Synthetic Shorting with ETFs*

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This Draft: December 2016

Abstract

We provide novel evidence that arbitrageurs use exchange-traded funds (ETFs) as an avenue to circumvent short-sale constraints at the stock level. Using a large sample of U.S. equity ETF holdings, we document that shorting activity on ETFs rises with the difficulty of shorting the underlying stocks. Stocks that are heavily shorted via their holding ETFs underperform those lightly shorted by 94 basis points per month. The return predictability of ETF short selling on individual stocks is distinct from stock-level shorting measures, and is concentrated among stocks that face the most severe arbitrage constraints. Across a broad set of capital market anomalies, we find that anomaly returns are significantly attenuated when ETF ownership is high. Our evidence suggests that ETFs contribute to a more informationally efficient market by allowing arbitrageurs to target overpriced stocks that are otherwise difficult to short.

JEL classification: G12, G14

Keywords: ETFs, Short Selling, Equity Lending, Limits to Arbitrage, Market Efficiency

*We are grateful to Nicholas Barberis, Utpal Bhattacharya, Paul Gao, Harrison Hong, Alexander Ljungqvist (discussant), Pengfei Li (discussant), Abhiroop Mukherjee, Rik Sen, Clemens Sialm, K.C. John Wei, Jialin Yu, Chu Zhang and the seminar participants at the PhD forum of 29th Australasian Finance and Banking Conference for useful comments.

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"If you are going short, you are looking for liquidity."

- James Ross, State Street Global Advisors, *The Institutional ETF Toolbox, p.68*

The market for exchange-traded funds (ETFs) has been growing exponentially during the recent decade. At the end of 2015, there were 1,594 ETFs managing $2.1 trillion in the U.S. market, up from 201 ETFs managing $296 billion in 2005[1]. Most ETFs are structured as open-ended investment companies and are traded on stock exchanges intraday. Usually, an ETF tracks a particular stock or bond index by physically holding all constituent securities (or a sample of them) as its underlying assets[2]. As an investment vehicle, ETFs provide investors with a cost-efficient way to passively manage their assets. This cost reduction derives in large part from the fact that by pooling securities together, ETFs are able to reduce asymmetric information, lower transaction costs, and enhance liquidity (Madhavan (2014)). At the same time, academics and practitioners share their misgivings that the rise of ETFs increases underlying stock volatility, propagates shocks across their constituents (Ben-David, Franzoni, and Moussawi (2012); Da and Shive (2012)), and may have contributed to the Flash Crash of May 2010 (Madhavan (2012)).

An important aspect of ETFs that has been largely unexamined is their short selling activities. Just as other exchange-traded securities, ETFs can be sold short as well. Many traders use ETF short sales to hedge market or sector exposures and to manage risks (Gastineau (2010)). Other market participants argue that ETFs provide a more cost-effective avenue to gain negative exposures to certain underlying stocks[3]. While we detail the advantages of ETF short selling in the next section, it is evident that the short selling activities of ETF products are highly active.[4] Figure 1 shows the aggregate level of ETF short interest compared to the size of the ETF market in our sample. The dollar value of ETF short selling exceeded $80 billion multiple times in our sample period, and it represents 10–40%

[1] "2016 Investment Company Yearbook" https://www.ici.org/pdf/2016_factbook.pdf

[2] A small fraction of ETFs track their indices using swaps or other derivatives. They are out of the scope of our research in this paper.

[3] For example, see Eurex Group: "The short of shorting ETFs: The art of create to lend". http://www.eurexchange.com/exchange-en/about-us/news/thought-leadership-kaminsky-sokolovski-art-of-create-to-lend/951206

[4] During our sample period, 3.9% of equity ETFs have average short interest ratios above 20% and 10.64% have average short interest ratios above 10% of shares outstanding. For stocks, the corresponding figures are 0.92% and 5.46%, respectively.

of their corresponding ETFs' market capitalization. For comparison, the dollar amount of short interests of US equity on average is about 3% of their market capitalization. To the best of our knowledge, this paper is the first in the literature to systematically examine the scope, the determinants, and the implications of ETF short selling activities.

What drives ETF short selling activities? While straightforward sector-betting is one important contributor, we argue that ETF short selling alleviates short-sale constraints for certain stocks that are otherwise hard to borrow. In a sense, ETF short selling and the short selling of its constituents are partial substitutes. In normal times, traders can gain negative exposure to the market, a sector, or a specific subgroup of stocks more effectively via shorting ETFs. In extreme cases, traders can put up a shorting position for a specific stock by shorting the ETF and hedging other stock constituents. Accounts by market participants collaborate this conjecture: For example, *MarketWatch* reports that "One hedge fund with which Weinhoffer is familiar was struggling to borrow a stock and instead shorted an ETF that contained the shares, ... The manager then took long positions in all the other stocks in the ETF"[5]. In this paper, we term such combination trading strategy *synthetic shorting with ETFs* and we hypothesize that such a strategy is an important driver of ETF short selling activities.

Our empirical analysis suggests that the ETF short ratio is high when the demand for shorting the underlying stocks is high, when the lending supply of underlying shares is low, and when the cost of shorting the underlying stocks is high. When we proxy the level of short-sale constraint of constituent stocks using idiosyncratic volatility and Amihud (2002) illiquidity measure, we find that ETF short selling is more active when the underlying stocks are less liquid or more volatile.[6] We also use the Regulation SHO Pilot Program as a quasi-natural experiment, since it reduces the friction in shorting stocks directly. ETFs that have a higher fraction of constituents included in the Pilot Program experience a decrease in short selling activities compared to control-group ETFs after the inception of the Pilot Program. Put together, these results lend credence to our claim that market participants use ETF

[5] "More equity hedge funds turn to shorting ETFs" http://www.marketwatch.com/story/more-equity-hedge-funds-are-shorting-etfs-rather-than-stocks

[6] In sharp constrast, short selling on stocks is more active when stock is more liquid and less volatile. See Table 2 of Hong, Li, Ni, Scheinkman, and Yan (2015) for evidence.

short selling to effectively short underlying stocks, especially when the underlying stocks are difficult to short.

If market participants are actively using ETF shorting as an avenue to circumvent shorting constraints, does ETF short selling have predictive power over the future return of the ETFs and their underlying stocks? The answer is yes. We find a significant predictive relation at the ETF level and an even stronger relation at the stock level. The higher the ETF short ratio, the lower the future ETF and stock returns. This is consistent with our understanding of why traders short ETFs: While some of the traders have a bearish view on the ETF as a whole, many of them effectively use ETFs to short a subset of constituent stocks. A short position in ETF and long positions in some constituents is equivalent to a "synthetic" short position in other constituent stocks of the ETF. Therefore, one would be able to more reliably glean information from ETF shorting activities by aggregating ETF short interests to the stock level. Stocks that lie in the intersection of several highly shorted ETFs are more likely to be the true targets of ETF short bets.

One of the key innovations of our paper is that we construct a short ratio for each stock from the short interests of all ETFs holding that particular stock. This measure, which we call the *ETF-based short ratio*, reflects the collective shorting demand of that stock through short selling ETFs. We find that the ETF-based short ratio strongly forecasts future returns, even after controlling for stock-level shorting activities. An equal-weighted, monthly rebalanced, long-short strategy that sells the decile of stocks that are most heavily shorted via their holding ETFs and buys the decile of stocks that are the most lightly shorted earns 94 basis points per month (t-stat = 3.21) after adjusting for the Carhart (1997) four factors. A similar strategy with value weights earns an abnormal return of 77 bp per month (t-stat = 2.47). Our strategy return is virtually unchanged after adjusting for the stock lending fees for both the long and short legs, suggesting that the abnormal return obtained by this strategy is not merely an artifact of the high lending cost of heavily shorted stocks. Rather, there is some degree of market inefficiency such that the information contained in the ETF shorting market is not fully incorporated by the stock market.

When we double-sort stocks first by proxies of short-sale constraints and then by their

ETF-based short ratio, we find that the return predictability of the ETF-based short ratio is concentrated within the group of stocks that are lightly-shorted at stock-level and are subject to greater impediments to arbitrage. Our proxies for arbitrage frictions include institutional ownership, lendable supply and lending fee from Markit, idiosyncratic volatility, and turnover. For example, the Carhart (1997) 4-factor alpha based on the ETF short ratio is a monthly 1.20% (t=3.59) in the tercile with lowest institutional ownership, while it is only 0.25% (t=1.51) for stocks with high institutional ownership. In the same vein, the predictive power of the ETF-based short ratio is more pronounced for stocks that have a low lending supply, high borrowing cost, high idiosyncratic volatility, and low trading volume. This is strong evidence that ETF short selling works as an alleviation mechanism for hard-to-short stocks.

In a Fama–MacBeth regression setting, we confirm that the ETF-based short ratio has additional explanatory power for future stock returns when we control for the stock-level shorting variables. Consistent with the literature, we find that both shorting demand and cost measures at the stock level strongly forecast future returns. Stocks that have a high short interest ratio or high shorting costs underperform other stocks. Importantly, the predictive power of the ETF-based short ratio is comparable in economic significance to these well-studied stock-level shorting activity measures. For example, a one standard deviation increase in ETF-based short ratio is associated with a lower future monthly return of 15 basis points, while a one standard deviation increase in stock short ratio decreases future return by 20 basis points.

Our multiple regression results suggest that ETF short selling contains negative information about its consitituent stocks that are not fully captured by stock-level shorting activities. This is to be expected when arbitrageurs face binding supply constraints in the equity lending market and stocks' short interests become unable to fully reveal the true demand for shorting (Chen, Hong, and Stein (2002)). When we interact the ETF-based short ratio with variables that indicate tightening stock lending market conditions, we find that the negative return predictability of the ETF-based short ratio is amplified within the groups of stocks facing the most severe short-sale constraints. For example, while the ETF-based short ratio generates an insignificant monthly return spread of 24 bp among unconstrained stocks, the spread increases to 122 bp for the stocks in the lowest quintile of institutional ownership. We obtain similar results when using lendable supply, shorting fee, utilization ratio, and the existence of an exchange-traded put option as proxies for short-sale constraints.

Our final set of tests explore the implication of ETF short selling on capital market anomalies. Since many argue that short sale constraints are important drivers of anomalies and ETF short selling alleviates such constraints, we expect that stocks with high ETF ownership would be priced more efficiently. ETF ownership may lead to a more efficient stock market through two potential channels: The first channel is the well-documented stock lending channel, as ETFs are among the main contributors to the equity lending market. By relaxing supply constraints in the equity lending market, ETFs help correct overvaluation. In this paper, we emphasize a second channel that ETF short selling directly contributes to market efficiency: ETFs allow arbitrageurs to establish synthetic short positions on stocks that are otherwise difficult to short.

To disentangle these two channels, we create portfolios with large spreads in ETF ownership but with similar levels of stock lending costs. We then examine the return spread based on anomaly characteristics in stocks with different levels of ETF ownership. Across 10 well-studied capital market anomalies, six have significantly attenuated return spreads when ETF ownership is high as compared to when ETF ownership is low. The evidence supports our conclusion that ETFs contribute to a more informationally efficient stock market, at least with respect to correcting overvaluation induced by short-sale constraints.

This paper contributes to several strands of the literature. First, it extends a large literature that exmaines the information content of the short interest ratio. Numerous studies document that a stock's short ratio is a strong contrarian predictor of future returns.[7] The common interpretation is that when investors have divergence of opinions and short-sale constraints are binding, the value of the stocks will only reflect the optimists' view, hence they are more likely to be overvalued (Miller (1977)).[8] Short interest is a proxy for the

[7]See for example, Figlewski (1981), Dechow, Hutton, Meulbroek, and Sloan (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), Boehme, Danielsen, and Sorescu (2006), Cohen, Diether, and Malloy (2007), among others.

[8]A large literature explores the effects of heterogeneous beliefs on equilibrium asset prices when short-

amount of negative information excluded from the market price (Figlewski (1981)). Different from the previous literature, our paper considers the information contained in ETF short interest for future stock returns. As pointed out by Chen, Hong, and Stein (2002), short interest could be a poor proxy for the degree of overvaluation, as variation across stocks in short interest could be driven by both supply and demand for short selling. A stock with low or zero short interest could be extremely difficult to short, which should translate into more overpricing, not less. Consistent with this intuition, we document that the ETF-based short ratio contains incremental predictability for stock returns even after controlling for the stock's own short ratio, especially among those most constrained by the availability of lendable shares.

A second related literature documents that frictions in the equity lending market is the key impediment to informational arbitrage and causes the persistence of several well-known asset pricing anomalies. Using institutional ownership as a proxy for lendable supply, Nagel (2005) finds that returns to a set of anomalies are concentrated among stocks with low institutional ownership. Hirshleifer, Teoh, and Yu (2011) document similar findings for the accrual anomaly. Using investor sentiment as a signal of overpricing, Stambaugh, Yu, and Yuan (2012) document that returns to 11 anomalies largely come from the short leg and are more pronounced following a high sentiment period, which suggests that impediments to short selling play a key role in explaining anomalies. With high-quality security lending data from Markit becoming available, several recent papers examine the effect of actual lendable supply (Beneish, Lee, and Nichols (2015)) or borrowing costs (Drechsler and Drechsler (2014)) on anomalies. Our paper is related to these studies in the sense that we document that ETF short selling works as an alleviation mechanism for stock-level short-sale constraints and attenuates cross-sectional mispricing, especially for stocks that are costly to short in the first place.

Our paper also contributes to the emerging literature that examines the effect of ETF investing on the stock market. Several papers document the dark side of ETF investing as non-fundamental demand shocks might transmit from the ETFs to their underlying se-

selling is constrained. e.g. Harrison and Kreps (1978), Scheinkman and Xiong (2003), Hong, Scheinkman, and Xiong (2006) and Duffie, Garleanu, and Pedersen (2002).

curities. Theoretically, Bhattacharya and O'Hara (2015) show that information feedback between ETFs and underlyings could cause propagation of shocks unrelated to fundamentals and market instability, especially for ETFs track hard-to-trade assets. Empirically, Ben-David, Franzoni, and Moussawi (2012) provide evidence that arbitrage activities between ETFs and their underlying stocks increase the volatility of their underlying assets. Da and Shive (2012) document that higher ETF trading activity leads to excess return comovement among the constituent stocks. Israeli, Lee, and Sridharan (2015) examine the effect of ETFs on the underlying assets from an information perspective. They find that an increase in ETF ownership is accompanied by a decline in pricing efficiency for the underlying component securities. Using data from a large German brokerage, Bhattacharya, Loos, Meyer, and Hackethal (2014) find that individuals investing in passive ETFs do not improve their portfolio performance, due to poor ETF timing and selection. On the bright side, Boehmer and Boehmer (2003) find the initiation of three ETFs increased liquidity and market quality. Glosten, Nallareddy, and Zou (2015) document that ETF trading increases informational efficiency for stocks with weak information environments. Dannhauser (2016) finds that corporate bond ETFs have a long-term positive valuation effect in its underlyings. By highlighting that one benefit of ETFs is to facilitate short selling on overvalued underlying stocks, our paper contributes to the growing debate on the consequences of index investing on the stock market.

The rest of this paper is organized as follows. Section 1 details the institutional background of ETF shorting selling and compares it to stock-level short selling. Section 2 describes the various data we used in the analysis and presents summary statistics. Section 3 examines the cross-sectional determinants of ETF short interest and the return predictability of ETF short interest at the ETF level. In Section 4, we examine the predictability of ETF short selling for cross-sectional stock returns. Section 5 examines the consequences of rising ETF ownership on capital market anomalies. Section 6 concludes.

1 Institutional Background

ETF short selling is prevalent despite its lack of attention from media and common investors. Leading practitioner books, such as Gastineau (2010), claim that "'[s]hort selling in the ETF marketplace is a large part of ETF trading volume, and ETF short positions are often so large relative to total ETF shares outstanding". Indeed, the most heavily shorted ETFs often have short ratios that are higher than 100%[9]. Moreover, some traders use short positions in an ETF and long positions in all but few of its constituent stocks to establish a "synthetic" short position in a few target stocks, because the stocks in question are difficult to borrow. How is ETF short selling different from stock short selling? What are the advantages of shorting ETFs relative to stocks? In this section, we provide some institutional background to this under-studied trading practice.

1.1 The "Create-to-Lend" Mechanism

When a trader attempts to short sell ETF shares, there are two routes to take: She can ask her broker to borrow ETF shares directly from institutional investors or brokerage firms with lending programs. Alternatively, the broker can borrow or purchase[10] the underlying securities, turn them to an Authorized Participant (AP), then let the AP create new units of the ETF so that the broker can lend these shares to the short seller. This mechanism uses the creation–redemption feature of ETFs and is dubbed "create-to-lend." In creating new units, APs sometimes only need to deliver a representative sample of all stocks that the ETF holds. Although it is unclear how much deviation is allowed between the submitted creation basket of securities and the actual ETF underlying holdings, this mechanism potentially opens the door for easier access to shorting the ETF as opposed to shorting specific hard-to-borrow assets.

Some empirical evidence suggests the create-to-lend mechanism is an important avenue for ETF short selling. For example, the average total short interest of the S&P500 Spider ETF is greater than the average lendable supply, suggesting that some fraction of short sell-

[9]Many industry websites, such as https://www.etfchannel.com/type/most-shorted-etfs/, continuously track the most heavily shorted ETFs.

[10]The broker would have to hedge her position by short selling the securities herself.

ing is borrowed through creation (Karmaziene and Sokolovski (2015)). Since ETF providers are often active participants in securities lending markets, they are usually able to locate underlying securities for borrowing. Asquith and Meulbroek (1995) and Danielsen and Sorescu (2001) cite several reasons why "ordinary" investors might face higher transaction costs in trying to establish short positions than brokers. The differential search costs in lending markets between prime brokers and traders is likely an important advantage for ETF short selling.

The create-to-lend mechanism also makes ETF short selling difficult to be squeezed. In order to short squeeze an ETF, one must not only buy the shares of the ETF, but also deplete the lending supply of underlying stocks. Otherwise, short sellers could simply create additional ETF shares to answer the call. ETF short squeezes are "virtually unknown" (Gastineau (2010)).

1.2 Other Advantages of ETF Short Selling

There are several important advantages for short selling via ETFs. First of all, ETF securities are usually more liquid than their underlying individual stocks. They are traded more frequently, have smaller bid-ask spread, and have shorter days-to-cover. Hong, Li, Ni, Scheinkman, and Yan (2015) argue that days-to-cover (DTC), defined as open short interest divided by average daily trading volume, is an important measure for the crowdness of short sale trades. In a sense, it captures how fast arbitrageurs are able to exit their short trades. In our sample, the average days-to-cover for ETFs is about 2 days (Table 1). This is significantly shorter than the average DTC for stocks (6.5 days in our sample period). Even for the ETFs in the highest short-ratio quintile, the average DTC is a little longer than 6 days (the number is 19 days for most shorted quintile of stocks). This means that short sellers would be able to cover their positions in reasonable speed and at reasonable costs should the market conditions turn against them. The short days-to-cover is an attractive feature for ETF short selling especially when short trades are getting crowded in the recent decade (Hanson and Sunderam (2014)).

Secondly, ETFs are also more lightly regulated in terms of short selling than using equities. Unlike stocks, ETFs have never been subject to an "uptick" rule. The uptick rule dictates that a short order must be placed above the last transaction price, or the "uptick." This rule has been shown to impede short selling activities (Alexander and Peterson (2008); Diether, Lee, and Werner (2009a)). The fact that ETFs are not subject to the uptick rule allows traders to implement more flexible trading strategies using ETFs to form synthetic short positions on the constituent stocks. During the 2008 Financial Crisis, the Securities and Exchange Commission (SEC) temporarily banned short sales in 797 financial stocks, but this ban list did not include any ETFs. Many market participants, as suggested by Karmaziene and Sokolovski (2015), circumvented the ban by short selling financial-sector ETFs instead.

Finally, ETF shorting provides some secrecy in a shorting environment that is increasingly crowded. It is difficult to detect the true shorting target from a synthetic strategy involving shorting an ETF. Such a strategy is advantageous both for avoiding a short squeeze and for minimizing the costs of borrowing.

1.3 Synthetic Shorting with ETFs

Given the features of ETF short selling discussed in the previous subsections, we argue that some short sellers would use ETFs to create "synthetic" short positions instead of directly shorting individual names. In order to do so, the trader would short the ETF that contains the target stock(s), and enter long positions in all of the ETF's underlying stocks except for the target(s). If the ETF is value weighted, a buy-and-hold synthetic shorting strategy would inversely track the performance of the target stock(s).

In evaluating the synthetic shorting strategy against direct shorting, the short seller must trade off the benefits and costs of shorting via ETFs. The most direct cost is the lending fee for borrowing ETF shares. This cost is partially offset by the management expense of the ETFs, which average about 44 basis points per annum. Another important source of costs are the transaction costs of entering the long positions of the synthetic shorting strategy. Since an ETF typically has hundreds of underlying stocks, establishing long positions in all but a few stocks can incur a non-trivial amount of transaction costs for the trader.[11] On the other hand, if the short seller does not fully hedge, she bears the risk of price movement of the ETF itself. Should the ETF unexpectedly appreciate, the short seller would suffer losses.

For a sub-period of our sample, we are able to obtain the actual lending costs for both ETFs and their underlying stocks and conduct back-of-envelope calculations[12]. For ETFs in our sample, their average lending fee is about 2.3 percentage points. Subtracting the average management fee of 44 basis points, the effective shorting cost for ETFs is roughly 1.8 percentage points. Meanwhile, the weighted-average lending fee for the underlying stocks of ETFs is 56 basis points. It seems that the consideration of using ETF for short selling is not completely fee-related. On the other hand, stocks' lending fees are positively skewed, and for each ETF, the most expensive-to-borrow decile of constituent stocks demand significantly higher lending fees. Those expensive-to-borrow stocks on average have a lending fee of 4.2 percentage points. It is possible that arbitrageurs find it more attractive to use synthetic shorting strategies with ETFs when short selling those stocks. In other words, the shorting demand of stocks "spill over" to the ETF shorting market when the short-sale constraints of individual stocks are binding. This key intuition is verified in the data and drives the core prediction of this paper, which is that short selling activities in ETFs have predictive power on future stock returns.

2 Data and Summary Statistics

2.1 Sample Construction

Our sample contains all U.S. domestic equity ETFs that physically replicate their indices.[13] To obtain a list of such ETFs, we start by intersecting all funds in the CRSP mutual fund

[11]A recent paper by Frazzini, Israel, and Moskowitz (2012) estimate that the actual trading costs faced by real-world arbitrageurs are an order of magnitude smaller than previous studies suggest. The mean transaction costs are about 11 bp and 21 bp in large cap and small cap stocks, respectively.

[12]Markit started providing lending costs quoted in percentage points from 2007. The variable is only available when the security in question is shorted by a Markit client hedge fund.

[13]Most ETFs in the U.S tend to physically replicate their underlying index. The Investment Act of 1940 requires ETFs to hold 80% of their assets in securities matching the fund's name.

database with ETF designation (etf_flag=F) with securities in CRSP monthly stock file with share code of 73. We then manually filter out non-domestic or non-equity ETFs by parsing the fund name[14]. To ensure that the ETFs in our sample physically replicate the indices instead of using derivatives, we further require that they have holdings information for at least 20 stocks from the Thomson Reuters Mutual Fund holdings database (S12). Our sample contains 343 ETFs from 2002 to 2013[15].

Monthly short interest series of both ETFs and stocks comes from Compustat. Each month, U.S. exchanges report the level of short interest on the 15th of each month[16]. To form the short interest ratio (SR), we normalize short interest by total shares outstanding from CRSP. We obtain stock lending supply (lendable shares divided by shares outstanding), the stock lending utilization ratio,[17] and stock lending fees from the Markit Securities Finance (formerly Data Explorer) database. Markit provides two variables that proxy for stock lending cost. The first variable, *SAF*, is the simple average fees of stock borrowing transactions from hedge funds in a given security, which is the difference between the risk-free rate and the rebate rate. SAF is only available for a stock to the extent that the stock is being shorted by a Markit client hedge fund. The second variable, *DCBS* (Daily Cost of Borrowing Score), which covers all stocks, is a score from 1 to 10 created by Markit using their proprietary information. This score is intended to capture the cost of borrowing the stock: A score of 1 represents the cheapest to short and 10 represents the most difficult. The SAF variable is available after November 2006, while the DCBS variable is available after October 2003.[18]

We use standard control variables in our empirical analysis. *Size* (LnME) is defined as the natural logarithm of market capitalization at the end of June in each year. *Book-to-market ratio* (LnBM) equals to the most recent fiscal year-end report of book value divided by the

[14]We search for terms in fund names such as "International", "World", "Ex-US", "Treasury", or "Municipal".

[15]Glosten, Nallareddy, and Zou (2015) reports a sample of 447 ETFs between 2004 to 2013. The discrepancy is mainly attributed to our requirement for ETFs to have short interest data from Compustat.

[16]After September 2007, short interest data are reported twice each month and we keep the last report of each month. Our results are not materially affected if we use mid-month report throughout our sample.

[17]Defined as shares on loan divided by lendable shares, both from Markit survey participants.

[18]See Saffi and Sigurdsson (2011) and Beneish, Lee, and Nichols (2015) for a detailed account of Markit equity lending database.

market capitalization at the end of calendar year t-1. Book value equals the value of common stockholders' equity, plus deferred taxes and investment tax credits, minus the book value of preferred stock. *Momentum* (Mom) is defined as the cumulative holding-period return from month t-12 and t-2. We follow the literature by skipping the most recent month's return when constructing the *Momentum* variable. The *short term reversal measure* (REV) is the prior month's return. *Turnover* is the daily trading volume over shares outstanding, averaged within a month. Since the dealer nature of the NASDAQ market makes its turnover difficult to compare with the turnover observed on NYSE and AMEX, we follow Gao and Ritter (2010) by adjusting trading volume for NASDAQ stocks.[19] *Institutional ownership* (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by total shares outstanding. *Idiosyncratic volatility* (IVOL) is the standard deviation of the residuals from the regression of daily stock excess returns on Fama and French (1993) 3-factor returns within a month (Ang, Hodrick, Xing, and Zhang (2006)). Firm-level variables are obtained from Compustat annual files. ETF and stock returns, trading volume, and market capitalization are from the CRSP monthly security file. Institutional ownership data of stocks are available from Thomson Reuters (formerly CDA/Spectrum) Institutional Holdings database (13F). Option data are from Option Metrics.

2.2 ETF Characteristics

ETFs are characterized by both ETF-level variables and the weighted-average characteristics of their underlying stocks. At the ETF level, our focus is the short ratio of the ETF, defined as open short interests divided by shares outstanding of the ETF. We are also interested in an ETF's market capitalization (CRSP Price * Shares Outstanding), turnover ratio (CRSP Volume/Shares Outstanding), past 12-month return, return volatility, and expense ratio. As for the underlying stocks, we aggregate the stock idiosyncratic volatility, market capitalization, book-to-market ratio, short ratio, institutional ownership, lendable supply, lending utilization, lending cost (DCBS score), and Amihud (2002) illiquidity measure by

[19] Specifically, we divide NASDAQ volume by 2.0, 1.8, 1.6, and 1.0 for the periods before February 2001, between February 2001 and December 2001, between January 2002 and December 2003, and after January 2004, respectively.

using a weighted average of these characteristics at the ETF level.

Panel A of Table 1 shows the summary statistics of ETF characteristics. Since we are interested in the short selling activities on ETFs, we further sort ETFs into quintile groups based on ETF short ratio and summarize the average characteristics for each group. The results are shown in Panel B of Table 1. One thing to note is that ETFs with the highest short ratio are significantly larger than ETFs with lowest short ratio. This in part explains why the value-weighted short ratio of ETFs (about 15%) is much larger than the simple average ETF short ratio (about 4%).

2.3 ETF-Based Short Ratio for Stocks

The key innovation of our paper is to aggregate the information content in ETF short selling activities to the stock-level and construct a variable that we call the "*ETF-based short ratio*" (or ETF-based SR). Intuitively, if a stock is overvalued but also difficult to short sell directly, traders can form "synthetic" short portfolios by combining short positions in ETFs and long positions in other ETF constituent stocks. However, since such a synthetic portfolio can be constructed in multiple ways if many ETFs contain the target stock, the negative information content is gleaned most efficiently by examining stocks that lie in the intersection of several heavily shorted ETFs.

To this end, we first calculate the total value of short interest for each ETF-month, and we attribute short interest to its constituent stocks proportional to the value of stocks held by the ETF. For Stock i during month t, the dollar value of short selling via ETF e equals

$$short\_value_{i,e,t} = short\_interest_{e,t} * P_{e,t} * \frac{shares\_held_{i,e,t} * P_{i,t}}{\sum_{j \in J_e} shares\_held_{j,e,t} * P_{j,t}} \tag{1}$$

where $P_{e,t}$ denotes the per share price of ETF e, $P_{i,t}$ denotes the per share price of Stock i, J_e denotes the set of stocks held by ETF e, and $shares\_held_{i,e,t}$ denotes the number of Stock i's shares held by ETF e at last quater end t.

Then, for Stock i, we aggregate the dollar value of short selling across all ETFs that hold

Stock i during month t, and scale it by the total dollar value of Stock i held by ETFs:

$$\text{ETF-based } SR = \frac{\sum_{e \in E_i} short\_value_{i,e,t}}{\sum_{e \in E_i} shares\_held_{i,e,t} * P_{i,t}} \tag{2}$$

where E_i is the set of ETFs that hold Stock i.

Figure 2 shows the time-series of the ETF-based short ratio for an average stock and compares it to the ratio for direct short selling. The figure shows two important considerations: First, the ETF-based short ratio is highly correlated with the stock short ratio; there is a significant spike during the recent financial crisis. Second, the ETF-based short ratio is considerably higher than the direct short ratio. For the majority of our sample, the ETF-based short ratio is above 10% while the direct short ratio is between 4–5%. This reflects the fact that a share of the same stock is more intensively shorted when it is held via an ETF than when it is directly held.

2.4 Stock Characteristics

Table 2 presents the summary statistics of the stock characteristics. Panel A reports the time-series average of the cross-sectional means and standard deviations of the variables for the full sample. The average short interest ratio (SR) in our sample period is 4.16%. The median SR is around 2.76%. This means that while most stocks have low shorting activity, a small fraction of stocks are heavily shorted. Our key variable of interest, the ETF-based short ratio (ETF_sr), has a mean of 15.97% and large cross-sectional variation, with a standard deviation of 15.8%. The median annualized lending fee SAF is small: only 28 bp. However, the distribution of the lending fee is highly skewed to the right, with the 75 percentile less than the mean level. This is consistent with the literature that although most stocks are easy to borrow, a small fraction of stocks with low lending supply have high shorting costs (D'avolio (2002)). And these stocks are the most prone to overpricing induced by short-selling constraints. The average lendable supply is 13.80% of shares outstanding, with a standard deviation of 8.29%. The remaining summary statistics are well known and do not require additional discussion.

Panel B reports the pairwise rank correlation among our variables where they overlap.

As we can see, the correlation between the stock level short ratio and the short ratio backed out from ETF holdings is moderate: only around 0.37. This means that the ETF-based short ratio contains incremental information in addition to the stock's own short interest. In our later empirical analysis, we show that the ETF-based SR predicts returns even after controlling for existing shorting demand or supply measures at the stock level. The correlation between the ETF-based SR and the lending fee SAF is 0.12, which is consistent with our hypothesis that arbitrageurs use ETFs to target hard-to-borrow stocks.

As there might be nonlinear relationship between the ETF-based SR and other stock characteristics, we further look at average stock characteristics across decile portfolios sorted on their ETF-based SR. As we can see from Panel C of Table 2, stocks with the lowest and highest ETF-based SR are, on average, much smaller, less liquid, and more volatile. More importantly, we find that these stocks are also more costly to short sell. They have higher lending fees and utilization ratios, as well as lower institutional ownership and lendable supply. Note that the U-shaped pattern between the ETF-based SR and the tightness of the lending market conditions is consistent with our argument, as ETFs may be unable to alleviate shorting constraints for stocks with an extremely low lending supply. The fact that stocks that are highly shorted via ETFs have higher-than-average short-selling costs is sufficient to show the existence of our proposed mechanism of arbitrage via ETF.

3 Determinants of ETF Short Interest

In this section, we examine the determinants of ETF short interest. To this end, we use both Fama-MacBeth cross-section regressions and a quasi-natural experiment of regulation SHO. If, as we hypothesize, ETF short selling provides an alternative mechanism for market participants to gain negative exposure to underlying stocks, we should expect ETF short interest to be affected by the tightness of the short-selling activities of the underlying stocks.

3.1 Fama–MacBeth Regressions

To understand what determines the level of short interest for ETFs, we run monthly Fama and MacBeth (1973) regressions of ETF short ratios on ETF characteristics and the characteristics of ETFs' underlying stocks. The dependent variable, ETF short ratio, is defined as the monthly short interest scaled by ETF shares outstanding. ETF characteristics include ETF turnover, the logarithm of ETF market capitalization (ME), the ETF annual expense ratio, the ETF's past 12-month return, the ETF's monthly return volatility, and the annual expense ratio of the ETF. The characteristics of underlying stocks include the logarithm of stock market capitalization (ME), the book-to-market ratio (BM), idiosyncratic volatility, and the Amihud stock illiquidity measure[20]. The final set of independent variables pertain to the short-selling activities of underlying stocks: stock short ratio, stock institutional ownership, stock lendable supply (scaled by shares outstanding), stock utilization ratio, and stock lending fee (i.e., the DCBS score between 1 and 10). All stock-related variables are value-weighted and aggregated to the ETF-month level.

Column (1) of Table 3 reports the effects of ETF and stock characteristics on the ETF short ratio. Both ETF size and ETF turnover have positive impact on the ETF short ratio, while smaller, more illiquid, and high-volatility (idiosyncratic) underlying stocks also imply higher ETF short ratios. It is worth noting that an ETF can heavily invest in small-cap stocks (low $StockLn(ME)$) while at the same time have a large market capitalization (high $ETFLn(ME)$).[21] This baseline result suggests that the ETF short ratio is high when the ETF itself is large and highly liquid and/or when the underlying stocks are difficult to short. This initial evidence hints that an ETF is an alternative channel for traders to short underlying stocks.

We then directly investigate how the short-selling activities of underlying stocks affect the short ratio of the corresponding ETFs. In Column (2) of Table 3, we include the weighted-average short ratio of underlying stocks as a regressor. There is a slightly positive, yet insignificant ($t = 0.50$), association between the average stock short ratio and the ETF

[20]We do not include stock past returns, since it is highly correlated with ETF past returns ($corr > .95$).

[21]For example, a small-cap ETF, Vanguard Small-Cap ETF(ticker: VB), is based on small-capitalization stocks, for which the underlying stocks are less liquid. However, VB holds close to \$50 billion in fund net assets and trades at very low costs.

short ratio. This is not surprising: The stock-level short ratio is an interaction result of stock shorting demand and stock lending supply. While stronger stock shorting demand should increase the shorting demand of its holding ETFs, an ample lending supply would reduce the attractiveness of indirectly shorting via ETF. To better understand the underlying mechanism that drives the ETF short ratio, one would have to disentangle the supply force of stock short selling from the demand force. This is exactly what we do in Columns (3) to (7).

In Columns (3) and (4), we respectively proxy for stock lending supply using 13F institutional ownership of underlying stocks and Markit lendable shares, both scaled by stock shares outstanding. We find that both proxies for stock supply have a negative effect on the ETF-level short ratio. A one percentage point decrease in stock institutional ownership is associated with 6.3 bp increase in ETF short ratio ($t = 3.00$), and a one percentage point decrease in stock lending supply is associated with a 15-bp increase ($t = 2.04$). In Column (5), we isolate the strength of shorting demand by using the stock lending utilization ratio (Markit reported lent shares divided by lendable shares). Our results suggest that demand for shorting underlying stocks have a significantly positive effect on the ETF short ratio. A one percentage point increase in the utilization ratio is associated with a 7.7 bp increase in the ETF short ratio ($t = 5.45$).

Finally, in Columns (6) and (7), we examine the lending fee of the ETF and of the underlying stocks on ETF short ratios. The lending fee for both ETFs and underlying stocks are proxied by the DCBS scores provided by Markit, ranging from 1 to 10. In Column (6), a one-point increase in ETF DCBS score is associated with a significant decrease of ETF short ratio and a one-point increase in the DCBS lending score of underlying stocks is associated with an increase of 1.3 bp ($t = 3.99$). In Column (7), we calculate the average lending fee for the most expensive-to-borrow stocks within an ETF's constituents and find that their average lending fee is driving the short ratio of holding ETFs ($t = 7.77$) and render the average lending fee of all consituent stocks insignificant. This is consistent with our hypothesis that ETFs short selling is particularly attractive for synthetically shorting their difficult-to-short constituents.

3.2 Evidence from a Randomized Experiment: Regulation SHO

One advantage of synthetic shorting via ETFs is that ETFs are not subject to the "uptick" rule. The uptick rule has been installed since 1938, and it requires (to state it simply) that a short sale order is placed above the last traded price, or "uptick". Previous research has shown that the uptick rule significantly impedes the abilities of traders when executing short sales (Alexander and Peterson (2008); Diether, Lee, and Werner (2009a)). Our study uses a policy change that suspended the uptick rule for a random sample of stocks to examine the causal impact of removing the uptick rule on the short-selling activities of ETFs that hold such stocks.

On July 28, 2004, the SEC announced the Regulation SHO program. It selected a pilot group that included 986 firms to test the impact of short-selling restrictions on the market and to facilitate related research.[22] These firms were selected from the Russell 3000 index. According to the SEC, firms were separated into three groups based on their respective stock exchanges (NYSE, AMEX, and NASDAQ). Within each group, firms were ranked from highest to lowest according to their average daily dollar trading volume over the past year. The SEC then selected every third stock from each of the three groups for the pilot program.

The pilot program went into effect on May 2005. Our difference-in-differences empirical design examines the short ratio of ETFs that have the most constituent stocks included in the pilot program against ETFs that have the least constituents in the program, both before and after the pilot inception date. If our argument that ETF shorting is a substitute for stock shorting holds true, we would expect that ETFs with the most constituents in the pilot program experience a more pronounced decrease in their short ratio compared to ETFs in the control group. Market participants should find it easier to directly short the underlying stocks once the uptick rule was lifted.

To test this hypothesis, we rank all available ETFs as of 2005Q1 (the last quarter-end before the inception of the SHO Pilot Program) based on the proportion of constituents that are included in the Pilot Program. Stock proportion is calculated either by number count

[22]For more complete background information regarding Regulation SHO Pilot Program and its effects, see Diether, Lee, and Werner (2009a), Grullon, Michenaud, and Weston (2015), among others.

("equal-weighted") or weighted by market capitalization ("value-weighted"). In untabulated tests, we plot the distribution of the proportion of stocks in the Pilot Program and confirm a large clustering around 0.33. To enhance the power of our test, we select the top 10 ETFs with the highest pilot proportion as "treatment" ETFs, and we select the bottom 10 ETFs as controls. As reported in Table 4, the average proportion of stocks in the Pilot Program is about 40% (equal-weighted) to 45% (value-weighted) for the treatment ETFs. For the control ETFs, the proportion is about 17% (equal-weighted) to 15% (value-weighted).

Our estimation window included the 12 months before the inception of the Pilot Program (May 2005) and the 12 months after. The dependent variable is the ETF monthly short ratio (short interest scaled by shares outstanding), and difference-in-differences specification is fairly standard:

$$Short\_Ratio_{i,t} = \beta_0 + \beta_1 Post_{t>=May2005} * Treatment_i + \beta_2 Treatment_i + \beta_3 Post_{t>=May2005} + \epsilon_{i,t} \tag{3}$$

Our hypothesis indicates that $\beta_1 < 0$.

Table 4 reports the regression results. Columns (1) and (3) show the baseline regression using equal-weighted sorting criteria and value-weighted soring criteria, respectively. When ETFs are sorted by their equal-weighted proportion of stocks in the Pilot Program, the ETFs that have the most pilot constituents experienced a 7.36% ($t = 2.01$) decrease in short ratio relative to ETFs with the least affected constituents *after* the Pilot Program started. When ETFs are sorted based on value-weighted proportion, the effect is reduced to 2.3% ($t = 1.85$). Importantly, there is no indication that the treatment ETFs have different levels of short ratio compared to the control ETFs before the Regulation SHO event.

In Columns (2) and (4), we include ETF-level fixed-effects to absorb heterogeneity on ETF characteristics that may confound our results. The equal-weighted sorting yields a significant difference-in-differences effect of 7.62% ($t = 1.81$), while the value-weighted sorting yields an insignificant but still positive effect of 1.7% ($t = 1.45$).

Taken together, our results provide causal evidence that a relaxation of short-sale constraints on the underlying stocks *causes* a decrease in the short-selling activities of ETFs that hold the stocks. This is consistent with our claim that shorting ETFs is an avenue for market participants to circumvent impediments to direct short sales.

3.3 Evidence for the "Create-to-Lend" Mechanism

There are several advantages of using ETFs to create a synthetic short position for a subset of its underlying stocks relative to direct short selling, as we have discussed in Section 1. One such advantage is that arbitrageurs can enter short positions via the "create-to-lend" mechanism. The prime brokers usually borrow all underlying securities of the ETF, create a new unit of the ETF, and lend it to short traders for a fee. If the said mechanism is cost effective for short sellers, one should expect the growth of ETF shares to covary with the short-selling activities of the ETF and its underlying components. To empirically test this hypothesis, we run panel regressions with ETF fixed-effects to examine the within-fund, time-series variation in the rate of share creation for ETFs.

The dependent variable of interest is the rate of ETF shares growth, $\Delta Shares_{t+1}/Shares_t$. A higher growth rate means more ETF shares are created as a fraction of existing shares. One can understand the variable as the "flow" measure in the mutual fund literature. In Column (1) of Table 5, ETF shares growth is regressed on the short ratio of the ETF at month t, and the regression coefficient is positive and highly significant ($t = 6.74$). This is consistent with the hypothesis that the shorting activities of an ETF is one main driver for the creation of the ETF shares because of the "create-to-lend" mechanism. As more and more arbitrageurs demand short positions in the ETF, their brokers create instead of borrowing ETF units and lend them to the traders.

In Columns (2), (3), and (4) of Table 5, the ETF shares growth rate is regressed on the short-selling demand and supply of the ETF's underlying stocks. When the demand of shorting underlying stocks is high or the supply of lendable shares is low, one should expect arbitrageurs to take advantage of the "create-to-lend" mechanism to short sell the ETF and, in the meantime, increase the number of shares of the ETF. This intuition is confirmed by the panel regression results: In Column (2), stock lending utilization, a proxy for shorting demand of underlying stocks, is positively correlated with ETF shares growth ($t = 2.19$). In Column (3), a higher underlying stock lending fee is associated with more rapid ETF shares growth ($t = 2.12$). In Column (4), the lending supply of underlying stocks is negatively related to ETF shares growth $t = -3.17$).

The evidence sheds light on the channels short sellers use to take short positions on ETFs and to ultimately gain short-side exposure to underlying securities. The "create-to-lend" mechanism appears to be an important advantage for synthetic short selling using ETFs.

3.4 Does ETF Short-Selling Predict ETF Returns?

The literature on stock short selling has shown that stock-level short ratios have predictive power over stock future returns (e.g., Figlewski (1981); Dechow, Hutton, Meulbroek, and Sloan (2001); Asquith, Pathak, and Ritter (2005)). A natural question to ask is whether ETF short selling has similar predictive power. A priori, the answer to this question is unclear. On the one hand, if most of the traders who short sell ETFs take short positions to hedge their other trades, highly shorted ETFs would not necessarily underperform lightly shorted ETFs. On the other hand, if ETF short sellers are betting against the whole market or sector, or if they use synthetic shorting strategy to gain exposure to a subset of ETFs' underlying constituent stocks, we would expect highly shorted ETFs to perform poorly compared to lightly shorted ETFs.

To empirically investigate this question, we sort ETFs into quintile portfolios each month based on their short ratio and hold them over the next month. The portfolio return is weighted either equally or by the market cap of the ETFs. A long-short portfolio is formed by taking a long position in the most lightly shorted ETF portfolio (Quintile 1) and a short position in the most heavily shorted ETF portfolio (Quintile 5). The return series runs from January 2002 to December 2013.

Table 6 reports the returns of five ETF portfolios as well as the return for the long-short portfolio. In Panel A, returns are equal-weighted. The monthly return spread for the long-short portfolio that buys ETFs that are lightly shorted and sells ETFs that are heavily shorted is 11 basis points with a t-stat of 1.08. After adjusting for the Fama and French (1993) three factors and the Carhart (1997) four factors, the long-short abnormal return is about 24 bp per month with a t-stat exceeding 3. The profitability of the long-short strategy indicates that heavily-shorted ETFs indeed underperform lightly-shorted one in the following month.

In Panel B, returns are value-weighted, and the return predictability of ETF short ratio is similar to the equal-weighted strategy. The profitability of the long-short strategy is about 16 to 20 basis points per month, depending on the risk-adjustment. The t-statistics range from 2.16 to 2.95.

Taken together, our empirical results echo the findings of predicative power on equity short ratio literature (e.g. Asquith, Pathak, and Ritter (2005)): ETF short sellers seem to have superior information about future returns of the ETFs, or at least some of their constituent stocks; and they are able to create abnormal returns by short selling. However, one can do better in utilizing the information content in ETF short ratios: if short sellers want to create synthetic short positions for a subset of stocks using ETFs, there are multiple ways of doing it. On average, a stock in our sample is held by more than 20 ETFs. Therefore, stocks that are held by multiple heavily-shorted ETFs are more likely to be the true targets of short sellers and have negative future returns. In the next section, we aggregate the information content in ETF short selling to the stock level and examine the return predictability of ETF shorting for individual stocks. We show that we are able to construct trading strategies that generate much larger abnormal returns.

4 ETF Short Selling and the Cross-Section of Stock Returns

To the extent that arbitrageurs use ETFs to express their bearish opinions on individual stocks, stocks that are heavily shorted via their ETF holdings should expect to earn negative returns in the future. Moreover, if arbitrageurs are more likely to switch to ETFs when their target stocks are difficult to borrow, then the return predictability of the ETF-based short ratio should be concentrated among stocks that have severe impediments to shorting. In this section, we test the return predictability of the ETF-based short ratio using both portfolio sorts and Fama-MacBeth regressions.

4.1 Portfolio Sorts

In this section, we show that stocks sorted on their ETF-based short ratio generate significant return spreads. We conduct the decile portfolio sorts as follows. At the end of each month, we sort stocks into deciles by their ETF-based short ratios. We then compute the average return of each decile portfolio over the next month, both equal-weighted and value-weighted. This gives us a time series of monthly returns for each decile. We use these time series to compute the average return of each decile over the entire sample. As we are most interested in the return spread between the two extreme portfolios, we also report the return to a long–short portfolio (i.e., a zero-investment portfolio that goes long the stocks in the lowest ETF-based short ratio decile and shorts the stocks in the highest decile). We report the average return (and associated t-statistics) of this long–short portfolio in the leftmost columns, with the Fama and French (1993) 3-factor adjusted alphas in the middle and the Carhart (1997) 4-factor alphas in the rightmost column. Our sample is from January 2002 to December 2013. Table 7 reports the result.

In Panel A of Table 7, the equal-weighted return decreases from 1.58% to 0.83% from the lowest decile to highest decile of ETF-based short ratio. The return spread for the long-short portfolio sorted on ETF-based short ratio is 0.76% per month, with a t-stat of 2.55. Adjusting for risk exposure to the Fama and French (1993) three-factors increases the long-short return spread to 0.90% (t=3.05). For four-factor adjusted alphas, the return spread is 0.94% per month, with a t-stat of 3.21. In Panel B, we see that the value-weighted results are weaker but are nonetheless statistically and economically significant across the board. For excess returns, the result is 0.42% with a t-statistic of 1.14. The figure increases to around 0.78% for the three- and four-factor alphas and both figures are now statistically significant. So, regardless of the metric, stocks that are heavily shorted via ETFs underperform those lightly shorted. The economic magnitude is quite impressive given the fact that many other well-documented anomalies are no longer profitable in our sample period (Chordia, Subrahmanyam, and Tong (2014)).

In Table A2, we look at the factor loadings of the long-short portfolio on the Carhart (1997) four factors. For equal-weighted portfolios, it loads negatively on the market and momentum factor, but does not load significantly on the size or value factor. For value-weighted portfolios, it loads negatively on the market and size factors, but positively on value factor. The large negatively loading on the market factor may explain why factor-adjusted alphas are even larger than the raw return spread.

In Table A3, we examine the robustness of our portfolio sorts. The first row shows the return spread when returns are weighted by past month gross return, as suggested by Asparouhova, Bessembinder, and Kalcheva (2013). The gross-return-weighted return spread is 0.8% (t=2.76). We next check whether our results hold when we augment the Carhart (1997) four-factors with the Pástor and Stambaugh (2003) liquidity factor, since stocks in the extreme deciles are less liquid as shown in the summary statistics tables. The Pástor and Stambaugh (2003) five-factor adjusted alpha is 0.88% (t=3.01) for the equal-weighted portfolio and 0.80% (t=2.52) for the value-weighted portfolio. The third row shows that our results hold when we use the Fama and French (2016) five factors to calculate alphas. Our results actually become stronger, with a monthly return spread of 1.14% (t=3.82) for the equal-weighted portfolio and 0.85% (t=2.56) for the value-weighted portfolio. This suggests our long-short portfolio is not merely loading on the profitability and investment factor as proposed by Fama and French (2016). The fourth row of Table A3 shows that our results survive when we exclude stocks that have a price less than $5 at the sorting month. Again, the strategy based on ETF-based short ratio generates a monthly excess return of 0.46% (t=2.39) and 0.48% (t=2.04) when equal-weighted or value-weighted, respectively. The fifth and sixth rows show that our results hold for stocks listed on both NYSE-Amex and NASDAQ stock exchanges. The seventh row shows that the long-short alphas are still highly significant if we skip a month between when we sort stocks and when we measure strategy returns. The last row reports the long-short alpha when we form decile portfolios based on the residual ETF-based short ratio, where the residual is obtained after purging out the effect of stock's own short ratio[23]. The equal-weighted long-short alpha is still 0.75% and highly

[23]Specifically, each month we run a cross-sectional regression of the ETF-based short ratio on stocks' own short ratio and take the regression residual as our sorting variable.

significant, although the value-weighted alpha is marginally insignificant. Across almost all the specifications in Table A3, stocks heavily shorted via ETFs underperform lightly shorted stocks.

4.2 Two-Way Sorts on ETF-Based Short Ratio and Limits to Arbitrage

Having established the return predictability of the ETF-based short ratio through univariate portfolio sorts, we next examine whether the return predictability varies across stocks with different level of direct stock short ratio and with different degree of limits to arbitrage. Our hypothesis is that some arbitrageurs short ETFs to circumvent short-selling constraints at the stock level, hence the return predictability of ETF-based short ratio should be stronger among such difficult-to-short stocks.

As a first pass, we conduct sequential doubt sorts first on stock-level short ratio and then on ETF-based short ratio. As will be discussed in later subsection within the context of Fama-MacBeth regressions, stock-level short ratio has been shown to negatively predict future stock returns. The double sorting tells us whether our ETF-based short ratio has information contents about future stock returns on top of stock-level short selling activities. To implement the sorting, at the end of each month, all stocks are sorted into terciles based on their stock-level short ratio, and within each tercile, we further sort the stocks into quintiles based on their ETF-based short ratio (ETF_sr).

The equal-weighted and value-weighted portfolio returns are reported in Table 8. In both equal-weighting and value-weighting results, the additional predicative power of ETF-based short ratio is significant within stocks that have the lowest direct short ratios. The monthly four-factor abnormal returns for the low-stock SR tercile is 0.77% (t = 2.60) for equal-weighted portfolio and 0.83% (t = 2.32) for value weighted portfolio, similar to results from unconditional sorts. For stocks in top two stock short ratio terciles, however, ETF-based short ratio generates portfolio spreads indistinguishable from zero.

The interpretation of the results from first two-way sorts is that ETF-based short ratio is particularly informative of future stock returns when stock-level short ratios are suppressed, potentially because of stock-level short sale constraints. To further explore the relation between informativeness of ETF-based short ratio and stock-level arbitrage frictions, we conduct a second group of sequential double sorts. At the end of each month, all stocks are sorted into terciles based on a specific proxy for limits to arbitrage, and within each tercile, we further sort the stocks into quintiles based on their ETF-based short ratio (ETF_sr). Returns are equally weighted within each portfolio. We use multiple measures of arbitrage frictions, including lendable supply, institutional ownership, lending fee, idiosyncratic volatility, turnover, and Amihud (2002) illiquidity. The first three measures are more closely related to the constraints in the equity lending market, while the latter three measures belong to more general arbitrage frictions.

Table 9 report the monthly Carhart (1997) four-factor alphas for each portfolio. In Panel A, we use the lendable share supply as a proxy for limits to arbitrage, which directly measures the tightness of the equity lending market. Consistent with our hypothesis, the return spread on the ETF-based short ratio is much higher among stocks with low lending supply. Specifically, the four-factor alpha is 0.73% (t=1.98) in the lowest lendable supply tercile. The figure is only 0.27% and 0.22% for the other two terciles, and is no longer significant. In Panel B, we show that the same pattern is observed when we use institutional ownership as a proxy for short-sale constraints (Nagel (2005)). Because institutional investors actively participate in stock lending programs, the fraction of shares owned by institutional investors is highly correlated with actual lending supply.[24] Consistent with our hypothesis, the four-factor alpha based on ETF_sr is 1.20% (t=3.59) in the tercile with lowest institutional ownership, while it decreases to 0.25% for stocks with high institutional ownership.

In panel C, we use the stock lending fee as a more direct proxy for short-sale constraints (Jones and Lamont (2002); Drechsler and Drechsler (2014)). Following the literature, we sort stocks into two groups based on whether a stock's DCBS score is above 2. As we can see, the return predictability of ETF-based short ratio is significantly amplified among stocks with elevated borrowing cost. The monthly four-factor alpha is 1.70% (t-stat=3.52) among stocks with DCBS scores above 2, and an insignificant 0.37% among stocks with DCBS scores below 2.

[24]Cross-sectional correlation between institutional ownership and lendable supply is 0.79 in our sample.

Pontiff (2006) argues that stocks with high idiosyncratic volatility are more costly to arbitrage. Duan, Hu, and McLean (2010) and Stambaugh, Yu, and Yuan (2015) provide empirical evidence supporting this argument. Panel D of Table 9 reports the double sorting results when we use idiosyncratic volatility as a proxy for limits to arbitrage. The monthly return spread is 0.99% (t=2.75) for stocks in the highest tercile of idiosyncratic volatility, and is much smaller in magnitude and less significant for stocks with low idiosyncratic volatility. Hong, Li, Ni, Scheinkman, and Yan (2015) argues that short selling is highly sensitive to stock liquidity, as arbitrageurs worry about crowded trades in illiquid securities. Panel E presents the results when we use monthly turnover as a proxy for limits to arbitrage. The monthly alpha is 0.98% (t=2.51) for stocks in the lowest turnover tercile, and close to 0% when stocks have high turnover. In Panel F, we use Amihud (2002) illiquidity as proxy for stock liquidity level and find similar results.

In summary, the stronger return predictability of ETF-based short ratio among stocks with low lending supply, high lending fee, high idiosyncratic volatility, and low liquidity is consistent with our hypothesis that arbitrageurs effectively use ETFs to create synthetic short positions on stocks that are costly to short.

4.3 Fama-MacBeth Regressions

We now test our main hypothesis using the Fama and MacBeth (1973) regression methodology. One advantage of this methodology is that it allows us to examine the predictive power of ETF-based short ratio while controlling for known predictors of cross-sectional stock returns. This is important because, as shown in Table 2, ETF-based short ratio is correlated with some of these predictors. We conduct the Fama-MacBeth regressions in the usual way. Each month, starting in February 2002 and ending in December 2013, we run a cross-sectional regression of stock returns on ETF_sr and a set of control variables known to predict returns, including the natural logarithm of the book-to-market ratio (LnBM), the natural logarithm of the market value of equity (LnME), returns from the prior month (Rev), returns from the prior 12-month period excluding month t-1 (Mom), institutional ownership (IO), and idiosyncratic volatility (IVOL).

Table 10 reports the time-series averages of the coefficients on the independent variables, and the t-statistics are Newey-West adjusted with twelve lags to control for heteroskedasticity and autocorrelation. We only include ETF-based short ratio (ETF_sr) in Column (1) as a baseline and it has a negative coefficient of -0.022 (t=2.52). This is consistent with our portfolio sorting results in which stocks that are heavily shorted via ETFs have lower future returns. In Column (2), we add the usual controls including size, book-to-market ratio, past 1-month returns, and past 12-month returns. The coefficient on ETF_sr decreases to -0.013 with a t-stat of 2.50. In Column (3), we further add institutional ownership and idiosyncratic volatility in the regression, and ETF_sr still negatively predicts future returns. The economic magnitude is also quite large. The difference of ETF-based short ratio between the lowest decile portfolio and highest decile portfolio is 0.48, which implies a monthly return spread of 60 bp between these two extreme deciles. The magnitude estimated from Fama-MacBeth regression is in line with our portfolio sorting results. For the control variables, the sign of coefficients is consistent with previous literature, except for momentum, which attracts a negative coefficient.[25] Due to the short sample period, however, the coefficients on most control variables are not significantly different from zero.

Our ETF-based short ratio is constructed as the dollar value of short interests via ETFs over the dollar value held by all ETFs for a stock. One might be concerned that the return predictability we document so far is driven by the denominator rather than the numerator in Equation (2). This could arise if ETF ownership is informative about future stock returns. To address this concern, we construct an alternative version of ETF-based SR (ETF_sr2) by replacing the demoninator in Equation (2) with the stock's market capitalization. Column (4) of Table 10 shows that this alternative ETF-based SR attracts a negative coefficient of -0.68 (t-stat=-2.57). Thus the return predictability of ETF-based SR is mainly driven by the shorting demand on individual stocks through ETFs, rather than the information content of ETF ownership.

In Table A4, we examine the persistence of the return predictability of ETF-based short ratio. The dependent variables from Columns (1) to (12) correspond to monthly stock

[25]This is due to the 2009 momentum crash, see Daniel and Moskowitz (2014). The coefficient on Momentum becomes positive once we exclude 2009 from our sample.

returns from 1 month to 12 month ahead. The predictive power of ETF_sr slowly decays from -0.012 to -0.002, but is still significant for forecasting returns up to seven months in the future. The strong persistence of the predictability of ETF-based short ratio support our hypothesis that arbitrageurs target difficult-to-short stocks via shorting ETFs, and the overpricing associated with these stocks are only slowly corrected over time.

4.4 Controlling for Stock-Level Short-Selling Measures

A large literature on short selling documents that stock-level short interest is a negative predictor of future returns. Several recent papers find that in addition to shorting demand, lending supply and borrowing costs also negatively predict stock returns.[26] To test whether our ETF-based short ratio contains incremental predictive power, we control for various measures of stock-level shorting measures in Fama-MacBeth regressions. The result is reported in Table 11. In Column (1), we add the stock's own short interest ratio (SR) in the regression. Consistent with prior literature, SR is a strong negative predictor of future returns, with a coefficient of -0.04 and t-stat of 4.55. The coefficient on ETF-based short ratio (ETF_sr), however, survives with a coefficient of -0.01 (t=2.03), which suggests that information extracted from ETFs' short interest is not fully absorbed by the stock's own short ratio. The economic effect of ETF-based short ratio on return is comparable to that of the stocks' short ratio. A one standard deviation shock to ETF-based short ratio translate into 15 bp of expected return, while the figure is 20 bp for stock short ratio. In Column (2), we add the stocks' lending fee measure (DCBS) in the Fama-MacBeth regression. Consistent with Drechsler and Drechsler (2014), the lending fee negatively and strongly predicts future returns with a t-stat of 5.62. More importantly, however, the coefficient on our ETF_sr is -0.011 and still significant at 1% level.

In Columns (3) and (4), we control for the stocks' utilization ratios and SIO, respectively. Utilization is the ratio of shares borrowed to shares made available by Markit lenders. SIO is the short interest ratio scaled by institutional ownership. These two variables measure the tightness of the securities lending market by taking the intersection of shorting demand and

[26] See for example, Drechsler and Drechsler (2014) and Beneish, Lee, and Nichols (2015), among others.

supply. A stock that is highly shorted despite its low supply of lendable shares means the stock is more likely facing binding short-sale constraints. As we can see, the coefficients on the utilization ratio and SIO are indeed significantly negative. However, ETF-based short ratio continues to predict returns with t-stats of around 2.10. In the last column of Table 11, we control for stocks' lendable supply and the return predictability of the ETF-based short ratio still holds.

4.5 ETF Short Selling and Short-Sale Constraints

In this section, we test our second prediction that ETF-bases short ratio has more pronounced return predictability among difficult-to-short stocks. We do so by running Fama-MacBeth regressions of returns on ETF-based short ratio (ETF_sr) and its interaction with variables indicating binding short-sale constraints. The results are reported in Table 12.

In Column (1), we create a dummy variable $LowIO$, which is equal to one when the stock is in the bottom quintile of institutional ownership ratio in the cross-section. Our controls always include stock-level SR, so any return predictability associated with a stock's own SR will be absorbed. Our variable of interest is $ETFsr\_lowIO$, the interaction between ETF_sr and $LowIO$ dummy. As we can see, the coefficient on $ETFsr\_LowIO$ is -0.02 with a t-stat of 2.67. The coefficient on ETF_sr itself is negative but no longer significant, which suggests that the negative predictability of the ETF-based short ratio is concentrated among stocks with greater short-sale constraints. This coefficient implies that the predictive power of ETF-based short ratio increases by 5 times for stocks in the bottom quintile of institutional ownership compared to stocks outside this group. In Column (2), we interact ETF_sr with a dummy $Lowsupply$, which indicates whether a stock is in the bottom quintile of lendable supply. The coefficient on this interaction term is negative with a t-stat of 1.04. In Column (3), we use the utilization ratio to proxy for the tightness of the lending market. $Highutil$ is a dummy variable that equals one when the stock is in the top quintile of utilization in the cross-section. The coefficient on the interaction between ETF_sr and $Highutil$ is again negative and significant at the 10% level. Column (4) reports the result when we use lending fee as proxy for shorting constraints. The variable $Highfee$ is a dummy equal to one when the stock is in the top quintile of lending fee distributions. The coefficient on this interaction term is -0.018 with a t-stat of 3.26. In Column (5), our proxy for frictions in the shorting market is stock turnover, as Hong, Li, Ni, Scheinkman, and Yan (2015) point out that short sellers are reluctant to take large positions in low-turnover stocks. Consistent with this intuition, ETF-based short ratio exerts stronger return predictability among stocks with low turnover. Our last proxy for short-sale constraints is whether the stock has any exchange-traded put option, as previous studies find that put options facilitate short sellers to express negative views through trading on the option market (Boehme, Danielsen, and Sorescu (2006); Danielsen and Sorescu (2001)). The variable $Noput$ is a dummy that equals one when the stock has no put option. Supporting our hypothesis, Column (6) shows that the return predictability of ETF-based short ratio is much more pronounced for the subset of stocks without a put option.

5 ETF Ownership and Capital Market Anomalies

Our final set of tests explore the implication of ETF short selling on capital market anomalies. Many papers argue that constraints in the equity lending market are the key impediment to information arbitrage and that these constraints drive the persistence of several well-documented stock return anomalies (Nagel (2005); Beneish, Lee, and Nichols (2015); Stambaugh, Yu, and Yuan (2012); Drechsler and Drechsler (2014)). We argue that the rise of ETFs could alleviate short-sale constraints and contribute to a more efficient stock market. There are two potential channels through which ETFs may lead to a more informationally efficient stock market. The first channel is the well-documented stock lending channel, as ETFs are among the main contributors to the short-selling market (Blocher and Whaley (2015); Massa, Zhang, and Zhang (2015)). Because the ETF industry thrives on its low-fee reputation, ETFs often lend out shares to short-sellers to generate additional income that allows them to reduce fees.[27] The second channel is what we propose in this paper: ETFs allow arbitrageurs to establish synthetic short positions on stocks that are otherwise difficult

[27] The Spearman correlation between ETF ownership and lendable supply is 0.73. The Spearman correlation between ETF ownership and lending fee DCBS scores is -0.32.

to short.

To distinguish between these two channels, we must create portfolios that have a large spread in ETF ownership but have a similar level of stock shorting costs. To achieve this, we conduct sequential triple sorts, first on stock lending fee, then on ETF ownership, and finally on anomaly characteristics. For each month, we sort stocks into two groups based on their lending score DCBS. Stocks with a DCBS score less than or equal to 2 are usually cheap to borrow and are called "general collateral". Stocks with DCBS larger than 2 are more costly to short and are called "special" stocks. Within each group, we further sort stocks into two buckets based on their ETF ownership. This essentially creates portfolios with large differences in ETF ownership but with similar levels of lending costs.[28] Within each ETF ownership sorted bucket, we sort stocks into terciles based on anomaly characteristics, and we calculate the bucket's long-short anomaly return as the difference between the returns of the extreme portfolios. We consider a total of 10 well-studied anomalies, including book-to-market (Lakonishok, Shleifer, and Vishny (1994)), accurals (Sloan (1996)), net operating assets (Hirshleifer, Hou, Teoh, and Zhang (2004)), asset growth (Cooper, Gulen, and Schill (2008)), capital investment (Titman, Wei, and Xie (2004)), long-run reversal (Bondt and Thaler (1985)), composite issuance (Daniel and Titman (2006)), gross profitability (Novy-Marx (2013)), return-on-assets (Fama and French (2006)) and price momentum (Jegadeesh and Titman (1993)). As ETF ownership only matters when stocks are subject to short-selling constraints in the first place, we focus on the anomaly returns for stocks with their DCBS scores greater than 2 in Table 13.

Panel A of Table 13 reports the monthly return spread. Across 10 anomalies, 6 have a larger return spread in the low-ETF ownership bucket. For example, the value premium is 1.04% (t=1.94) among low ETF-ownership stocks, and it is only 0.55% (t=1.36) among high-ETF ownership stocks. We observe a similar pattern for accrual, net operating assets, asset growth, investment, and long-run reversal. For composite equity issuance, the return spread is quite similar between low- and high- ETF ownership bucket. However, for three anomalies, we actually find a more pronounced return spread when ETF ownership is high.

[28] As we see from Table 13, the difference in lending fees between the two ETF ownership sorted buckets are economically small.

Panel B reports the four-factor adjusted alphas, and the pattern is similar to the raw return spread reported in Panel A.

On balance, the evidence presented in this section suggests that ETFs could alleviate stock-level short selling constraints, as it allows arbitrageurs to take short positions on certain stocks and contributes to an informationally efficient capital market.

6 Conclusion

ETFs have become an important asset class in recent years. In this paper, we provide the first empirical evidence of the scope, the determinants and the implications of ETF short selling on the stock market. ETFs are more liquid, and are not not subject to "uptick rule". In addition, new ETF shares could be created for the sole purpose of short selling. For these reasons, short selling ETFs could be used by arbitrageurs to create synthetic short positions on stocks that are otherwise costly to short. Consistent with this hypothesis, we find that shorting activities on ETFs increase with the difficulty of shorting their underlying stocks. Using Regulation SHO as a quasi-natural experiment, we confirm that a relaxation of short-sale constraints on the underlying stocks causes a decrease in the shorting activities of the ETFs that hold the stocks.

We then construct a stock-level short ratio (SR) based on the short interests of all ETFs holding this stock, which reflects the collective shorting demand on this stock through short selling ETFs. We find that this ETF-based short ratio strongly predicts future returns, even after controlling for stock-level shorting measures. A strategy that takes a long position in the stocks most lightly shorted via ETFs and sells the stocks most heavily shorted generates a Carhart (1997) four-factor alpha of 94 bp on an equal-weighted basis, or 77 bp on a value-weighted basis. The return predictability of the ETF-based short ratio is amplified among stocks that face the most severe shorting constraints, which supports our conjecture that ETFs are used by arbitrageurs as an avenue to circumvent short-sale constraints for difficult-to-short stocks.

Last, we explore the implication of growing ETF ownership on stock market efficiency. Across a broad set of return anomalies, we find that anomaly returns are significantly attenuated conditional on high ETF ownership. Overall, our evidence suggests that ETFs contribute to a more informationally efficient market by allowing arbitrageurs to target overvalued stocks that are otherwise difficult to short.

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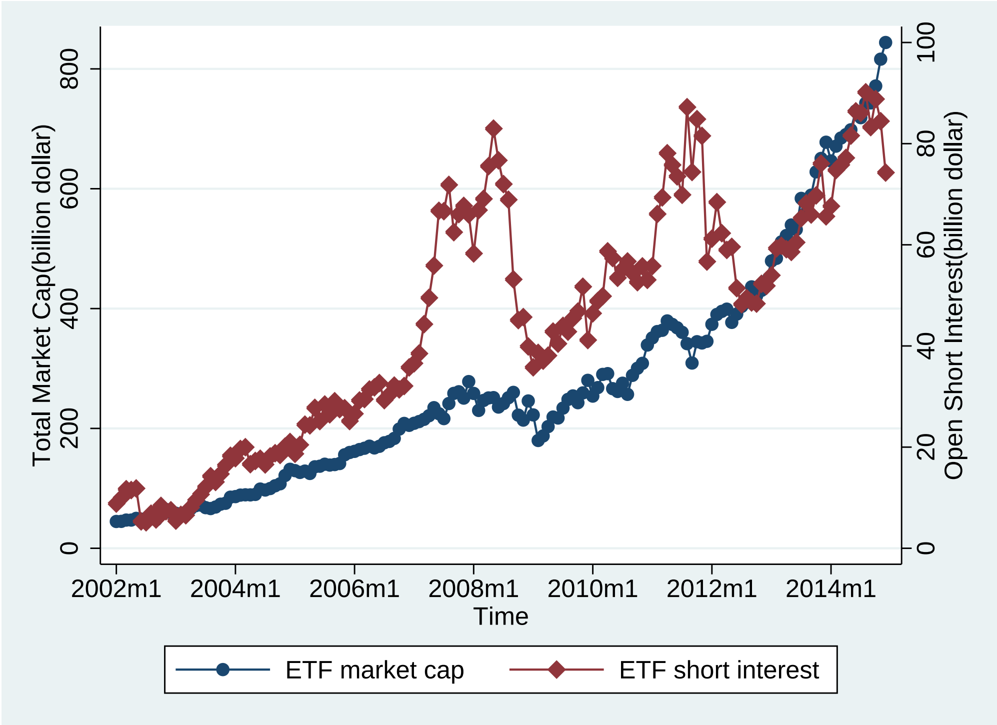
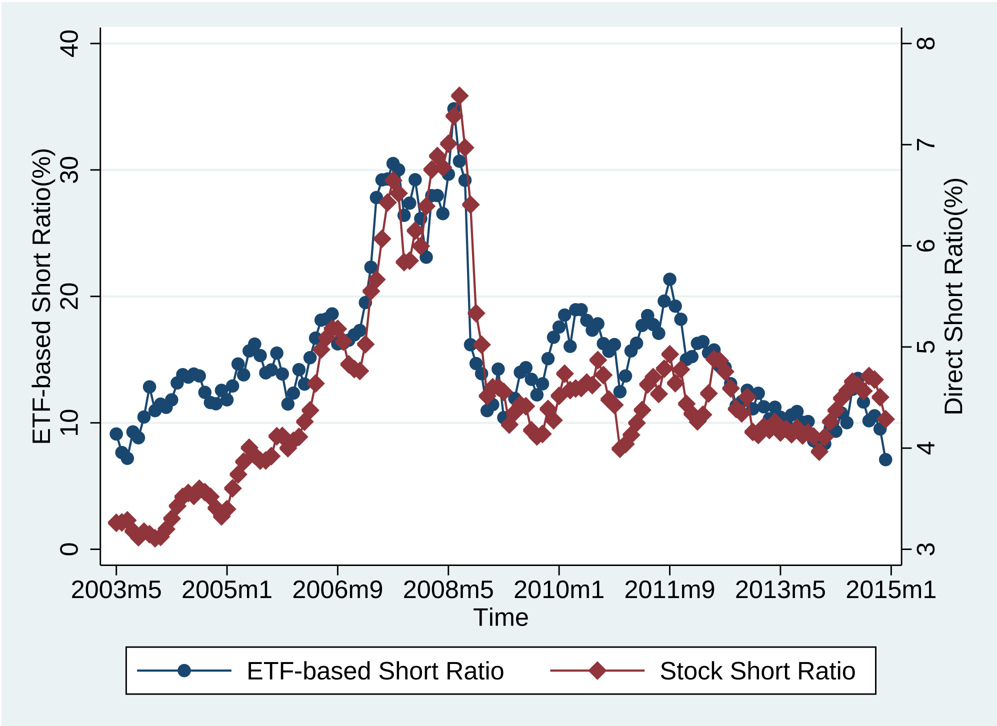
Figure 1: **ETF Total Market Capitalization and Total Short-Selling Value**



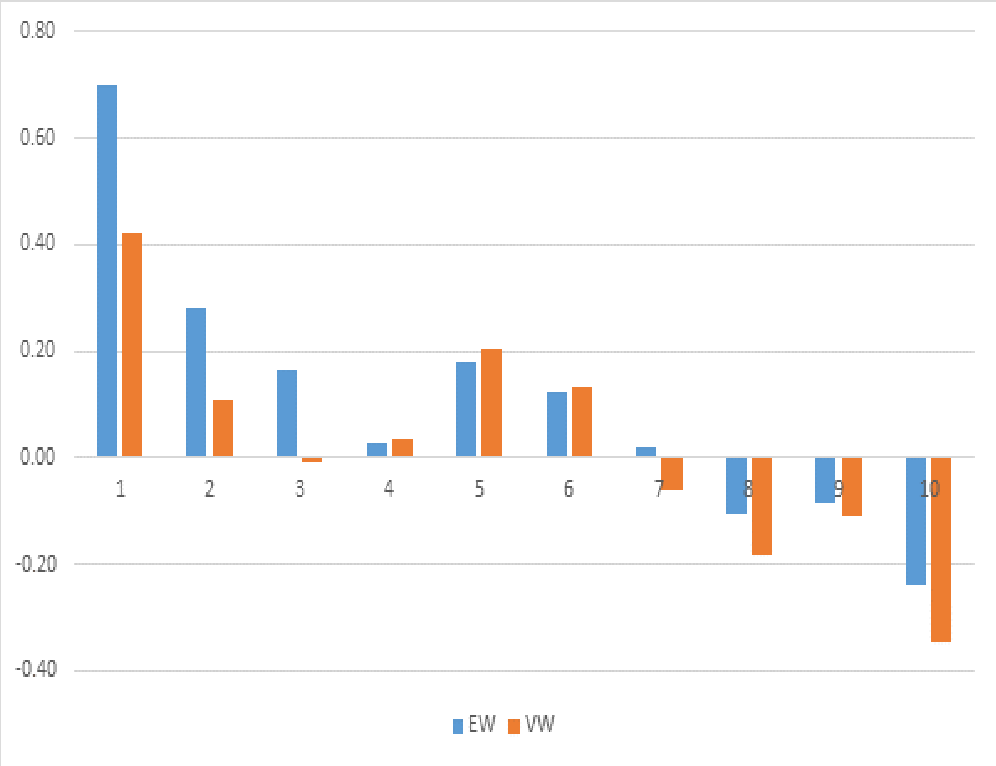
This figure shows the total market capitalization of all physically replicating domestic ETFs and the aggregate value of their mid-month open short interests. The total market cap is measured in billions of dollars and is shown on the left axis. The value of open short interest is measured in billions of dollars and is shown on the right axis.

Figure 2: **ETF-based Stock Short Ratio and Direct Short Ratio**



This figure shows the average (1) ETF-based short ratio (left axis); and (2) direct short ratio of stocks (right axis). The ETF-based short ratio is calculated as the dollar value of stock shorted via ETFs divided by the total value of stock held by the ETFs. The direct short interest ratio is calculated as the number of shares shorted directly divided by the total number of shares outstanding.

Figure 3: **4-Factor Alphas of Decile Portfolios Sorted on ETF-based Short Ratio**



This figure shows the monthly Carhart (1997) 4-factor alpha for decile portfolios sorted on ETF-based stock short ratio. The y-axis is the monthly alpha (in percentage), and the x-axis is the decile portfolio from low to high. The sample runs from January 2002 to December 2013.

Table 1: Summary Statistics: ETF characteristics

This table shows the characteristics of ETFs and their underlying stocks. Panel A reports the average, the median, the 25th percentile, the 75th percentile, and the standard deviation of characteristics in the pooled full sample. In Panel B, we sort ETFs into five portfolios for each month based on their short ratio. Characteristics are first averaged within each portfolio-month and then averaged across months.

Panel A: Full Sample	Mean	Median	P25	P75	Std
Short Ratio(%)	4.08	0.90	0.31	2.72	10.32
Market Cap(mn)	1,386	182	46	737	3,712
12-month Return(%)	9.39	12.51	-2.87	23.53	24.98
Return Volatility(%)	5.47	4.65	3.24	6.74	3.06
Turnover Ratio(%)	2.70	0.93	0.56	1.83	6.62
Expense Ratio (%)	0.44	0.40	0.24	0.65	0.25
Days-to-Cover (*doc*)	2.1	0.9	0.3	2.3	3.4
Number of Stocks	417	211	88	467	558
Weighted-average characteristics of underlying stocks					
Market Cap(mn)	68,506	44,971	4,909	121,042	698,08
Book-to-Market	0.48	0.07	0.02	0.3	1.04
Idiosyncratic Volatility(%)	1.50	1.35	1.07	1.75	0.59
Short Ratio(%)	3.86	3.22	2.20	5.09	2.16
Lending Supply(%)	23.53	24.60	22.88	26.92	6.42
Lending Utilization(%)	15.18	12.47	8.23	19.21	10.03
Lending Cost	1.11	1.05	1.01	1.15	0.16
Amihud Illiquidity(%)	0.32	0.04	0.01	0.15	1.05

Panel B: ETFs Sorted by Short Ratio	Low SR	2	3	4	High SR
Short Ratio(%)	0.23	0.85	1.80	3.67	18.98
Market Cap(mn)	501	1,301	1,549	1,286	2,728
12-month Return(%)	9.05	11.05	11.84	12.60	12.09
Return Volatility(%)	4.55	4.52	4.67	5.02	5.73
Turnover Ratio(%)	1.02	1.09	1.27	1.95	7.39
Expense Ratio(%)	0.44	0.35	0.38	0.42	0.47
Days-to-Cover (*doc*)	0.4	1.3	2.2	3.7	6.1
Number of Stocks	380	466	433	464	603
Weighted-average characteristics of underlying stocks					
Market Cap(mn)	71,363	78,902	72,648	73,356	64,460
Book-to-Market	0.43	0.37	0.38	0.41	0.67
Idiosyncratic Volatility(%)	1.41	1.38	1.41	1.44	1.55
Short Ratio(%)	3.54	3.41	3.63	3.72	4.20
Lending Supply(%)	20.31	20.22	20.41	20.60	20.64
Lending Utilization(%)	17.04	15.78	16.52	16.78	18.88
Lending Cost	1.12	1.12	1.11	1.11	1.14
Amihud Illiquidity(%)	0.30	0.23	0.22	0.24	0.49

Table 2: **Stock-Level Descriptive Statistics**

This table presents the summary statistics of our variables. Panel A reports the summary statistics for the full sample. Panel B reports the pairwise rank correlation among our variables where they overlap. Panel C reports the characteristics of the ETF-based Short Ratio (ETF_sr) sorted portfolios. For each month, we sort all stocks into deciles based on their ETF-based stock short ratio. We first calculate the mean of each variable for each decile each month and then calculate the time-series average of cross-sectional means. The overall sample period is from January 2002 to December 2013.

Panel A: Summary Statistics

	Mean	Median	P25	P75	Std.
ETF_sr	15.97%	14.18%	1.72%	24.31%	15.77%
SR	4.16%	2.76%	1.06%	5.53%	4.61%
IOR	58.51%	62.85%	34.95%	82.14%	28.91%
Mktcap	3507.8	571.4	177.3	2062.3	9760.6
LnBM	-0.654	-0.578	-1.111	-0.130	0.815
MOM	0.124	0.060	-0.143	0.298	0.457
Turnover	0.79%	0.61%	0.31%	1.04%	0.71%
IVOL	0.025	0.020	0.013	0.030	0.017
DCBS	1.499	1.005	1.001	1.160	1.285
SAF	85.9	28.2	22.5	36.1	229.7
Supply	13.80%	14.23%	6.55%	20.10%	8.29%
Utilization	34.12%	16.10%	5.68%	39.38%	54.30%

Table 2 Continued

Panel B: Rank Correlations

	ETF_sr	SR	IO	LnME	LnBM	MOM	Turnover	IVOL	DCBS	Ln(SAF)	Supply	Utilization
ETF_sr	1.000											
SR	0.366	1.000										
IO	0.229	0.475	1.000									
LnME	0.129	0.351	0.564	1.000								
LnBM	-0.144	-0.242	-0.138	-0.293	1.000							
MOM	0.057	0.005	0.110	0.136	0.009	1.000						
Turnover	0.165	0.666	0.581	0.464	-0.255	0.036	1.000					
IVOL	-0.047	-0.008	-0.262	-0.506	0.044	-0.169	0.030	1.000				
DCBS	-0.094	0.020	-0.384	-0.352	-0.044	-0.181	-0.041	0.344	1.000			
Ln(SAF)	0.122	0.217	-0.154	-0.275	-0.035	-0.122	0.096	0.299	0.467	1.000		
Supply	0.231	0.468	0.789	0.602	-0.076	0.147	0.522	-0.344	-0.442	-0.247	1.000	
Utilization	0.296	0.678	0.086	0.060	-0.214	-0.083	0.390	0.158	0.339	0.363	-0.014	1.000

Panel C: Summary Statistics of ETF-based SR sorted Decile Portfolios

Portfolio	# of stocks	ETF_sr	SR	IO	Mktcap	lnBM	MOM	Turnover	IVOL	DCBS	SAF	Supply	Utilization	# of ETFs
1	341	0.08%	1.24%	23.51%	386.9	-0.229	0.110	0.38%	0.038	2.211	343.0	3.82%	52.70%	2
2	342	0.62%	3.06%	50.74%	2017.1	-0.536	0.148	0.73%	0.027	1.673	90.6	11.47%	59.90%	15
3	340	1.77%	3.20%	55.29%	2345.7	-0.599	0.107	0.79%	0.025	1.648	106.8	11.88%	35.39%	16
4	341	5.44%	3.49%	61.10%	4504.7	-0.703	0.102	0.88%	0.023	1.500	82.1	13.26%	27.28%	22
5	341	11.26%	3.44%	69.26%	15353.8	-0.807	0.114	0.91%	0.017	1.204	42.6	17.42%	18.63%	32
6	342	17.69%	5.58%	72.36%	3140.4	-0.573	0.114	0.86%	0.020	1.258	59.4	20.20%	30.26%	23
7	341	20.66%	6.16%	74.26%	1885.8	-0.716	0.117	0.95%	0.021	1.233	62.3	19.91%	35.65%	22
8	341	24.27%	5.65%	66.50%	2037.8	-0.705	0.131	0.88%	0.023	1.328	88.8	15.96%	39.57%	18
9	341	29.46%	5.63%	62.85%	1617.5	-0.852	0.141	0.87%	0.025	1.482	115.3	14.07%	45.95%	15
10	341	48.46%	4.27%	48.87%	652.3	-0.803	0.173	0.66%	0.028	1.751	153.5	9.83%	50.38%	11

Table 3: Cross-Sectional Determinants of ETF Short Ratio

This table reports the results from the Fama and MacBeth (1973) regression of the monthly ETF short interest ratio on ETF characteristics and constituent stocks' characteristics. ETF Return and ETF Return Vol are the 12-month mean and volatility, respectively, of the ETF monthly return. Stock-level characteristics are weighted-average characteristics within an ETF's quarterly holdings. Stock IVol is stock idiosyncratic volatilities per Ang, Hodrick, Xing, and Zhang (2006). Stock short ratio is the mid-month open short interests divided by shares outstanding. Institutional Ownership is the fraction of ownership held by 13F institutions. Short Supply is the total lendable shares from Markit divided by shares outstanding. Lending fee is a score from 1 to 10 created by Markit to capture the difficulty of shorting a stock. Illiquidity is the Amihud (2002) illiquidity measure. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ETF Turnover	1.456***	1.443***	1.443***	1.441***	1.446***	1.456***	1.438***
	(15.28)	(15.38)	(15.39)	(15.36)	(15.32)	(15.42)	(15.59)
ETF Ln(ME)	0.00269***	0.00268***	0.00260***	0.00287***	0.00265***	0.000569	0.000565
	(6.58)	(7.31)	(7.04)	(7.82)	(7.08)	(1.02)	(1.02)
ETF Return	-0.0290*	-0.0244	-0.0239	-0.0195	-0.0231	-0.0209	-0.0269
	(-1.66)	(-1.62)	(-1.37)	(-1.22)	(-1.47)	(-1.24)	(-1.57)
ETF Return Vol	0.0649	-0.144	-0.192	-0.0909	-0.107	-0.0687	-0.0188
	(0.40)	(-1.04)	(-1.31)	(-0.66)	(-0.76)	(-0.47)	(-0.13)
ETF Expense Ratio	0.290	0.861	0.421	0.656	0.769	0.508	0.559
	(0.57)	(1.65)	(0.80)	(1.31)	(1.45)	(0.96)	(1.27)
ETF Lending Fee						-0.00735***	-0.00759***
						(-5.00)	(-5.42)
Stock Return IVol	1.686**	3.555***	4.577***	3.860***	2.944***	3.611***	2.390***
	(2.54)	(5.50)	(6.73)	(7.13)	(5.77)	(6.16)	(4.41)
Stock Illiquidity	1.959***						
	(4.55)						
Stock Short Ratio		0.0542					
		(0.50)					
Stock Institutional Ownership			-0.0634***				
			(-3.00)				
Stock Lending Supply				-0.147**			
				(-2.04)			
Stock Lending Utilization					0.0769***		
					(5.45)		
Stock Lending Fee						0.0126***	-0.00270
						(3.99)	(-0.88)
Top Decile Stock Lending Fee							0.0108***
							(7.77)
Stock Ln(ME)	-0.00158**	0.000597	-0.00121*	-0.00115*	0.00173*	-0.000478	-0.000571
	(-2.32)	(0.69)	(-1.74)	(-1.74)	(1.89)	(-0.65)	(-0.76)
Stock BM	-0.00513**	0.00213	-0.00170	0.000967	0.00130	-0.000162	-0.000679
	(-2.24)	(1.39)	(-0.80)	(0.60)	(0.81)	(-0.08)	(-0.35)
R^2	0.460	0.449	0.450	0.448	0.449	0.456	0.467

Table 4: **ETF Short Ratio Before and After Regulation SHO Pilot Program**

This table reports the ETF-level short ratio in a difference-in-differences specification using the Regulation SHO's Pilot Program as a natural experiment. An ETF is defined as a "treatment" fund if the proportion of stocks (equal-weighted or value-weighted) that were included in the pilot program is ranked in the top 10 among all ETFs. An ETF is defined as a "control" fund if it is ranked in the bottom 10. The observations are made at the fund-month level, and we include, at most, 12 months before and 12 months after the inception of the Pilot Program (May 2005). Post is a dummy variable that equals one when the short ratio is observed after May 2005. All standard errors are clustered at the fund level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	Equal-weighted Proportion		Value-weighted Proportion	
Average Pilot Proportion:	Treatment ETFs=40.9%		Treatment ETFs=45.9%	
	Control ETFs=17.4%		Control ETFs=14.9%	
	(1)	(2)	(3)	(4)
High Pilot Program Rate * Post	-0.0736*	-0.0762*	-0.0230*	-0.0170
	(-2.01)	(-1.81)	(-1.85)	(-1.45)
High Pilot Program Rate	0.0208		0.00605	
	(0.42)		(0.26)	
Post SHO Pilot Program	0.0143	0.0250	-0.00459	0.000723
	(1.04)	(1.04)	(-0.74)	(0.12)
Observations	380	380	391	391
Adjusted R^2	0.025	0.479	0.035	0.661
Fund-level Fixed-Effects	N	Y	N	Y

Table 5: ETF Shares Growth and Shorting Demand

This table reports the results of panel regressions on ETF shares growth with ETF fixed-effects. The dependent variable, ETF shares growth, is defined as $\Delta Shares_{t+1}/Shares_t$. All independent variables are measured at month t. ETF Short Ratio is the short interest of ETF scaled by the ETF's shares outstanding. Stock Lending Utilization is the ratio of shares borrowed to shares made available by Markit lenders. DCBS is a score from 1 to 10 created by Markit capturing the cost of borrowing the stock. Lending supply is the number of shares made available to lend by Markit lenders, scaled by shares outstanding. Standard errors are clustered at the month level. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
ETF Short Ratio	0.241***			
	(6.74)			
Stock Lending Utilization		0.0605**		
		(2.19)		
Stock Lending Fee			0.0371**	
			(2.12)	
Stock Lending Supply				-0.111***
				(-3.17)
ETF Ln(Shares)	-0.0791***	-0.0788***	-0.0733***	-0.0849***
	(-6.39)	(-6.17)	(-6.33)	(-6.30)
ETF Ln(ME)	0.0472***	0.0458***	0.0396***	0.0532***
	(4.27)	(4.01)	(3.87)	(4.23)
ETF Turnover	0.379***	0.473***	0.476***	0.485***
	(4.70)	(6.08)	(5.22)	(6.18)
ETF Return	0.0138	0.0153	0.0166*	0.00930
	(1.00)	(1.10)	(1.92)	(0.63)
ETF Return Vol	0.127	0.121	0.115	0.134
	(1.40)	(1.23)	(1.17)	(1.40)
Stock Return IVol	0.791	0.677	0.402	0.979**
	(1.57)	(1.35)	(1.09)	(2.15)
Stock Ln(ME)	-0.00321	-0.00265	-0.00337	-0.00270
	(-1.09)	(-0.91)	(-0.89)	(-0.93)
Stock BM	0.000762	0.00132	0.000735	0.000930
	(0.35)	(0.60)	(0.30)	(0.41)
Observations	16947	16947	16947	16947
R^2	0.105	0.093	0.093	0.094
ETF Fixed-Effects	Y	Y	Y	Y

Table 6: **ETF Portfolio Returns Sorted on ETF Short Ratio**

This table reports the monthly average returns, Fama and French (1993) 3-factor alpha, and Fama and French (1993) and Carhart (1997) 4-factor alpha for each of the five quintile portfolios formed by ETF funds, as well as the long-short portfolio (Low-High). At the end of each month, all ETF funds are sorted into quintiles based on their mid-month reported short ratio, and a long-short portfolio is formed by buying the lowest quintile and shorting the highest quintile portfolio. Portfolio returns are computed over the next month. Panel A reports results for equally weighted portfolios, and Panel B shows results for value-weighted portfolios. The sample runs from January 2002 to December 2013.

Panel A: Equal-weighted Quintile Portfolio Returns and Alphas

	Mean	t-stat	FF(93)	t-stat	Carhart(97)	t-stat
Low	0.70	1.77	0.01	0.21	0.01	0.12
2	0.68	1.77	0.01	0.14	0.00	0.05
3	0.69	1.72	-0.01	-0.16	-0.02	-0.37
4	0.62	1.47	-0.12	-1.75	-0.13	-1.96
High	0.58	1.25	-0.23	-2.97	-0.24	-3.11
Low - High	0.11	1.08	0.24	3.26	0.24	3.31

Panel B: Value-weighted Quintile Portfolio Returns and Alphas

	Mean	t-stat	FF(93)	t-stat	Carhart(97)	t-stat
Low	0.77	2.09	0.13	1.97	0.13	1.93
2	0.64	1.69	-0.03	-0.75	-0.03	-0.81
3	0.62	1.65	-0.04	-0.92	-0.05	-1.05
4	0.68	1.68	-0.03	-0.38	-0.04	-0.54
High	0.61	1.59	-0.07	-2.63	-0.07	-2.90
Low - High	0.16	2.16	0.20	2.92	0.20	2.95

Table 7: **Portfolio Returns Sorted on ETF-based Stock SR**

This table reports the monthly average returns, Fama and French (1993) 3-factor alpha, and Fama and French (1993) and Carhart (1997) 4-factor alpha for each of the 10 decile portfolios, as well as the long-short portfolio (Low-High). At the end of each month, all stocks are sorted into deciles based on their ETF-based stock short ratio (ETF_sr) and a long-short portfolio is formed by buying the lowest decile and shorting the highest decile portfolio. Portfolio returns are computed over the next month. Panel A reports results for equally weighted portfolios and Panel B shows results for value-weighted portfolios. The sample runs from January 2002 to December 2013.

Panel A: Equal-weighted Decile Portfolio Returns and Alphas

	Mean	t-stat	FF(93)	t-stat	Carhart(97)	t-stat
Low	1.58	2.97	0.62	1.99	0.70	2.30
2	1.22	2.30	0.21	0.91	0.28	1.30
3	1.07	2.11	0.10	0.53	0.16	0.89
4	0.95	1.94	-0.01	-0.09	0.03	0.20
5	1.02	2.28	0.13	1.11	0.18	1.76
6	1.13	2.32	0.10	0.97	0.13	1.32
7	1.09	2.12	-0.01	-0.07	0.02	0.24
8	1.00	1.84	-0.14	-1.16	-0.10	-0.93
9	1.00	1.80	-0.14	-0.85	-0.08	-0.56
High	0.83	1.54	-0.27	-1.69	-0.24	-1.51
Low - High	0.76	2.55	0.90	3.05	0.94	3.21

Panel B: Value-weighted Decile Portfolio Returns and Alphas

	Mean	t-stat	FF(93)	t-stat	Carhart(97)	t-stat
Low	0.98	2.51	0.46	1.68	0.42	1.56
2	0.72	1.71	0.09	0.57	0.11	0.65
3	0.66	1.43	-0.02	-0.10	-0.01	-0.06
4	0.63	1.53	0.04	0.33	0.03	0.31
5	0.68	1.91	0.19	2.31	0.20	2.47
6	0.78	1.90	0.13	0.98	0.13	1.02
7	0.72	1.61	-0.02	-0.11	-0.06	-0.44
8	0.67	1.41	-0.14	-0.86	-0.18	-1.22
9	0.76	1.52	-0.09	-0.54	-0.11	-0.62
High	0.56	1.09	-0.32	-1.87	-0.35	-2.03
Low - High	0.42	1.14	0.78	2.51	0.77	2.47

Table 8: **Two-way sorts on Stock Short Ratio and ETF-based Short Ratio**

This table reports monthly Carhart (1997) 4-factor alphas (in percentages) sorted on stock's short ratio and ETF-based stock short ratios (ETF_sr). At the end of each month, all the stocks are sorted into terciles based on stock's short ratio, and within each tercile the stocks are further sorted into quintiles based on their ETF-based short ratios. Panel A reports equal-weighted returns and panel B for value-weighted return. The sample runs from January 2002 to December 2013.

Panel A: Equal-weighted Return

	ETF-based Stock Short ratio					
Stock SR	Low	2	3	4	High	Low-High
Low	1.10	0.69	0.54	0.31	0.32	0.77
	3.52	2.62	2.50	1.97	1.99	2.60
2	-0.09	0.11	0.34	0.15	0.02	-0.11
	-0.43	0.95	3.17	1.07	0.14	-0.48
High	-0.47	-0.11	-0.14	-0.50	-0.65	0.18
	-2.55	-1.04	-1.34	-4.21	-3.75	0.88

Panel B: Value-weighted Return

	ETF-based Stock Short ratio					
Stock SR	Low	2	3	4	High	Low-High
Low	0.92	0.23	0.24	0.03	0.09	0.83
	3.23	1.12	1.14	0.26	0.43	2.32
2	0.00	0.13	0.29	-0.01	0.11	-0.11
	0.01	1.21	2.11	-0.08	0.61	-0.48
High	-0.35	-0.19	-0.09	-0.39	-0.50	0.15
	-2.21	-1.51	-0.72	-3.06	-2.88	0.66

Table 9: **Two-way sorts on Short-Sale Constraints and ETF-based Short Ratio**

This table reports monthly Carhart (1997) 4-factor alphas (in percentages) sorted on proxies of short-sales constraints and ETF-based stock short ratios (ETF_sr). At the end of each month, all the stocks are sorted into terciles based on a proxy for short-sale constraints, and within each tercile the stocks are further sorted into quintiles based on their ETF-based short ratios. Returns are equally weighted within each portfolio. We use lendable supply, institutional ownership, lending fee, idiosyncratic volatility, stock turnover, and Amihud (2002) illiquidity as proxy for short-sale constraints in Panels A, B, C, D, E, and F, respectively. The overall sample runs from January 2002 to December 2013. The lending fee and lendable supply sample is from January 2004 to December 2013.

Panel A: Lendable Supply and ETF-based SR

	ETF-based Stock Short ratio					
Lendable Supply	Low	2	3	4	High	Low-High
Low	0.43	0.34	-0.03	-0.21	-0.31	0.73
	1.22	1.01	-0.10	-1.12	-1.30	1.98
2	0.40	0.05	0.26	0.06	0.14	0.27
	2.33	0.42	2.51	0.48	0.90	1.10
High	0.05	-0.02	0.15	-0.07	-0.17	0.22
	0.35	-0.24	1.48	-0.75	-1.67	1.31

Panel B: Inst.Ownership and ETF-based SR

	ETF-based Stock Short ratio					
Inst. Ownership	Low	2	3	4	High	Low-High
Low	0.81	0.44	-0.02	-0.21	-0.39	1.20
	2.51	1.42	-0.07	-1.46	-2.10	3.59
2	0.44	0.12	0.33	0.07	0.14	0.29
	2.26	1.01	3.15	0.55	0.81	1.44
High	0.04	0.04	0.12	-0.11	-0.21	0.25
	0.25	0.42	1.10	-1.03	-1.50	1.51

Panel C: Lending fee and ETF-based SR

	ETF-based Stock Short ratio					
Lending Fee	Low	2	3	4	5	Low-High
Low	0.50	0.27	0.15	0.12	0.13	0.37
	2.33	1.80	2.18	1.56	1.02	1.50
High	0.24	-0.74	-1.41	-1.02	-1.47	1.70
	0.50	-1.78	-4.35	-3.85	-4.25	3.52

Table 9 Continued

Panel D: Idiosyncratic Vol. and ETF-based SR						
	ETF-based Stock Short ratio					
Idiosyncratic Vol	Low	2	3	4	High	Low-High
Low	0.40	0.25	0.23	0.10	0.09	0.30
	3.57	2.79	2.76	0.90	0.73	2.02
2	0.36	0.02	0.00	-0.02	0.04	0.32
	2.02	0.11	-0.02	-0.12	0.27	1.54
High	0.59	0.18	-0.02	-0.17	-0.40	0.99
	1.55	0.52	-0.11	-0.99	-1.84	2.75

Panel E: Stock Turnover and ETF-based SR						
	ETF-based Stock Short ratio					
Turnover	Low	2	3	4	5	Low-High
Low	1.00	0.59	0.25	0.02	0.02	0.98
	2.99	2.32	1.03	0.10	0.08	2.51
2	0.55	0.10	0.25	0.04	-0.09	0.65
	2.35	0.87	2.21	0.33	-0.56	2.72
High	-0.47	-0.10	-0.05	-0.09	-0.45	-0.03
	-1.89	-0.72	-0.43	-0.64	-2.01	-0.11

Panel F: Amihud Illiquidity and ETF-based SR						
	ETF-based Stock Short ratio					
Illiquidity	Low	2	3	4	5	Low-High
Low	0.10	0.00	0.18	0.17	-0.08	0.18
	0.76	-0.04	2.06	2.27	-0.76	1.33
2	-0.18	0.01	0.10	-0.22	-0.13	-0.05
	-1.27	0.05	0.82	-1.49	-0.80	-0.28
High	0.81	0.58	0.35	0.12	-0.09	0.90
	2.40	1.75	1.15	0.60	-0.45	2.64

Table 10: **Fama-MacBeth Regression: Baseline**

This table reports the results from the Fama and MacBeth (1973) regression of monthly stock returns on ETF-based short ratio (ETF_sr). ETF_sr2 is the dollar value of short interests on the stock via ETFs over stock's market capitalization. Size (LnME) is the natural log of a firm's market capitalization at the end of the June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). All t-statistics are Newey-West adjusted with twelve lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
ETF_sr	-0.0219**	-0.0125**	-0.0124***	
	(-2.52)	(-2.50)	(-2.69)	
ETF_sr2				-0.6826**
				(-2.57)
LnME		-0.0007	-0.0012**	-0.0013**
		(-0.94)	(-2.34)	(-2.21)
LnBM		0.0012	0.0009	0.0009
		(1.31)	(0.95)	(0.85)
REV		-0.0181***	-0.0188***	-0.0188***
		(-3.49)	(-3.48)	(-3.41)
MOM		-0.0055	-0.0043	-0.0044
		(-0.81)	(-0.72)	(-0.76)
IO			0.0049*	0.0064
			(1.67)	(1.61)
IVOL			-0.0498	-0.0477
			(-0.60)	(-0.58)
Constant	0.0145**	0.0146	0.0165**	0.0167**
	(2.14)	(1.45)	(2.19)	(2.19)
Ave.R-sq	0.005	0.029	0.039	0.040
N.of Obs.	432063	432063	432062	430407

Table 11: **Fama-MacBeth Regression: Controlling for Stock-level Shorting Variables**

This table reports the results from the Fama and MacBeth (1973) regression of monthly stock returns on ETF-based short ratios (ETF_sr) while controlling for variables related to stock lending. Size (LnME) is the natural log of a firm's market capitalization at the end of the June of each year. Book-to-market (LnBM) is the natural log of the book-to-market ratio. The cases with negative book value are deleted. Momentum (MOM) is defined as the cumulative returns from month t-12 to t-2. The short term reversal measure (REV) is the lagged monthly return. Institutional ownership (IO) is the sum of shares held by institutions from 13F filings in each quarter divided by the total shares outstanding. IVOL is the idiosyncratic volatility, calculated following Ang, Hodrick, Xing, and Zhang (2006). Short interest ratio (SR) is the number of shares shorted over total shares outstanding. DCBS is a score from 1 to 10 created by Markit using their proprietary information and is intended to capture the cost of borrowing the stock. SIO is the short interest ratio (SR) divided by institutional ownership. Lendable shares (supply) is the shares held and made available to lend by Markit lenders divided by total shares outstanding. Utilization is the ratio of shares borrowed to shares made available by Markit lenders. All t-statistics are Newey-West adjusted with twelve lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)
ETF_sr	-0.0097**	-0.0114***	-0.0123**	-0.0094**	-0.0115***
	(-2.03)	(-2.66)	(-2.10)	(-2.08)	(-2.77)
LnME	-0.0014***	-0.0012**	-0.0010*	-0.0012**	-0.0011**
	(-2.71)	(-2.32)	(-1.78)	(-2.40)	(-2.17)
LnBM	0.0012	0.0002	0.0005	0.0009	0.0011
	(1.30)	(0.18)	(0.53)	(1.05)	(1.28)
REV	-0.0243***	-0.0187***	-0.0189***	-0.0244***	-0.0169***
	(-5.05)	(-3.20)	(-3.26)	(-5.23)	(-3.49)
MOM	-0.0056	-0.0037	-0.0027	-0.0056	-0.0039
	(-0.96)	(-0.58)	(-0.41)	(-0.95)	(-0.69)
IO	0.0087***	0.0028	0.0064**	0.0037	0.0094**
	(2.92)	(1.07)	(2.09)	(1.36)	(2.18)
IVOL	0.0113	-0.0744	-0.0542	0.0329	-0.0273
	(0.14)	(-1.34)	(-0.84)	(0.40)	(-0.28)
SR	-0.0445***				
	(-4.55)				
DCBS		-0.0031***			
		(-5.62)			
Utilization			-0.0056***		
			(-2.93)		
SIO				-0.0247***	
				(-7.68)	
Supply					-0.0148**
					(-2.35)
Constant	0.0163**	0.0203***	0.0130*	0.0179**	0.0153**
	(2.17)	(2.79)	(1.68)	(2.40)	(2.14)
Ave.R-sq	0.043	0.042	0.042	0.044	0.040
N.of Obs.	382372	385102	362249	382230	420203

Table 12: **Fama-MacBeth Regression: Interaction between ETF-based SR and Short-Sale Constraint Measures**

This table reports the results from the Fama and MacBeth (1973) regression of monthly stock returns on ETF-based stock short ratios (ETF_sr) and its interaction with several dummies that indicate binding short-sale constraints. LowIO (Lowsupply) is a dummy equal to one when the stock is in the bottom quintile of institutional ownership ratio (lendable supply) in the cross-section. Highutil (Highfee) is a dummy equal to one when the stock is in the top quintile of utilization (lending fees) in the cross-section. Lowturn is a dummy equal to one when the stock is in the bottom quintile of past 12-month average turnover in the cross-section. Noput is a dummy equal to one when the stock has no exchange-traded put option. Other control variables are the same as in the previous tables. All t-statistics are Newey and West (1987) adjusted with twelve lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ETFsr	-0.0055	-0.0086*	-0.0073	-0.0073	-0.0071	-0.0001
	(-1.12)	(-1.68)	(-1.35)	(-1.61)	(-1.30)	(-0.02)
ETFsr_lowIO	-0.0202***					
	(-2.67)					
LowIO	-0.0036					
	(-1.64)					
ETFsr_lowsupply		-0.0041				
		(-1.04)				
Lowsupply		-0.0010				
		(-0.84)				
ETFsr_highutil			-0.0073*			
			(-1.75)			
Highutil			-0.0008			
			(-0.46)			
ETFsr_highfee				-0.0176***		
				(-3.26)		
Highfee				-0.0026		
				(-1.18)		
ETFsr_lowturn					-0.0082*	
					(-1.72)	
Lowturn					-0.0024	
					(-1.07)	
ETFsr_Noput						-0.0137**
						(-2.19)
Noput						-0.0018
						(-0.79)
SR	-0.0383***	-0.0463***	-0.0411***	-0.0325***	-0.0583***	-0.0622***
	(-4.07)	(-4.66)	(-3.68)	(-3.48)	(-4.91)	(-5.09)
LnME	-0.0011**	-0.0014***	-0.0013**	-0.0014***	-0.0016***	-0.0018***
	(-2.20)	(-2.66)	(-2.23)	(-2.72)	(-2.94)	(-3.01)
LnBM	0.0012	0.0011	0.0005	0.0010	0.0012	0.0012
	(1.33)	(1.28)	(0.56)	(1.07)	(1.33)	(1.43)
REV	-0.0243***	-0.0244***	-0.0200***	-0.0251***	-0.0262***	-0.0258***
	(-5.04)	(-5.08)	(-3.82)	(-5.18)	(-4.91)	(-4.84)
MOM	-0.0057	-0.0057	-0.0036	-0.0058	-0.0044	-0.0045
	(-0.96)	(-0.96)	(-0.54)	(-0.98)	(-0.82)	(-0.82)
IVOL	0.0096	0.0145	-0.0696	0.0231	-0.0167	0.0065**
	(0.12)	(0.18)	(-1.12)	(0.29)	(-0.21)	(2.38)
IO		0.0078***	0.0109***	0.0063**	0.0058*	-0.0184
		(2.65)	(3.60)	(2.37)	(1.78)	(-0.23)
Constant	0.0201**	0.0171**	0.0120	0.0172**	0.0192**	0.0202***
	(2.42)	(2.18)	(1.44)	(2.24)	(2.56)	(2.80)
Ave.R-sq	0.043	0.044	0.042	0.045	0.050	0.050
N.of Obs.	382372	382372	325433	382372	399047	399047

Table 13: **Anomaly Returns Conditional on ETF Ownership**

This table reports monthly excess returns (in percentages) and Carhart (1997) 4-factor alphas (in percentages) for 10 well-studied anomalies. For each month, we sort stocks with DCBS scores greater than two into two groups based on ETF ownership. We then further sort stocks into terciles based on anomaly characteristics. The long-short anomaly return of the category is given by the difference between the returns of the extreme portfolios. Panel A reports the monthly long-short returns for each anomaly and ETF ownership category. Panel B reports the corresponding Carhart (1997) 4-factor alphas. The sample runs from January 2004 to December 2013.

	Lending Fees		**Anomalies**									
ETF Ownership Bucket	DCBS	SAF	B/M	Accurals	NOA	AG	CI	LT REV	CS	GP	ROA	MOM
					Panel A: Monthly Returns (%)							
Low ETF Ownership	4.22	773.90	1.04	0.78	1.28	1.59	0.67	0.83	1.13	0.32	-0.08	-1.19
(t-stat)	62.36	13.31	1.94	1.45	2.32	2.50	1.24	1.28	1.93	0.50	-0.11	-1.84
High ETF Ownership	4.07	659.99	0.55	0.27	0.39	0.73	0.02	0.07	1.31	0.99	1.05	0.46
(t-stat)	72.07	21.87	1.36	0.76	0.90	1.58	0.05	0.13	3.22	2.15	2.13	0.82
					Panel B: Cahart four-factor alpha (%)							
Low ETF Ownership			1.12	0.74	1.40	1.50	0.65	0.60	1.28	0.49	-0.02	-1.17
(t-stat)			2.07	1.38	2.56	2.34	1.21	0.93	2.24	0.79	-0.02	-2.15
High ETF Ownership			0.50	0.19	0.45	0.63	-0.06	-0.06	1.41	1.07	1.19	0.47
(t-stat)			1.40	0.55	1.03	1.57	-0.14	-0.14	3.61	2.37	2.60	1.15

Appendices

Table A1: Cross-Sectional Determinants of ETF Short Ratio: Interaction with ETF Turnover

This table reports the results from the Fama and MacBeth (1973) regression of monthly ETF short interest ratios on ETF characteristics, constituent stocks' characteristics, and the interaction between ETF turnover and constituents' characteristics. *High Turnover* is a dummy variable that equals one if the turnover ratio of the ETF is above the cross-sectional median. We interact this dummy with the *Stock illiquidity* measure of Amihud (2002), stock lending supply, stock lending utilization ratio, and the stock lending fee from Markit. All t-statistics are Newey-West adjusted to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
ETF Ln(ME)	0.0132***	0.0136***	0.0129***	0.0133***
	(19.69)	(19.06)	(20.87)	(20.40)
ETF Return	-0.0361**	-0.0386**	-0.0416**	-0.0538***
	(-2.12)	(-2.25)	(-2.58)	(-2.75)
ETF Return Vol	0.819***	0.786***	0.742***	0.833***
	(5.77)	(5.45)	(5.24)	(5.51)
High ETF Turnover	0.0433***	0.0213	0.00980**	0.0405***
	(29.17)	(1.33)	(2.52)	(10.82)
Stock Illiquidity	-1.087***			
	(-4.48)			
High ETF Turnover*Stock Illiquidity	6.076***			
	(8.91)			
Stock Lending Supply		-0.00140		
		(-0.01)		
High ETF Turnover*Stock Lending Supply		-0.505*		
		(-1.75)		
Stock Lending Utilization			-0.0587***	
			(-4.10)	
High ETF Turnover*Stock Lending Utilization			0.250***	
			(13.06)	
Stock Lending Fee				0.0212
				(1.12)
High ETF Turnover*Stock Lending Fee				0.143***
				(5.60)
Stock Return IVol	1.027*	3.528***	2.013***	2.989***
	(1.86)	(5.63)	(3.88)	(4.73)
Stock Ln(ME) and BM	Y	Y	Y	Y
Observations	16947	16947	16947	16947
R^2	0.218	0.199	0.203	0.201

Table A2: **Factor Loadings**

This table reports the factor loadings of the Carhart (1997) Four Factor model. MKTRF, SMB, HML, and UMD stand for the market factor, size factor, value factor, and the momentum factor, respectively. Panel A reports results for equal-weighted portfolios, and Panel B shows results for value-weighted portfolios. The sample runs from January 2002 to December 2013.

Panel A: Equal-weighted alphas and factor loadings					
	Alpha	MKTRF	SMB	HML	UMD
Low	0.698	0.807	0.814	0.233	-0.216
	2.30	10.01	5.90	1.79	-3.28
High	-0.239	1.028	0.986	0.178	-0.098
	-1.51	24.42	13.68	2.63	-2.86
Low - High	0.937	-0.221	-0.172	0.055	-0.118
	3.21	-2.85	-1.29	0.44	-1.86

Panel B: Value-weighted alphas and factor loadings					
	Alpha	MKTRF	SMB	HML	UMD
Low	0.423	0.693	0.226	0.377	0.098
	1.56	9.62	1.83	3.25	1.67
High	-0.347	1.141	0.688	0.134	0.073
	-2.03	25.18	8.87	1.84	1.96
Low - High	0.770	-0.448	-0.462	0.242	0.025
	2.47	-5.40	-3.25	1.82	0.38

Table A3: **Robustness of Portfolio Sorts**

This table reports 4-factor alphas for robustness tests. In the first set of robustness tests, we report the 4-factor alpha of gross return-weighted portfolio returns in which the weights are 1 + the stock's lagged monthly return, following Asparouhova, Bessembinder, and Kalcheva (2013). The second set of robustness tests shows alphas when the Pástor and Stambaugh (2003) liquidity factor is included with the Fama-French factors and the momentum factor. In the third set of tests, we report the alphas using the Fama and French (2015) Five Factor model. In the fourth set of analyses, we exclude stocks with a price lower than $5. The fifth and sixth set of analyses report alphas for stocks listed on NYSE-Amex and NASDAQ exchanges, respectively. In the seventh panel, we skip a month between the moment at which ETF-based SR is constructed and the moment at which we start measuring returns. In the eighth panel, we first regress ETF-based SR on stock's own SR and form decile portfolios based on the residual ETF-based SR. The sample runs from January 2002 to December 2013.

	EW	VW
Gross return-weighed portfolio	0.804	N/A
	(2.76)	
FF + Cahart + PS Factor	0.884	0.795
	(3.01)	(2.52)
FF five factor (2015)	1.144	0.846
	(3.82)	(2.56)
Exclude Price<=$5	0.459	0.477
	(2.39)	(2.04)
NYSE-Amex	0.795	0.453
	(2.68)	(1.51)
NASDAQ	0.695	0.342
	(2.00)	(0.97)
Skip a month	0.775	0.801
	(2.70)	(2.51)
Residual ETF-based SR	0.750	0.406
	(2.87)	(1.64)

Table A4: **Fama-MacBeth Regression: 1- to 12-months ahead return predictability**

This table reports the results from the Fama and MacBeth (1973) regression of monthly stock returns on ETF-based stock short ratios (ETF_sr). The dependent variables are monthly stock returns from 1 month to 12 months ahead. The control variables are the same as in the previous tables. All t-statistics are Newey-West adjusted with twelve lags to control for heteroskedasticity and autocorrelation. ***, **, and * represent significance levels of 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
ETF_sr	-0.0124***	-0.0126***	-0.0099**	-0.0069	-0.0093*	-0.0100**	-0.0089**	-0.0064	-0.0034	-0.0060	-0.0020	-0.0019
	(-2.69)	(-3.05)	(-2.38)	(-1.45)	(-1.85)	(-2.19)	(-2.10)	(-1.54)	(-1.02)	(-1.50)	(-0.62)	(-0.70)
LnME	-0.0012**	-0.0013***	-0.0010**	-0.0009*	-0.0008*	-0.0010**	-0.0007	-0.0006	-0.0004	-0.0004	-0.0005	-0.0003
	(-2.34)	(-2.67)	(-2.44)	(-1.95)	(-1.94)	(-2.17)	(-1.63)	(-1.45)	(-0.87)	(-1.09)	(-1.15)	(-0.87)
LnBM	0.0009	0.0007	0.0008	0.0012	0.0009	0.0007	0.0009	0.0009	0.0011	0.0011	0.0010	0.0013
	(0.95)	(0.67)	(0.86)	(1.30)	(1.00)	(0.68)	(0.92)	(0.94)	(1.23)	(1.25)	(1.19)	(1.57)
REV	-0.0188***	-0.0052	0.0038	-0.0073	0.0020	0.0015	-0.0006	0.0002	-0.0011	-0.0020	0.0078	0.0019
	(-3.48)	(-0.77)	(0.61)	(-1.35)	(0.28)	(0.20)	(-0.11)	(0.04)	(-0.18)	(-0.26)	(1.37)	(0.35)
MOM	-0.0043	-0.0044	-0.0055	-0.0054	-0.0047	-0.0032	-0.0035	-0.0044	-0.0038	-0.0027	-0.0038	-0.0028
	(-0.72)	(-0.81)	(-0.94)	(-0.85)	(-0.91)	(-0.78)	(-0.85)	(-1.28)	(-1.43)	(-1.18)	(-1.48)	(-1.14)
IO	0.0049*	0.0049*	0.0058**	0.0051**	0.0047*	0.0049**	0.0056**	0.0052**	0.0045*	0.0052*	0.0055**	0.0055**
	(1.67)	(1.78)	(2.35)	(2.08)	(1.91)	(2.03)	(2.38)	(2.01)	(1.72)	(1.95)	(2.02)	(2.12)
IVOL	-0.0498	-0.0496	-0.0031	0.0043	-0.0201	-0.0457	-0.0133	-0.0145	0.0272	-0.0021	-0.0042	0.0092
	(-0.60)	(-0.58)	(-0.04)	(0.05)	(-0.29)	(-0.74)	(-0.24)	(-0.22)	(0.43)	(-0.03)	(-0.06)	(0.12)
Constant	0.0165**	0.0170**	0.0139**	0.0133*	0.0132*	0.0138*	0.0118*	0.0111*	0.0094	0.0095	0.0095	0.0082
	(2.19)	(2.25)	(2.02)	(1.81)	(1.93)	(1.84)	(1.81)	(1.82)	(1.33)	(1.52)	(1.46)	(1.32)
Ave.R-sq	0.039	0.035	0.035	0.033	0.031	0.031	0.028	0.027	0.025	0.025	0.026	0.026
N.of Obs.	432062	429688	427259	424808	422364	419935	417505	415077	412662	410264	407884	405523