor rebalancing value: $r_t = a + \beta SSI_{t-1} + \gamma rebal_{t-1} + \epsilon_t$ in which r_t is the index monthly return, SSI_{t-1} is the lagged Speculation Sentiment Index value, β is the estimated coefficient on SSI_{t-1}, $rebal_{t-1}$ is the lagged pseudo investor rebalancing value, γ is the estimated coefficient on $rebal_{t-1}$, and ϵ_t is the error term. The sample runs from December 2006 through December 2016. All variables, except for returns, are standardized.

Panel A: Contemporary Effect

	(1) EW CRSP r_t	(2) VW CRSP r_t	(3) S&P 500 CRSP r_t
SSI_t	-3.21***	-2.66***	-2.49***
	(8.40)	(7.86)	(7.53)
R^2	0.37	0.34	0.32
Adj R^2	0.37	0.34	0.32
N	121	121	121

Panel B: SSI and Rebalancing

	(1) SSI_t
$rebal_t$	0.58***
	7.95
R^2	0.35
Adj R^2	0.34
N	121

Panel C: Return Predictability

	(1) EW CRSP r_t	(2) VW CRSP r_t	(3) S&P 500 CRSP r_t
SSI_{t-1}	-1.67***	-1.48***	-1.30***
	(3.00)	(3.00)	(2.72)
$rebal_{t-1}$	-0.37	0.10	0.12
	(0.67)	0.20	0.24
R^2	0.13	0.10	0.08
Adj R^2	0.12	0.08	0.06
N	121	121	121

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

Table OA19: Return predictability and *SSI* institutional ownership. In Panel A, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, 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 ETF, β is the estimated coefficient on net_{t-1}, and ϵ_t is the error term. In Panel B, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged net difference in institutional ownership for leveraged-long and leveraged-short ETFs: $r_t = a + \beta inst_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $inst_{t-1}$ is the lagged net difference in institutional ownership for leveraged-long and leveraged-short ETF, β is the estimated coefficient on $ints_{t-1}$, and ϵ_t is the error term. In Panel C, Regressions (1)-(3) regresses the CRSP equal weighted, CRSP value weighted, or S&P 500 index monthly returns on the lagged net difference in share changes for leveraged-long and leveraged-short ETFs minus lagged net difference in institutional ownership for leveraged-long and leveraged-short ETFs: $r_t = a + \beta netMINUSinst_{t-1} + \epsilon_t$ in which r_t is the index monthly return, $netMINUSinst_{t-1}$ is the lagged net difference in share changes for leveraged-long and leveraged-short ETFs minus lagged net difference in institutional ownership for leveraged-long and leveraged-short ETFs, β is the estimated coefficient on $netMINUSinst_{t-1}$, and ϵ_t is the error term. The sample runs from May 2010 through December 2018. All variables, except for returns, are standardized.

	Panel A: *net*		
	(1) EW CRSP r_t	(2) VW CRSP r_t	(3) S&P 500 r_t
net_{t-1}	-1.56**	-1.22*	-1.09*
	(2.26)	(1.89)	(1.72)
R^2	0.05	0.03	0.03
Adj R^2	0.04	0.02	0.02
N	104	104	104

	Panel B: *inst*		
	EW CRSP r_t	VW CRSP r_t	S&P 500 r_t
$inst_{t-1}$	0.94**	0.86**	0.79**
	2.60	2.54	2.36
R^2	0.06	0.06	0.05
Adj R^2	0.05	0.05	0.04
N	104	104	104

	Panel C: $netMINUSinst$		
	EW CRSP r_t	VW CRSP r_t	S&P 500 r_t
$netMINUSinst_{t-1}$	-1.04***	-0.91***	-0.83**
	(2.81)	(2.66)	(2.46)
R^2	0.07	0.06	0.06
Adj R^2	0.06	0.06	0.05
N	104	104	104

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table OA20: Correlation of SSI measures based on data from Bloomberg, ProShares, Compustat, and CRSP. The daily, weekly, monthly, and quarterly series are formulated using data from each respective data source and pairwise correlations are computed.

	Daily			
Bloomberg	1.00			
ProShares	0.75	1.00		
Compustat	0.02	0.01	1.00	
CRSP	0.01	0.00	0.04	1.00
	Weekly			
Bloomberg	1.00			
ProShares	0.94	1.00		
Compustat	0.64	0.60	1.00	
CRSP	0.11	0.06	0.29	1.00
	Monthly			
Bloomberg	1.00			
ProShares	0.99	1.00		
Compustat	0.88	0.87	1.00	
CRSP	0.86	0.85	0.99	1.00
	Quarterly			
Bloomberg	1.00			
ProShares	1.00	1.00		
Compustat	0.96	0.96	1.00	
CRSP	0.96	0.96	1.00	1.00

Figure OA1: 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 β_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.