# Short Selling Efficiency

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First draft: February 19, 2020
This draft: December 18, 2020

**ABSTRACT**

Short selling efficiency (SSE), measured each month by the slope coefficient of cross-sectionally regressing abnormal short interest on an overpricing score, significantly and negatively predicts stock market returns both in-sample and out-of-sample, suggesting that mispricing gets corrected after short sales are executed on the right stocks. The predictive power is stronger in the presence of large short interest and during periods of recession, high volatility, and less public information. Finally, low SSE precedes the months when the CAPM performs well and signals efficient market. Overall, our evidence highlights the importance of the disposition of short sales in stock markets.

*Keywords*: Short selling efficiency, return predictability, mispricing, market efficiency
*JEL Classification*: G11, G23

* We thank Boone Bowles, Lauren Cohen, Tony Cookson, Friedrich Lorenz, Adam Reed, Matthew Ringgenberg, Wei Wu, Guofu Zhou, and seminar and conference participants at Texas A&M University, the 2020 Paris December Finance Meeting, the 2020 Australian Finance and Banking Conference, and the 2020 China International Risk Forum and China Finance Review International Joint Conference for helpful comments and suggestions. We are grateful to Zhuo Chen, Amit Goyal, Zhiguo He, Bryan Kelly, Asaf Manela, Robert Shiller, Robert Stambaugh, Ivo Welch, Jeffrey Wurgler, Jianfeng Yu, and Guofu Zhou for making a large amount of data available to us. A research award from the Global Association of Risk Professionals (GARP) is gratefully acknowledged. Chen is at Mays Business School, Texas A&M University, College Station, TX 77843, Email: ychen@mays.tamu.edu; Da is at the Mendoza College of Business, University of Notre Dame, Notre Dame, IN 46556, Email: zda@nd.edu; Huang is at the Bryan School of Business, University of North Carolina at Greensboro, Greensboro, NC 27412, Email: d_huang@uncg.edu. We are responsible for all remaining errors.

## 1. Introduction

Short selling is an essential trading activity in modern finance. The impact of short selling, as well as its constraints, in financial markets has received tremendous attention among academics. Indeed, a large literature has examined the effects of short selling on expected stock returns, both theoretically and empirically.[1] Many studies have identified a significant relation between short selling and stock returns in the cross section. In contrast to the rich evidence in the cross section, however, little is known about the time-series relation of short selling to aggregate stock returns. Rapach, Ringgenberg, and Zhou (2016), as one important exception, show that short interest can predict stock market returns. Their analysis, however, does not distinguish between short sales executed on different stocks. In theory, short sales of overpriced stocks should impose stronger price effects than those of underpriced stocks, because the former is more informative. In this paper, we combine the information of short sales with stock mispricing to examine the role of short selling *efficiency* in the aggregate stock market.

Efficient short selling means that the scarce resources for short sales are allocated to places where positive investment opportunities exist (i.e., overpriced stocks). Motivated by this fundamental economic insight, we measure short selling efficiency (SSE) by the slope coefficient of a simple cross-sectional regression. In each month, we regress abnormal short interest (i.e., the ratio of the shares sold short and the total number of shares outstanding) on the overpricing measure of Stambaugh, Yu, and Yuan (2015) constructed from stock anomalies. Since the slope coefficient measures the covariance between abnormal short interest and overpricing across stocks,

[1] The studies on the effects of short selling and its constraints on stock prices in the cross section are too voluminous to list in the present paper. For theoretical work, see, e.g., Miller (1977), Harrison and Kreps (1978), Diamond and Verrechia (1987), Duffie, Garleanu, and Pedersen (2002), Hong and Stein (2003), Scheinkman and Xiong (2003), and Hong, Scheinkman, and Xiong (2006). An incomplete list of the empirical studies includes Asquith and Meulbroek (1995), Danielsen and Sorescu (2001), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Geczy, Musto, and Reed (2002), Jones and Lamont (2002), Christophe, Ferri, and Angel (2004), Ofek, Richardson,and Whitelaw (2004), Asquith, Pathak, and Ritter (2005), Nagel (2005), Bris, Goetzmann, and Zhu, (2007), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a, 2009b), Engelberg, Reed, and Ringgenberg (2012), Blocher, Reed, and Van Wesep (2013), Boehmer, Jones, and Zhang (2013), Boehmer and Wu (2013), Hanson and Sunderam (2014), Drechsler and Drechsler (2016), Jones, Reed, and Waller (2016), Chen, Da, and Huang (2019), and Hwang, Liu, and Xu (2019). See Reed (2013) for a survey of the short selling literature.

it captures the efficiency of short selling activity. The higher the slope coefficient is, the more short sales are placed in the right stocks that are more overpriced. Repeating the regression each month, we obtain a time-series measure of short selling efficiency.

By construction, SSE contains information about both short interest and stock mispricing, and thus differs from the aggregate short interest used in prior research (which happens to be the intercept term in the cross-sectional regression). In general, while the aggregate short interest may indicate the level of overpricing, it does not guarantee that mispricing will be corrected immediately. In contrast, high SSE reflects active trading of arbitrageurs on mispriced stocks and thus mispricing gets corrected more quickly. As shown in our empirical analysis, such a contrast can be related to the predictability at different forecasting horizons. Another benefit of SSE lies in its ability to reduce the effect of measurement error in short interest. In practice, not all short sales are driven by overpricing in the stocks, but some are used to hedge positions in bonds and options. Consequently, treating all short interest as signals of overvaluation would inevitably introduce measurement error. The emphasis of SSE on overpriced stocks, however, helps mitigate the impact of measurement error and hence provides powerful stock return prediction.

First, we show that SSE is a strong predictor of stock market returns both in-sample and out-of-sample. Over the period 1974–2017, SSE has statistically and economically significant predictive power for the equity premium. When we regress future excess stock market returns on SSE at a monthly frequency, we obtain a regression coefficient of -0.61 (t-value = -3.50) and an R-squared of 1.64%. The predictive power persists over a year. At the 12-month forecasting horizon, the regression coefficient is -0.40 (t-value = -3.69) and the R-squared is 8.49%. The predictability is robust to controlling for the aggregate short interest and other return predictors, suggesting that SSE contains distinct information about future market returns. While the results are robust to various forecasting horizons, SSE predicts stock market returns particularly well over short horizons, suggesting that efficient short-sales allocation signals active arbitrage trading and fast price correction follows. Our out-of-sample tests, following Campbell and Thompson (2008) and Goyal and Welch (2008), confirm that SSE has favorable forecasting ability relative to the historical average of stock market returns. In addition, the out-of-sample results are robust to imposing economic restrictions about the predicted equity premium.

Second, SSE and aggregate short interest appear to reinforce each other in forecasting stock market returns, in that the predictive power of SSE is stronger in the presence of a higher level of aggregate short interest, and vice versa. When aggregate short interest is higher (lower) than the median level, the predictive regression for stock returns in the next three months based on SSE produces a regression coefficient of -0.81 (-0.53), with a t-value of -2.80 (-1.65) and an adjusted R-squared of 9.13% (1.51%). This makes sense, because the correction of overpricing would require two conditions: a sufficiently high level of short selling, and short selling placed in the right stocks. In a sense, Rapach, Ringgenberg, and Zhou (2016) focus on the first condition, while our paper highlights the important, while distinct, role of the second condition.

Third, to infer the source of the predictive power of SSE, we examine how the predictive power varies with market conditions and information environments. Kacperczyk, Nieuwerburgh, and Veldkamp (2016) argue that information processing is especially valuable in recessions when aggregate payoff shocks are more volatile. Hence, SSE is expected to forecast well in such conditions. Consistent with the expectation, we find that the predictive power of SSE is particularly strong in recessions and high volatility periods. In addition, the predictive power is stronger in the periods with less public information (e.g., earnings announcements) than the periods with more public information. These findings complement the existing evidence from the cross section of stocks and support the notion that short sellers are informed (e.g., Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012).

Fourth, we link short selling efficiency to the overall stock market efficiency. We provide evidence that the behavior of short selling, in terms of both SSE and aggregate short interest, is closely related to the performance of the capital asset pricing model (CAPM) and hence impacts market efficiency. Specifically, immediately following periods of low SSE and aggregate short interest, a significant upward slope of the security market line (which delineates the relation between market exposure and expected stock return) emerges, supporting the main prediction of the CAPM. Based on ten decile portfolios formed on stock betas, the corresponding security market line has a slope of 1.03 (t-value = 5.34). In contrast, following periods when the stock market features high SSE and aggregate short interest, the security market line is flat or even downward sloping. Similarly, the return spread between the two extreme decile portfolios formed on the Stambaugh, Yu, and Yuan (2015) mispricing score appears to be large only in the months following high levels of SSE and aggregate short interest.

Finally, our inference survives a battery of sensitivity tests. Since our main analysis is based on detrended series of SSE, we verify the predictive power of SSE using the un-detrended series. Next, we obtain the same inference from an alternative measure of SSE based on the spread in short interest between the top and bottom deciles ranked by the Stambaugh-Yu-Yuan mispricing score. Furthermore, our results are robust to including micro-cap stocks in the sample. We also show evidence of the out-of-sample predictive power of SSE over longer horizons up to one year. In addition, motivated by the finding of Chen, Da and Huang (2019) that combining the long and short sides provides a more complete picture about arbitrage trading, we compute the arbitrage trading efficiency (ATE) in a similar fashion to SSE by replacing abnormal short interest with the net arbitrage trading measure. We find that ATE negatively predicts future market returns. The quarterly availability of ATE, however, weakens the statistical power of the time-series tests. For this reason, we prefer to use monthly SSE as our primary measure. Finally, we provide further evidence of the predictive power of SSE for stock market returns based on daily data.

Our paper makes several contributes to the literature. First, our paper relates to the large literature of how short sales predict stock returns. Prior research mostly focuses on the *cross-sectional* predictability of short selling and its constraints, including Nagel (2005), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a), Engelberg, Reed, and Ringgenberg (2012), Hanson and Sunderam (2014), and Drechsler and Drechsler (2016). Among these papers, Nagel (2005) and Hanson and Sunderam (2014) have also examined the relation between short sales and return anomalies. Our paper complements the extant research by investigating the predictive power of short selling efficiency for *aggregate* stock returns.

Second, our paper is most closely related to Rapach, Ringgenberg, and Zhou (2016), who show that the level of short interest predicts the equity premium. The authors assert that "short interest is arguably *the* strongest predictor of the equity market premium identified to date" (p. 46). Combining mispricing information (i.e., stock anomalies) with short interest, our predictor of short selling efficiency includes distinctive signals and sheds new light on how short sellers influence stock markets at the aggregate level. Importantly, our study is motivated by the fundamental economic insight that how scarce resources for short selling are allocated across different stocks should impact the overall market efficiency. To the best of our knowledge, our paper is the first to link short selling efficiency to aggregate stock price movement.

Finally, our study relates to the literature on the aggregate return predictability. Given the importance of the equity premium in practice, there has been decades-long research about this topic (see, e.g., Goyal and Welch (2008) and Rapach and Zhou (2013) for excellent surveys).[2] Numerous studies have examined the predictive power of variables constructed from firm fundamentals (e.g., payout ratio and book-to-market ratio) and macroeconomic conditions (e.g., bond yield spread and investor sentiment). Our innovation is to show that the efficiency of arbitrageurs such as short sellers contains significant predictive signals for stock market returns and impacts overall market efficiency.[3]

[2] A partial list of recent studies on forecasting the equity premium since 2008 includes Boudoukh, Richardson, and Whitelaw (2008), Campbell and Thompson (2008), Cochrane (2008), Goyal and Welch (2008), Lettau and van Nieuwerburgh (2008), Pastor and Stambaugh (2009), Rapach, Strauss, and Zhou (2010), Dangl and Halling (2012), Huang, Jiang, Tu, and Zhou (2015), Rapach, Ringgenberg, and Zhou (2016), Da, Huang, and Yun (2017), Chen, Eaton, and Paye (2018), among others. In particular, Goyal and Welch (2008) analyze both in-sample and out-of-sample predictability for nearly twenty return predictors. For earlier research in the literature, see, e.g., Rapach and Zhou (2013) for a survey.

[3] In recent years, over 80% of short selling has been performed by hedge funds. See, e.g., Brunnermeier and Nagel (2004), Ben-David, Franzoni, and Moussawi (2012), Chen, Da, and Huang (2019), and Chen, Kelly, and Wu (2020) for discussions and evidence about the stock trading behavior of hedge funds.

The paper process as follows. Section 2 describes the construction of the SSE measure. Section 3 summarizes the sample of SSE along with other return predictors. Section 4 presents the main results. In Section 5, we provide robustness tests and additional analysis. Finally, Section 6 concludes.

## 2. Measuring Short Selling Efficiency (SSE)

In our setting, short selling is efficient if more short sales occur to overpriced stocks relative to the other stocks (especially undervalued stocks). We propose an empirical measure of the efficiency based on the following cross-sectional regression:

$$ASI_{i,t} = a_t + b_t\, MISP_{i,t} + e_{i,t}, \qquad (1)$$

where ASI is the abnormal short interest. For each stock in our sample, we calculate its monthly short interest as the number of shares sold short in the month divided by the total number of shares outstanding. Similar to Chen, Da, and Huang (2019), we define abnormal short interest for each stock in each month as the value of short interest in the current month minus the average short interest over the past 12 months. MISP measures stock mispricing, with a large (small) value indicating overpricing (underpricing). For our empirical analysis, we adopt the comprehensive mispricing percentile ranking measure of Stambaugh, Yu, and Yuan (2015). To ease interpretation of the regression coefficients, MISP is demeaned cross-sectionally.

The regression coefficient of interest is the slope coefficient $b_t$, capturing short selling efficiency in month t. In the regression, the slope coefficient measures the covariance between ASI and MISP (scaled by the variance of MISP which is a constant). All else being equal, a large positive value of *b* indicates that short selling is executed on the right stocks, i.e., overpriced stocks.

Therefore, combining information from both the magnitude and the location of short interest, SSE serves as a potential predictor for aggregate stock returns.

In addition, since MISP has zero mean, the intercept $a_t$ is the mean level of abnormal short interest in month t, i.e., the equal-weighted average abnormal short interest across individual stocks, which is studied in Rapach, Ringgenberg, and Zhou (2016) for stock return prediction. As shown in Rapach, Ringgenberg, and Zhou (2016), the aggregate short interest is related to the level of mispricing in the market.

Short selling efficiency (coefficient $b$) differs from aggregate short interest (coefficient $a$) in important aspects. While aggregate short interest does not distinguish between different stocks, SSE will take a large value when short selling is aligned with overpricing. In practice, not all short sales are for arbitrage purposes, and sometimes short selling can even occur to undervalued stocks. For example, investors may sell short a stock simply to hedge their positions in other stocks, bonds and options. Chen, Da, and Huang (2019) show that separating short interest in overpriced stocks versus the other stocks (e.g., undervalued stocks) enhances the power of using shorting selling to predict stock returns in the cross section. Thus, our SSE measure contains important information about the stock market over and above the aggregate short interest. Moreover, the emphasis of SSE on overpriced stocks mitigates the impact of measurement error that arises from short sales for non-arbitrage purposes. Since noises in the predictor hamper the detection of a forecasting relation, mitigating the effect of measurement error will improve the test power. In sum, we expect SSE to possess significant forecasting power for the equity premium over and above the aggregate short interest.

## 3. Data

### 3.1 The SSE measure

The first element to measure SSE is abnormal short interest at the stock level. We employ short interest data from the Compustat Short Interest File, which reports monthly short interest for stocks listed on the NYSE, AMEX, and NASDAQ. Since the Compustat Short Interest File only started the coverage of NASDAQ stocks from 2003, we follow the literature to supplement our sample with short interest data on NASDAQ prior to 2003 obtained directly from the exchange. The data have been used in several previous studies to examine the impact of short interest on stock prices (e.g., Asquith, Pathak, and Ritter, 2005; Hanson and Sunderam, 2014; Chen, Da, and Huang, 2019). Based on the data, we calculate the abnormal short interest for each stock each month from January 1974 to December 2017. In particular, we use the short interest as of the middle of the month to ensure that it is in investors' information set when forming expectations of next-month market returns.

The second element required for computing SSE is a stock-level measure of mispricing. We adopt the mispricing measure of Stambaugh, Yu, and Yuan (2015), constructed from a combination of 11 well-known stock return anomalies.[4] The original measure is a composite rank between 1 and 100 across stocks based on various stock characteristics, with a higher rank indicating overpricing and a lower rank indicating underpricing. To suit our analysis, we rescale and demean the rank measure each month so the most overvalued (undervalued) stock in the cross-section has a value of 50 (-50). The resulting variable is MISP used in regression (1). Each month, the intercept and slope coefficient of the regression correspond to the short selling level (SSL) and short selling efficiency (SSE) for that month, respectively.[5]

In our baseline analysis, we require stocks to have non-missing values of ASI and MISP to be included in regression (1). In addition, we exclude micro-cap stocks and stocks whose price are

[4] These stock return anomalies include financial distress, o-score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investment to assets.

[5] Note that although SSL shares the same economic meaning as the short interest index (SII) proposed in Rapach, Ringgenberg, and Zhou (2016), there exist differences in the construction of these two variables. For example, SII is constructed using a sample of common stocks, American depositary receipts (ADRs), exchange traded funds (ETFs), and real estate investment trusts (REITs). However, SSL is obtained from common stocks only, because the mispricing score, used to measure both SSE and SSL in our paper, is compiled based on stock anomalies and hence available for stocks only.

less than five dollars. As robustness checks, we later include micro-cap stocks in the analysis in Section 6.

As documented by Rapach, Ringgenberg, and Zhou (2016), there has been an upward trend in short selling since the 1970s, perhaps reflecting the rise of hedge funds as the main group of short sellers in the US stock market. As a result, the monthly time series of both SSE and SSL display upward trends. Following Rapach, Ringgenberg, and Zhou (2016), we remove the time trend in both SSE and SSL and standardize both variables to mitigate the effect of secular trend on our results. Our inference remains unchanged if we do not detrend the predictors (see Section 6 for details).

Panel A of Table 1 summarizes the SSE measure over the sample period from January 1974 to December 2017. In this paper, our focus lies in the time-series properties of SSE. Indeed, we observe substantial variation of SSE over time, suggesting that short sellers do not always allocate trades to the right stocks. Meanwhile, the series of SSE exhibit a first-order autocorrelation of 0.84.

[Insert Table 1 about here.]

Figure 1 delivers a similar message by plotting the time series of SSE during the sample period. A few large values of SSE occur near some famous market downturns such as the tech bubble burst, the subprime mortgage crisis, and the 2008-2009 financial crisis. Such a pattern could be explained by the fact that it is easier to locate overpriced stocks at these episodes. More importantly, as can be seen from Figure 1, SSE departs from SSL to a substantive extent over time, suggesting that these variables capture different information. For example, while the level of short selling dropped substantially during the short sale ban around September 2008, the drop in short selling efficiency is less severe. In addition, SSE seems more volatile than SSL during the first half of our sample period.

[Insert Figure 1 about here.]

### 3.2 Other return predictors

In Panel A of Table 1, we also report the summary statistics of other return predictors that will be used for comparison purposes. Specifically, we collect data of the following return predictors, including both classic predictors in the literature and recently proposed predictors. The data sources are Compustat, the Fed Reserve Bank of St. Louis, and the websites of several researchers.[6] All the variables except price multiples are multiplied by 100 in the table.

1. Short selling level (SSL): detrended equal-weighted average abnormal short interest, similar to the short interest index used in Rapach, Ringgenberg, and Zhou (2016).
2. Investor sentiment (Sent): aggregate sentiment measure of Baker and Wurgler (2006), constructed as a composite of six variables: equity new issues, closed-end fund premium, NYSE share turnover, the number and average first-day returns of IPOs, and the dividend premium.
3. Price-earnings ratio (PE10): log value of the ratio of stock price to the moving average earnings per share over the recent ten years, as in Campbell and Shiller (1988a).
4. Price-dividend ratio (PD): log value of the ratio of stock price to dividend payment, as in Ball (1978), Campbell and Shiller (1988a, 1988b), among others.
5. Credit spread (CS): the difference in bond yield between BAA- and AAA-rated corporate bonds, as in Keim and Sambaugh (1986) and Fama and French (1989).
6. Term-spread (TS): the difference in bond yield between long-term government bonds and the three-month T-bill, as in Campbell (1987) and Fama and French (1989).

[6] We are grateful to Zhuo Chen, Amit Goyal, Zhiguo He, Bryan Kelly, Asaf Manela, Robert Shiller, Robert Stambaugh, Ivo Welch, Jeffrey Wurgler, Jianfeng Yu, and Guofu Zhou for making a large amount of data used in their research available to us.

7. Three-month T-bill rate (TB3): three-month T-bill rate, as in Campbell (1987) and Hodrick (1992).
8. Funding liquidity spread (FLS): aggregate funding liquidity measured by the return spread between stocks with high margins and stocks with low margins, proposed by Chen and Lu (2019).
9. Capital ratio (CAPR): aggregate funding liquidity measured by the equity capital ratio of major financial intermediaries, proposed by He, Kelly, and Manela (2017).

The summary statistics of these predictive variables are consistent with the literature. Many of the variables exhibit substantial first-order autocorrelation. In fact, all of them, except the funding liquidity spread, have the autocorrelation coefficients greater than 0.90.

Panel B of Table 1 presents the correlations between SSE and the other return predictors. Not surprisingly, SSE and the short selling level (SSL) are positively correlated, with a correlation coefficient of 0.6, as the existence of overpricing should motivate arbitrageurs to short more stocks, especially the most overpriced ones. Meanwhile, SSE bears relatively low correlations with the rest of other predictors, suggesting that SSE contains different information from the predictors constructed from firm fundamentals and macroeconomic conditions.

## 4. The Predictive Power of SSE

In this section, we first evaluate the in-sample forecasting power of SSE for stock market returns and compare it with other existing return predictors. Second, we assess the out-of-sample predictive ability of SSE. Third, we examine the predictability of SSE jointly with the short interest level (SSL). Finally, we explore the source of the forecasting power of SSE based on conditional predictability.

### 4.1 In-sample predictability

We start by examining how well SSE performs using the following univariate predictive regression, in which the dependent variable is the subsequent excess market returns over various forecasting horizons.

$$r_{t:t+s} = \alpha + \beta x_t + \varepsilon_{t:t+s}, \qquad (2)$$

where $r_{t:t+s} = (r_{t+1} + \cdots + r_{t+s})/s$, i.e., the average monthly excess market return over the forecasting horizon *s*. The excess market return is measured by the CRSP value-weighted aggregate stock index return in excess of one-month T-bill return for each month. Our inference is robust to using alternative measures of the excess market return, such as the one based on the S&P 500 index. The forecasting horizon *s* varies from one, three, six, to 12 months. *x* is the return predictor at a month frequency. For comparison purposes, we perform the same analysis for the other predictors. The reported regression coefficients are multiplied by 100. Following Rapach, Ringgenberg, and Zhou (2016), we report t-values based on the Newey-West (1987) standard errors with eight lags, and we verify that our inference remains unchanged using the Hodrick (1992) t-values.

Table 2 presents the regression results. Focusing on the main predictor of interest—SSE, the regression coefficient with a one-month forecasting horizon is -0.61 (t-value = -3.50), implying that a one-standard deviation increase in SSE would be followed by a decrease of the excess market return by 0.61% in the next month. The adjusted R-squared is as large as 1.64%. Moving to longer forecasting horizons, SSE still predicts future excess market returns, which is both economically and statistically significant. For example, at the 12-month horizon, the regression coefficient is -0.40 (t-value = -3.69) with an adjusted R-squared 8.49%. The finding of increased R-squared at longer forecasting horizons is consistent with the existing literature (e.g., Fama and French, 1988; Boudoukh, Richardson, and Whitelaw, 2008). In addition, the relatively long-horizon result suggests that the forecasting power is less likely to arise from temporary price pressure but more likely from market-wide information.

[Insert Table 2 about here.]

The predictive power of SSE compares favorably with the other return predictors. Consistent with Rapach, Ringgenberg, and Zhou (2016), we find that a high level of abnormal short interest precedes low excess market returns. The regression coefficients for SSL are -0.22, -0.43, -0.56 and -0.45 at the one-, three-, six- and 12-month horizons, respectively, compared with the coefficients for SSE at -0.61, -0.64, -0.62, and -0.40 over the same horizons. Since both of the predictors have been normalized, their regression coefficients can be compared directly. Thus, we find that SSE performs as least as well as SSL and possesses strong predictive power at all the four forecasting horizons.

Other predictors, such as financial ratios and market conditions, generally show correct signs in forecasting aggregate stock returns, but they are not statistically significant especially over shorter horizons. As the forecasting horizon extends to a longer period, their predictive ability appears better judging by t-value and adjusted R-squared. For example, the price-dividend ratio predicts excess market returns with a coefficient of -0.02 (t-value = -1.87) and an adjusted R-squared of 4.58% at the 12-month horizon, compared with a coefficient of -0.01 (t-value = -1.10) and an adjusted R-squared of 0.08% at the one-month horizon.

To test whether SSE has distinct forecasting power for the equity premium, we perform bivariate predictive regressions that control for the other predictors, one at each time. Table 3 reports the findings, with each panel corresponding to one of the four forecasting horizons. Panel A shows that SSE still forecasts the equity premium well in the presence of the control variables. For example, when we include both SSE and SSL in the one-month forecasting regression, SSE has a regression coefficient of -0.75 (t-value = -3.03), compared with the coefficient of 0.22 (t-value = 0.90) on SSL. Thus, SSE continues to exhibit significant predict power for stock market returns after controlling for the aggregate short interest. Similarly, controlling for the other predictors does not subsume the forecasting power of SSE. We obtain the same inference at longer forecasting horizons, as shown in Panels B through D.

Interestingly, at the 12-month horizon, SSL exhibits stronger predictive power than SSE judging by the regression coefficient and the t-value. In addition, the adjusted R-squared from the bivariate regression including both SSE and SSL, 12.16%, is higher than that from the univariate regression for SSE at 8.49%. This finding suggests that SSE does not strictly dominate SSL in predicting stock market returns. While SSE predicts market returns well at short horizons, SSL carries information about the stock market over long horizons. This contrast makes sense. SSE captures active trading on mispriced stocks and thus mispricing gets corrected more quickly. In contrast, SSL reflects the level of overpricing but does not guarantee that mispricing will be corrected immediately. This intuition explains the comparative advantage of SSE in predicting stock market returns over short horizons and the relative strength of SSL over long horizons.

[Insert Table 3 about here.]

In sum, we show evidence that SSE contains significant predictive power for the equity premium. The predictive power is over and above the existing return predictors including the aggregate short interest. We also find that SSE predicts stock market returns particularly well over short horizons.

### 4.2 Out-of-sample predictability

Recent research on stock return predictability (e.g., Goyal and Welch, 2008) emphasizes the importance of out-of-sample forecasting performance to help validate in-sample performance.

In this subsection, we evaluate the predictive power of SSE for aggregate stock returns based on out-of-sample tests. Following the literature, we test whether SSE can outperform the historical average of stock market returns in forecasting the equity premium.

We first run the following time-series regression using a subsample with information up to month t:

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t, \tag{3}$$

where $r_t$ is excess market return for month t, and $x_{t-1}$ is one-month lagged value of the predictor. Then, based on the regression coefficient estimates only using information up to month t, we compute the forecast of the equity premium for month t +1.

Next, we either expand the subsample by one additional month each time (expanding approach) or use a fixed rolling window of 10-year data (rolling approach), and thereby generate the sequence of equity premium forecasts, $\hat{r}_{t+1}$, $\hat{r}_{t+2}$, …, $\hat{r}_T$. Following Campbell and Thompson (2008) and Goyal and Welch (2008), the out-of-sample *R*-squared compares the mean-squared errors obtained from the predictor with those from the historical average. That is,

$$R^2 = 1 - \frac{\sum_{\tau=t+1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=t+1}^{T}(r_\tau - \bar{r}_\tau)^2}\ , \tag{4}$$

where $\bar{r}_\tau$ is the historical average of excess market returns up to month τ - 1, and *T* is the total number of months over our entire sample period. A positive out-of-sample R-squared indicates outperformance of the predictor over the historical average. We compute p-values for the test statistic based on the Clark and West (2007) method.

Similar to Campbell (1991), we remove the time trend in SSE and SSL stochastically by using information up to month t. Specifically, we use the data from January 1974 to December 1975 as the first subsample to remove the time trend. Then, we normalize the residuals of the time trend regression and retain the last observation to be matched with stock market return over the next month. We extend the subsample by one month at a time. This stochastic detrending procedure ensures real-time forecasting. In addition, we winsorize SSE and SSL at 1% and 99% only using data up to month t. For both the expanding and the rolling approaches, our initial regression uses stock market return data of 10 years (January 1976–December 1985) and thus the out-of-sample prediction (i.e., month t + 1 in Equ. (4)) starts from January 1986.

Following Campbell and Thompson (2008), we consider three cases of economic restrictions. The first case imposes no restriction. The second case imposes the coefficient sign restriction, which sets an equity premium forecast to the historical average when the coefficient sign is incorrect (e.g., a positive coefficient for SSE). The third case imposes the premium sign restriction, which sets an equity premium forecast to zero when the forecast value is negative.

Table 4 presents the results of out-of-sample performance. Based on both the expanding approach and the rolling approach, we find evidence that SSE performs significantly better than the historical average in forecasting the equity premium across all three cases. With the expanding sample, the out-of-sample R-squared for SSE is positive and significant in all of the three cases, ranging from 0.99% (p-value = 0.04) to 1.41% (p-value = 0.02). Similarly, using the 10-year rolling window, we observe out-of-sample R-squared varying from 1.03% (p-value = 0.02) to 1.67% (p-value = 0.02).

[Insert Table 4 about here.]

Meanwhile, SSL also exhibits significant out-of-sample forecasting power, consistent with the result of Rapach, Ringgenberg, and Zhou (2016). In contrast, the out-of-sample performance of the other predictors is not strong over our sample period 1974–2017, except that sentiment shows significant outperformance over the historical average in certain cases. Such results about those other predictors largely echo the finding of Goyal and Welch (2008) that many predictors do not outperform the historical average in out-of-sample tests. Nonetheless, none of the predictors significantly underperforms the historical average judging by their p-values.

To summarize, the out-of-sample tests show that SSE outperforms the historical average in predicting the equity premium. This suggests that SSE, which combines information of short selling and stock mispricing, could potentially guide asset-allocation decisions in real time. Therefore, both in-sample and out-of-sample results strongly support the view that the efficiency of short selling contains economically and statistically significant signals about future stock market returns.

### 4.3 Interacting SSE and SSL

We now investigate how SSE interacts with SSL in predicting aggregate stock returns. Specifically, we examine the predictive power of SSE in subsamples that feature different levels of SSL relative to the median value of the full sample. The goal is to check whether short selling efficiency, as the disposition of short sales to the correct stocks, contains particularly useful forecasting signals in the presence of large aggregate short interest.

Table 5 shows the results. First, we observe stronger forecasting power of SSE when SSL is above the median. For example, at the three-month horizon, the univariate regression produces a coefficient on SSE of -0.81 (t-value = -2.80) and an adjusted R-squared of 9.13% when SSL is high. In contrast, when SSL is low, the regression coefficient on SSE is -0.53 (t-value = -1.65) with an adjusted R-squared 1.51%. This difference holds across all the forecasting horizons from one to 12 months. Meanwhile, even when SSL is low, SSE still exhibits significant forecasting power, but to a lesser extent. In short, SSE performs particularly well when SSL is high.

[Insert Table 5 about here.]

Similarly, SSL shows strong predictive ability when SSE is above the median, but does not work as well when SSE is below the median. For example, at the 12-month horizon, we obtain a regression coefficient on SSL of -0.57 (t-value = -4.29) with an R-squared 16.24% in the high SSE subsample, whereas the coefficient on SSL is -0.26 (t-value = -1.52) with an R-squared of 3.17% in the low SSE subsample. As before, we find that SSL predicts better over longer horizons (e.g., the three- to 12-month horizons) compared with the one-month horizon.

Therefore, SSE and SSL reinforce each other in forecasting the equity premium, as the predictive power of each predictor gets stronger in the presence of a high level of the other predictor. This seems sensible, because correction of overpricing would require two conditions: a sufficiently high level of short selling (SSL), and short selling executed on the right stocks (SSE). While Rapach, Ringgenberg, and Zhou (2016) focus on the first condition, our paper highlights the distinct and important role of the second condition.

### 4.4 The source of the predictive power

So far, we have shown significant and robust predictive power of SSE for market returns. Here, we investigate the source of such predictability by examining its time variation. We hypothesize that, if SSE captures the information advantage of short sellers, its predictive power should be related to information environments of the stock market. Specifically, SSE should forecast well under the conditions when information acquisition is particularly valuable. To test such hypothesis, we examine three information-related market conditions: recession, market volatility, and volume of public information. In all the tests, to forecast excess market return of month t + 1, we use SSE and the condition variables measured in month t.

We first check whether and how the forecasting power of SSE is related to recessions and market volatility. In a rational model, Kacperczyk, Nieuwerburgh, and Veldkamp (2016) show that information processing is more valuable during recessions when aggregate payoff shocks are more volatile, and hence fund managers should possess market timing skill in recessions. Empirically, Chen and Liang (2007) find that the ability of hedge funds to time the stock market appears especially strong when the market is bearish and volatile, suggesting better market return predictability during these market states.[7] In addition, Chen, Da, Huang (2019) find that during the 2007-2009 financial crisis when capital constraints are likely binding, the stock anomalies that arbitrageurs choose to actively exploit realize large future abnormal returns. For these reasons, we expect SSE to contain greater forecasting signals during recessions and the periods of high market volatility than normal times and the periods of low market volatility.

Panel A of Table 6 reports the predictive power of SSE in normal versus recession periods. The recession periods are defined based on the NBER recession indicators. Specifically, we test the predictive power for excess market returns over the next month during normal and recession months separately. The results reveal significant predictive ability of SSE in both types of periods rather than concentrated in one of them. However, consistent with the hypothesis, SSE exhibits much stronger forecasting power during recessions than during normal times. The coefficient on SSE from a univariate predictive regression is -1.16 (t-value = -2.35) in recessions, compared with -0.43 (t-value = -2.32) in normal times. In other words, the prediction coefficient during recessions appears nearly three times as large as that during normal times and close to twice as large as the coefficient from the entire sample (with that coefficient of -0.61 as shown in Table 2). Moreover, the adjusted R-squared of the predictive regression is 3.37% during recessions, compared with 0.78% during normal times.

[Insert Table 6 about here.]

[7] Kacperczyk, Nieuwerburgh, and Veldkamp (2014) also find that mutual fund managers have market timing skill during recessions, in support of the theory of Kacperczyk, Nieuwerburgh, and Veldkamp (2016). Unlike hedge funds that constitute a major group of short sellers, however, mutual funds generally do not hold short positions in stocks (e.g., Almazan, Brown, Carlson, and Chapman, 2004).

In Panel B of Table 6, we present the predictability conditional on market volatility proxied by the VIX index. SSE shows much stronger forecasting power in volatile periods. For example, at the one-month horizon, the coefficient on SSE from a univariate predictive regression is -1.15 (t-value = -2.49) during high volatility periods when VIX exceeds the time-series median, in contrast to -0.32 (t-value = -1.97) during low volatility periods when VIX falls below its median. Meanwhile, the adjusted R-squared is 3.86% (0.93%) for high (low) volatility periods. Therefore, the results in these two panels lend support to the notion that information advantage is the driving force of SSE's predictive power.

Next, we examine the variation of the predictive power of SSE related to the public information environment. If SSE captures superior information about mispricing, we expect stronger return predictability in months with less public information since otherwise mispricing would have been corrected with more public information. For the cross section of stocks, Cohen, Diether, and Malloy (2007) show that short selling demand has better predictive ability for stock returns when there is less public information. While our analysis in essence is similar to their investigation, we focus on return predictability of the aggregate stock market. As such, we define high information months as the first two months (e.g., January and February) of each quarter, since earnings announcements are more prevalent in these months.[8] Accordingly, the last month of the quarter is low information months. We test the predictive power for excess market returns following high and low information months separately.

Panel C of Table 6 reports the predictive power of SSE during high versus low public information months. To forecast the equity premium of month t + 1, we measure SSE and the information-month status in month t. The regression coefficient on SSE is -1.00 (t-value = -2.95) in low information months, compared with -0.43 (t-value = -2.12) in high information months. The adjusted R-squared is also much larger for months with low public information than for months

[8] See, e.g., Frazzini and Lamont (2006) and Hartzmark and Solomon (2018) for evidence of seasonality in earnings announcements at the firm level.

with high public information. Relatedly, the first month of each quarter (i.e., January, April, July, and October) is also the periods when quarterly earnings announcements first appear and mispricing gets corrected, contributing to stronger return predictability. Thus, these results provide further support to the information-based explanation for the predictive power of SSE.

Taken together, our inference suggests that SSE reflects information advantage of short sellers, as the predictive power is much stronger when information acquisition is more valuable. This complements the evidence from the cross-sectional analyses that short sellers are informed (Cohen, Diether, and Malloy, 2007; Boehmer, Jones, and Zhang, 2008; Engelberg, Reed, and Ringgenberg, 2012; among others).

## 5. Short Selling Activity and the CAPM

Short sellers as a group attempt to exploit overpricing, and thus their trading can in turn relate to the equilibrium asset prices and market efficiency. In this section, we investigate the relation between short selling activity and the performance of the capital asset pricing model (CAPM, see Sharpe, 1964; Lintner, 1965). The CAPM predicts that expected returns on individual stocks are positively and linearly related to their sensitivity (i.e., beta) to aggregate price movement in equilibrium, and such a relation is termed the security market line. As an influential model, however, the CAPM has been seriously challenged in empirical work, in that actual data from stock markets fail to produce a positive-sloped security market line.

Could short selling be related to the performance of the CAPM? We hypothesize that the CAPM would perform well when both SSE and SSL are low, given our results that a high level of such variables signals relative prevalence of stock overpricing. To test the hypothesis, we divide the sample period into subperiods depending on whether SSE and SSL are above or below their respective time-series median values. We are particularly interested in the two subperiods when both SSE and SSL are low (LL subperiod) and when both SSE and SSL are high (HH subperiod), for which we examine the security market line separately.

Panel A of Figure 2 shows the results about the security market line. We first estimate CAPM beta for each individual stock over the entire sample period. Then, for each subperiod, we form ten decile portfolios of stocks based on stocks' CAPM betas. Next, we compute average returns for each decile portfolio in the next month. In the figure, each dot corresponds to the average next-month return of a decile portfolio formed in a particular subperiod. Immediately following the LL subperiod, the portfolio of lowest-beta stocks exhibits a market beta of 0.56 and a value-weighted average return of 0.86% per month, whereas the portfolio of highest-beta stocks has a market beta of 1.67 and a value-weighted average return of 1.90% per month. Based on betas and returns of the ten portfolios, the security market line, shown as the upper fitted line, has a positive slope of 1.03 (t-value = 5.34), consistent with the CAPM. However, immediately following the HH subperiod, the security market line, shown as the lower fitted line, has a negative slope of -0.60 (t-value = -4.25), deviating from the CAPM prediction. Thus, such a stark contrast suggests that the prediction of the CAPM holds only when the level of mispricing, revealed through short selling activity, appears low. On the other hand, pervasive mispricing, which attracts arbitrage trading, would lead to a lack of support for the equilibrium asset pricing model.

[Insert Figure 2 about here.]

Panel B of Figure 2 presents the returns of the decile portfolios formed on the Stambaugh, Yu, and Yuan (2015) mispricing score. Looking at the portfolio returns over the months immediately following the LL subperiod, we find essentially no difference in return between these portfolios. In contrast, from returns over the months immediately following the HH subperiod, the portfolio of stocks with high mispricing scores (overpriced) exhibits significantly lower average return than the portfolio of stocks with low mispricing scores (undervalued). In addition, the average return across these portfolios following the HH subperiod appears significantly lower than the average return following the LL subperiod by about 0.93% per month, confirming that large short selling activity is associated with stock overpricing and low expected returns.

As robustness checks, we repeat the analysis using equal-weighted average returns on these portfolios. As shown in Panels C and D of Figure 2, we continue to find that the security market line is significantly positive in accordance with the CAPM following the LL subperiod, along with significant return spreads associated with the mispricing scores following the HH subperiod.

The results presented in this section are sensible. The CAPM, as an equilibrium model, builds on the assumption that all investors are equally informed. Thus, the model can fail to fit data when substantial information asymmetry exists. Indeed, as theorized by Grossman and Stiglitz (1980), investors are asymmetrically informed due to differential costs and compensation they face in gathering information. Empirically, Chen, Kelly, and Wu (2020) show that hedge funds have comparative advantage compared with other types of institutions (such as mutual funds) in information acquisition. Given that short sellers, most of whom are hedge funds, may collect and process information better than other investors, we expect the CAPM to perform poorly when short selling activity is pervasive. However, following the period when the stock market experiences low short selling activity, the core prediction of the CAPM, in the form of a positive security market line, is more likely to be observed.

In sum, we show that short selling activity serves as an important condition for the validity of the CAPM. Recent research finds that the CAPM behaves differently under alternative market circumstances, such as those related to investor sentiment (Antoniou, Doukas, and Subrahmanyam, 2016) and margin requirement (Jylha, 2018). Our study provides new evidence on how arbitrage activity at the aggregate level affects the performance of the CAPM and hence stock market efficiency.

## 6. Robustness Tests and Additional Analyses

In this section, we check the robustness of the forecasting power of SSE as well as performing several additional analyses. First, we investigate the prediction ability of un-detrended SSE. Second, we examine an alternative measure of SSE based on the spread in abnormal short interest across stocks sorted by the mispricing score. Third, we include micro-cap stocks in the sample so that the resulting SSE covers nearly all public firms. Fourth, we examine the out-of-sample return predictability over horizons longer than one month. Fifth, we test the predictive power of a measure of arbitrage trading efficiency by supplementing short selling with the long side of arbitrage trading proxied by hedge funds' stock holdings. Finally, we present evidence based on daily data.

### 6.1 Un-detrended SSE

Both SSE and SSL exhibit a time trend, reflecting a steady rise of short selling activity. To avoid potential impact of the time trend on our inference, we have detrended the predictors in Section 4. Here, we examine the predictive power of the un-detrended SSE for two purposes. First, it checks the robustness of SSE as a market return predictor. Second, we can evaluate the effect of time trend on our inference.

The specification (1) of Table 7 reports both in-sample and out-of-sample predictive power of the un-detrended SSE. We find that SSE continues to exhibit significant forecasting ability for stock market returns. In the in-sample test (Panel A), the coefficient on SSE from the univariate predictive regression is -0.47 (t-value = -2.21) at the one-month horizon, -0.48 (t-value = -2.33) at the three-month horizon, -0.47 (t-value = -2.57) at the six-month horizon, and -0.31 (t-value = -2.20) at the 12-month horizon. While the magnitude is slightly weaker than that from the detrended series presented in Table 2, the result nonetheless suggests that un-detrended SSE remains an effective predictor of the equity market premium.

Panel B of Table 7 reports the out-of-sample test result. As before, we use two alternative approaches—expanding the sample and rolling a 10-year window. As before, for each approach, we consider three different cases with respect to economic restrictions (see Section 4 for details). From both approaches, the un-detrended SSE exhibit a positive out-of-sample R-squared across the three cases, indicating that the predictor outperforms the historical average in forecasting stock market returns.

[Insert Table 7 about here.]

Hence, our inference is robust to whether or not we detrend SSE. Nonetheless, the detrended SSE exhibits slightly stronger predictive power than the raw SSE. As discussed before, in light of the secular trend of SSE over time, we prefer to follow the literature (e.g., Rapach, Ringgenberg, and Zhou, 2016) to remove the time trend in the main analysis.

### 6.2 Alternative measure of SSE

Our main measure of SSE comes from the slope coefficient of the regression of abnormal short interest on the overpricing score of Stambaugh, Yu, and Yuan (2015) across stocks. A large value of SSE shows high co-movement between short sales and overpricing in the cross section. As an alternative measure, we simply use the spread in abnormal short interest between stocks in the top decile (overpriced) and those in the bottom decile (underpriced) ranked by the mispricing score. That is, we assign a weight of +1 (-1) to the top (bottom) decile of mispriced stocks in each month, and a weight of 0 to all other stocks. This spread SSE measure has the benefit of simplicity without using any regression. As a trade-off, it drops information imbedded in the remaining eight stock deciles (i.e., 80% of the sample).

We present the results from the spread SSE measure in the specification (2) of Table 7. As can be seen, the spread SSE measure significantly and negatively predicts stock market returns at all horizons ranging from one to 12 months. For example, the coefficient on spread SSE from the univariate predictive regression is -0.54 (t-value = -3.48) with an R-squared of 1.25% at the one-month forecasting horizon. Furthermore, as presented in the specification (2) of Panel B in the table, the out-of-sample result also suggests that spread SSE can predict stock market returns better than the historical average, based on both the expanding approach and the rolling approach. Taken together, our inference is robust to the alternative measure of short selling efficiency.

### 6.3 Including micro-cap stocks

The sample used in our main analyses excludes micro-cap stocks. To evaluate whether this subset of stocks could affect our inference, we perform a robust check by adding back such stocks and hence use nearly the entire stock market to form SSE. The rationale for the test is that perhaps short sales are heavily placed on extremely small stocks, due to severe information asymmetry. On the other hand, given their small firm sizes, these stocks do not have a large representation in the value-weighted market returns, and so their presence seems unlikely to alter our inference.

The specification (3) of Panel A in Table 7 repeats the univariate regression analysis for the expanded sample. SSE continues to exhibit significant forecasting power at all forecasting horizons examined. Specifically, the coefficient on SSE is -0.55 (t-value = -3.40) at the one-month horizon, -0.55 (t-value = -3.41) at the three-month horizon, -0.43 (t-value = -2.97) at the six-month horizon, and -0.27 (t-value = -2.34) at the 12-month horizon. These numbers are close to, though somewhat smaller than, those obtained from the main sample excluding micro-cap stocks, suggesting that the effect of adding such stocks to the analysis is relatively minor.

In the specification (3) of Panel B in the table, we report the out-of-sample test result for SSE computed based on the full sample. As can be seen, the reconstructed SSE outperforms the historical average in forecasting future aggregate stock returns. From the expanding approach, SSE's out-of-sample R-squared is between 0.80% and 1.12% with p-values of 0.05 or lower in all of the three cases. The result from the rolling approach delivers a similar message. Therefore, our findings are robust to the inclusion of micro-cap stocks in the sample.

### 6.4 Out-of-sample predictability at longer-horizons

So far, our analyses of out-of-sample prediction focus on one-month-ahead stock market returns. In this subsection, we evaluate the out-of-sample predictive power at longer horizons of three, six, and 12 months. To this end, we continue to use the detrended SSE (as in Section 4) and perform out-of-sample tests with the average monthly excess market return over each forecasting horizon as the left-hand-variable in regression (3). As before, we consider three cases regarding economic restrictions.

Panel C of Table 7 presents the results. Based on both the expanding and the rolling approaches, we find that SSE significantly outperforms the historical average in forecasting the equity premium at these long horizons. This finding holds across all three cases. For example, in the expanding approach with no economic restriction, the out-of-sample R-squared for SSE is 1.53% (p-value = 0.06) at the three-month horizon and 5.26% (p-value = 0.01) at the six-month horizon. Imposing the restriction about the sign of the regression coefficient enhances the out-of-sample forecasting power. At the 12-month horizon, the out-of-sample R-squared for SSE somewhat weakens but continues to be statistically significant for most cases.

Overall, the out-of-sample tests over long forecasting horizons show that SSE outperforms the historical average of market returns in predicting the equity premium up to one year.

### 6.5 Incorporating the long side of arbitrage trading

Textbook description of arbitrage trading involves two sides with short selling as one side. Chen, Da and Huang (2019) show that combining the long sides and the short side together provides a more complete picture about the role of arbitrage in asset pricing. In this subsection, we measure arbitrage trading efficiency (ATE) by supplementing short selling with stock purchases of arbitrageurs as the long side, and then we investigate ATE's predictive power for the equity premium. This way, we use information of both sides of arbitrage trading along with the mispricing score to forecast aggregate stock returns.

Following Brunnermeier and Nagel (2004), we infer the long side of arbitrage trading on individual stocks by hedge fund stock holdings. Specifically, we employ the hand-collected data of hedge fund stock holdings by manually matching information from six hedge fund databases to the Securities and Exchange Commission (SEC)'s Form 13F filings.[9] Existing research shows that hedge fund activities influence stock market efficiency (e.g., Brunnermeier and Nagel, 2004; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015; Kokkonen and Suominen, 2015; Sias, Turtle, and Zykaj, 2016; Chen, Da, and Huang, 2019; Chen, Kelly, and Wu, 2020). In particular, Chen, Da, and Huang (2019) propose a stock-level measure of net arbitrage trading (NAT) as the difference between abnormal hedge fund holdings (the long side) and abnormal short interest (the short side).[10] The former is defined as the percentage change of current hedge fund holding from the average hedge fund holding in the previous four quarters, while the latter is the percentage change of current short interest from the average short interest in the previous four quarters. The sample period for the NAT measure spans from 1990:Q1 to 2017:Q4 at a quarterly frequency.

We perform regression (1) but change the left-hand-side variable from ASI (abnormal short interest) to NAT (net arbitrage trading) and the data frequency from monthly to quarterly. Consequently, the coefficient on the mispricing measure is the covariance between NAT and MISP (scaled by a constant variance), which captures the overall arbitrage trading efficiency (ATE). As before, we filter both ATE and the aggregate NAT with a simple time trend and examine their forecasting ability for aggregate stock returns.

Table 8 presents the evidence on the predictive power for one-quarter-ahead stock market returns. When including both ATE (the efficiency measure) and NAT (the level measure) as the independence variables, we find that the coefficient on ATE is 2.07 (t-value = 2.25). This result is consistent with our findings in Section 4 that the efficiency of arbitrage activity contains important predictive signals for future aggregate stock returns. Including the other predictors in the bivariate regression provides similar results.

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[9] The six hedge fund databases are TASS, HFR, CISDM, Bloomberg, Barclay Hedge, and Morningstar. Under the Securities Exchange Act of 1934, all institutional investors (including hedge fund companies) with investment over $100 million are required to report their stock holdings to the SEC through quarterly Form 13F filings in which stock positions greater than 10,000 shares or $200,000 in market value are subject to disclosure.

[10] The stock-quarter level data of net arbitrage trading (NAT) can be downloaded from the following websites. http://people.tamu.edu/~ychen; https://www3.nd.edu/~zda/; https://sites.google.com/a/uncg.edu/dayong-huang/.

[Insert Table 8 about here.]

Therefore, including the long side of arbitrage trading in the analysis, we obtain the same inference that arbitrage efficiency can significantly forecast stock market returns. Nonetheless, we prefer to use SSE as the main measure of arbitrage efficiency, because the data of SSE have a higher frequency (monthly) and a longer period (starting from the 1970s) than ATE and thus the tests are potentially more powerful. In addition, prior studies (e.g., Stambaugh, Yu, and Yuan, 2012) generally document larger price changes from the short side than from the long side due to greater limits-to-arbitrage associated with short sales. Hence, focusing on the short side through SSE should be able to capture the main force of arbitrage efficiency.

**6.6 Evidence from daily data**

In this subsection, we provide further evidence of the predictive ability of SSE based on daily data. We construct daily SSE using the daily short selling data obtained from Markit, Ltd. Our sample begins in July 2006 when the data became available at daily frequency and extends to March 2011. To remove the impacts of the shorting ban, we exclude the period July 2008–January 2009. For each stock in day t, daily abnormal short interest (ASI) is defined as the difference of short interest in the day and the average short interest in the past 30 days. In each cross section, stocks are ranked from 1 to 100 based on their mispricing scores at the beginning of the month, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and the mispricing score. Then, we regress ASI on the demeaned mispricing ranks in each day to compute daily SSE based on the slope coefficient. In the test of forecasting power, the daily SSE is the average in the past five days and normalized. We exclude micro-cap stocks and stocks whose price are less than five dollars at the beginning of the month.

Figure 3 shows the daily evidence. The y-axis is the coefficient from regressing future cumulative excess market returns on the daily SSE. The x-axis is the number of days, from one up to 15 trading days, into the future. We observe a steady negative coefficient over the different horizons of days, suggesting that the daily SSE is negatively associated with future cumulative stock market returns. The confidence band confirms statistical significance of the negative relation between daily SSE and future market returns. In addition, the relation extends to 15 trading days with no reversal. This evidence suggests that the predictive ability of SSE is more likely to reflect information advantage rather than short-term price impact of short selling, which corroborates with the findings in Section 4.4. about the source of the predictive power of SSE.

[Insert Figure 3 about here.]

## 7. Conclusion

In this paper, we explore the economic insight that how efficiently arbitrage trading is allocated to individual stocks should affect future price movement at the aggregate level. In particular, we measure short selling efficiency (SSE) by the slope coefficient of a cross-sectional regression of abnormal short interest on the mispricing measure. All that is required to construct the measure are short interest and mispricing score on individual stocks, both of which are readily available. Our results show that SSE contains significant forecasting signals for aggregate stock returns. The findings are robust to both in-sample and out-of-sample tests. The forecasting signals of SSE are distinct from those of short selling level studied by Rapach, Ringgenberg, and Zhou (2016) as well as other return predictors used in the literature. The insight from our study can provide useful asset-allocation guidance in practice.

Moreover, we present evidence that short selling activity is related to the performance of the CAPM that describes the stock beta-return relation in the cross section. Following periods when the stock market features low short selling activity, the CAPM works well in the sense that a significantly positive relation between beta and stock returns is observed. However, following periods when short selling activity is pervasive in terms of SSE and SSL, the security market line appears flat or even negative. This result confirms that arbitrage activity is related to equilibrium asset prices and stock market efficiency.

For future research, one could consider examining whether the time variation in SSE can serve as a systematic factor, the exposure to which affects expected stock return. It would also be interesting to extend our investigation to international markets, where both short selling and stock mispricing vary substantially across countries.

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**Table 1 Summary Statistics**

This table presents summary statistics of SSE and other return predictors in time series. For each stock in month t, abnormal short interest (ASI) is defined as the difference of short interest in the month and the average short interest in the past 12 months. In each cross section, stocks are ranked from one to 100 based on their mispricing scores, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and mispricing score. We demean these mispricing ranks and then regress ASI on these demeaned mispricing ranks in each month to compute SSE (the slope coefficient) and short selling level SSL (the intercept). We remove time trend and normalize both SSE and SSL. In the main analysis, we exclude micro-cap stocks and stocks whose price are less than five dollars at the time of portfolio formation. Other return predictors include sentiment (SENT), price-earnings ratio (PE10), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), and capital ratio (CAPR). These variables are described in detail in Section 3.2. All the variables except price multiplies are multiplied by 100. Panel A present summary statistics, while Panel B reports correlations among the variables. AR1 is the first-order autocorrelation. The sample period is from January 1974 to December 2017.

Panel A: Summary of the predictors

| | Mean | Median | Std. Dev. | 5th | 25th | 75th | 95th | AR1 |
|---|---|---|---|---|---|---|---|---|
| SSE | 0.00 | -11.25 | 100.00 | -149.29 | -54.08 | 42.98 | 174.92 | 0.839 |
| SSL | 0.00 | -6.38 | 100.00 | -115.62 | -23.41 | 26.65 | 136.23 | 0.907 |
| SENT | 3.19 | 7.32 | 89.55 | -189.27 | -24.54 | 53.72 | 128.72 | 0.981 |
| PE10 | 20.24 | 20.50 | 8.86 | 8.74 | 11.60 | 25.96 | 37.28 | 0.997 |
| PD | 41.70 | 37.86 | 17.83 | 19.04 | 26.23 | 53.40 | 76.69 | 0.996 |
| CS | 1.10 | 0.96 | 0.46 | 0.61 | 0.77 | 1.29 | 2.03 | 0.963 |
| TS | 0.75 | 0.71 | 0.73 | -0.34 | 0.18 | 1.30 | 2.02 | 0.975 |
| TB3M | 5.72 | 5.83 | 3.61 | 0.64 | 2.44 | 8.03 | 12.62 | 0.995 |
| FLS | 0.91 | 0.97 | 3.88 | -4.96 | -1.08 | 3.16 | 6.63 | 0.171 |
| CAPR | 6.15 | 5.33 | 2.46 | 3.33 | 4.36 | 7.63 | 11.64 | 0.985 |

Panel B: Correlations

| | SSE | SSL | SENT | PE10 | PD | CS | TS | TB3M | FLS |
|---|---|---|---|---|---|---|---|---|---|
| SSL | 0.60 | | | | | | | | |
| SENT | 0.09 | 0.22 | | | | | | | |
| PE10 | 0.08 | 0.14 | 0.34 | | | | | | |
| PD | 0.12 | 0.17 | 0.34 | 0.96 | | | | | |
| CS | -0.11 | -0.26 | -0.10 | -0.54 | -0.46 | | | | |
| TS | -0.12 | -0.15 | -0.03 | 0.12 | 0.20 | 0.00 | | | |
| TB3M | 0.01 | 0.05 | 0.09 | -0.59 | -0.61 | 0.31 | -0.70 | | |
| FLS | -0.11 | -0.12 | 0.03 | 0.01 | 0.00 | -0.04 | 0.06 | -0.01 | |
| CAPR | 0.11 | 0.20 | 0.36 | 0.88 | 0.85 | -0.54 | -0.07 | -0.29 | 0.07 |

**Table 2 Forecasting Excess Market Returns: Univariate Regression**

This table reports the predictive power of SSE and other return predictors in a univariate regression at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. The other return predictors include short selling level (SSL), sentiment (SENT), price-earnings ratio (PE10), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), and capital ratio (CAPR). The dependent variable is monthly excess market returns. In each panel, Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and $R^2$ is the adjusted R-squared. The regression coefficients are multiplied by 100.

| | SSE | SSL | SENT | PE | PD | CS | TS | TB3M | FLS | CAPR |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Forecasting one-month return | | | | | | | | | | |
| Coeff | -0.61 | -0.22 | -0.21 | -0.02 | -0.01 | 38.01 | 38.47 | -5.91 | -2.30 | -10.50 |
| t-value | -3.50 | -1.34 | -0.81 | -0.77 | -1.10 | 0.61 | 1.38 | -1.04 | -0.28 | -1.16 |
| $R^2$ (%) | 1.64 | 0.05 | -0.01 | -0.07 | 0.08 | -0.04 | 0.20 | 0.03 | -0.15 | 0.13 |
| Panel B: Forecasting three-month return | | | | | | | | | | |
| Coeff | -0.64 | -0.43 | -0.20 | -0.02 | -0.01 | 46.55 | 34.18 | -4.64 | -0.77 | -10.82 |
| t-value | -3.27 | -2.83 | -0.84 | -0.90 | -1.25 | 0.85 | 1.34 | -0.85 | -0.11 | -1.29 |
| $R^2$ (%) | 5.30 | 2.38 | 0.25 | 0.25 | 0.67 | 0.45 | 0.68 | 0.20 | -0.18 | 0.78 |
| Panel C: Forecasting six-month return | | | | | | | | | | |
| Coeff | -0.62 | -0.56 | -0.25 | -0.02 | -0.02 | 62.53 | 28.92 | -3.74 | -0.85 | -10.59 |
| t-value | -3.56 | -3.54 | -1.20 | -1.15 | -1.50 | 1.45 | 1.28 | -0.70 | -0.22 | -1.36 |
| $R^2$ (%) | 9.45 | 7.99 | 1.10 | 1.02 | 1.85 | 2.01 | 1.00 | 0.29 | -0.16 | 1.58 |
| Panel D: Forecasting 12-month return | | | | | | | | | | |
| Coeff | -0.40 | -0.45 | -0.23 | -0.03 | -0.02 | 47.17 | 25.68 | -2.27 | -1.13 | -9.51 |
| t-value | -3.69 | -3.92 | -1.38 | -1.50 | -1.87 | 1.45 | 1.42 | -0.49 | -0.58 | -1.44 |
| $R^2$ (%) | 8.49 | 10.96 | 2.15 | 3.07 | 4.58 | 2.48 | 1.83 | 0.18 | -0.09 | 2.91 |

**Table 3 Forecasting Excess Market Returns: Bivariate Regression**

This table reports the predictive power of SSE along with the other return predictors, one at a time, in bivariate regressions at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. The other return predictors include short selling level (SSL), sentiment (SENT), price-earnings ratio (PE10), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), and capital ratio (CAPR). In each panel, the top two lines correspond to SSE, while the next two lines correspond to one other predictor in each column. The dependent variable is monthly excess market returns. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and $R^2$ is the adjusted R-squared. The regression coefficients are multiplied by 100.

| | | SSL | SENT | PE | PD | CS | TS | TB3M | FLS | CAPR |
|---|---|---|---|---|---|---|---|---|---|---|
| Panel A: Forecasting one-month return | | | | | | | | | | |
| SSE | Coeff | -0.75 | -0.60 | -0.60 | -0.56 | -0.60 | -0.59 | -0.61 | -0.63 | -0.59 |
| | t-value | -3.03 | -3.41 | -3.48 | -2.91 | -3.32 | -3.25 | -3.55 | -3.63 | -3.22 |
| Other predictor | Coeff | 0.22 | -0.15 | -0.01 | 1.65 | 23.13 | 29.07 | -5.73 | -3.94 | -7.96 |
| | t-value | 0.90 | -0.60 | -0.54 | 1.33 | 0.36 | 1.02 | -1.02 | -0.51 | -0.94 |
| | $R^2$ (%) | 1.61 | 1.54 | 1.51 | 1.84 | 1.51 | 1.68 | 1.66 | 1.57 | 1.52 |
| Panel B: Forecasting three-month return | | | | | | | | | | |
| SSE | Coeff | -0.59 | -0.63 | -0.63 | -0.61 | -0.62 | -0.62 | -0.64 | -0.65 | -0.61 |
| | t-value | -2.70 | -3.19 | -3.23 | -3.10 | -3.05 | -3.02 | -3.29 | -3.43 | -3.03 |
| Other predictor | Coeff | -0.08 | -0.13 | -0.01 | 1.09 | 29.86 | 24.11 | -4.66 | -2.57 | -8.17 |
| | t-value | -0.39 | -0.59 | -0.61 | 0.99 | 0.53 | 0.91 | -0.88 | -0.41 | -1.04 |
| | $R^2$ (%) | 5.18 | 5.32 | 5.30 | 5.73 | 5.38 | 5.55 | 5.51 | 5.26 | 5.45 |
| Panel C: Forecasting six-month return | | | | | | | | | | |
| SSE | Coeff | -0.43 | -0.60 | -0.60 | -0.60 | -0.59 | -0.60 | -0.62 | -0.63 | -0.59 |
| | t-value | -2.46 | -3.48 | -3.54 | -3.46 | -3.37 | -3.28 | -3.55 | -3.71 | -3.36 |
| Other predictor | Coeff | -0.30 | -0.19 | -0.02 | 0.73 | 46.14 | 19.14 | -3.86 | -2.54 | -8.02 |
| | t-value | -1.49 | -0.98 | -0.83 | 0.87 | 1.11 | 0.81 | -0.75 | -0.77 | -1.09 |
| | $R^2$ (%) | 10.79 | 9.99 | 9.87 | 9.91 | 10.45 | 9.79 | 9.78 | 9.52 | 10.04 |
| Panel D: Forecasting 12-month return | | | | | | | | | | |
| SSE | Coeff | -0.20 | -0.39 | -0.38 | -0.37 | -0.38 | -0.38 | -0.40 | -0.41 | -0.38 |
| | t-value | -1.48 | -3.65 | -3.66 | -3.23 | -3.53 | -3.20 | -3.65 | -3.83 | -3.51 |
| Other predictor | Coeff | -0.33 | -0.19 | -0.02 | 0.88 | 35.79 | 19.52 | -2.48 | -2.28 | -7.88 |
| | t-value | -2.09 | -1.27 | -1.24 | 1.07 | 1.19 | 1.03 | -0.57 | -1.38 | -1.24 |
| | $R^2$ (%) | 12.16 | 9.93 | 10.46 | 9.62 | 9.83 | 9.47 | 8.76 | 8.75 | 10.28 |

**Table 4 Out-of-Sample Predictability**

This table reports the out-of-sample predictability. We test the forecasting power of each predictor for one-month-ahead stock market returns. First, we run the following time-series regression:

$$r_t = \alpha + \beta x_{t-1} + \varepsilon_t,$$

where $r_t$ is excess market return for month t, and $x_{t-1}$ is one-month lagged value of the predictor. Then, based on the regression coefficient estimates only using information up to month t, we compute the forecast of the equity premium for month t+1. We either expand the subsample by one month each time (expanding approach) or use a 10-year rolling window (rolling approach) to generate the time series of equity premium forecast, i.e., $\hat{r}_{t+1}$, $\hat{r}_{t+2}$, …, $\hat{r}_T$. The out-of-sample *R*-squared compares the mean-squared errors obtained from the predictor with those from the historical average.

$$R^2 = 1 - \frac{\sum_{\tau=t+1}^{T}(r_\tau - \hat{r}_\tau)^2}{\sum_{\tau=t+1}^{T}(r_\tau - \bar{r}_\tau)^2},$$

where $\bar{r}_\tau$ is the historical average of excess market returns up to month $\tau$ - 1, and *T* is the total number of months over the entire sample period. A positive out-of-sample R-squared indicates outperformance of the predictor over the historical average. We winsorize SSE and SSL at 1% and 99% and remove their time trend stochastically by only using information up to month t. Specifically, we use the sample from January 1974 to December 1975 as the first subsample to remove the time trend. Then, we normalize the residuals of the time trend regression and retain the last observation. We extend the subsample by one month at a time. Our initial regression uses data of 10 years (January 1976–December 1985), and thus the out-of-sample prediction for excess stock market returns starts from January 1986. In each approach (expanding or rolling), we consider three cases of economic restrictions. Case 1 imposes with no restriction. Cases 2 imposes the coefficient sign restriction, which sets an equity premium forecast to the historical average when the coefficient sign is incorrect. Case 3 imposes the premium sign restriction, which sets an equity premium forecast to zero when the forecast value is negative. We compute p-values (p1, p2, and p3) based on the Clark and West (2007) method. The predictors include short selling efficiency (SSE), short selling level (SSL), sentiment (SENT), price-earnings ratio (PE10), price-dividend ratio (PD), credit spread (CS), term spread (TS), the three-month T-bill rate (TB3M), funding liquidity (FLS), and capital ratio (CAPR).

Table 4, continued.

| | | Case 1 | Case 2 | Case 3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|
| SSE | Expanding | 1.17 | 1.41 | 0.99 | 0.04 | 0.02 | 0.04 |
| | Rolling | 1.38 | 1.67 | 1.03 | 0.03 | 0.02 | 0.02 |
| SSL | Expanding | 0.33 | 0.44 | 0.33 | 0.15 | 0.09 | 0.15 |
| | Rolling | 0.84 | 1.03 | 0.68 | 0.06 | 0.04 | 0.07 |
| SENT | Expanding | 0.17 | 0.23 | 0.17 | 0.22 | 0.16 | 0.22 |
| | Rolling | -0.09 | 0.07 | 0.95 | 0.15 | 0.13 | 0.06 |
| PE10 | Expanding | -2.21 | -1.72 | -1.41 | 0.89 | 0.81 | 0.85 |
| | Rolling | -2.59 | -1.68 | -1.48 | 0.73 | 0.49 | 0.53 |
| PD | Expanding | -1.90 | -1.37 | -1.41 | 0.79 | 0.64 | 0.73 |
| | Rolling | -3.67 | -2.70 | -1.80 | 0.78 | 0.58 | 0.57 |
| CS | Expanding | -0.97 | -0.74 | -0.83 | 0.78 | 0.69 | 0.73 |
| | Rolling | -2.69 | -0.84 | -0.15 | 0.42 | 0.56 | 0.23 |
| TS | Expanding | -0.45 | -0.43 | -0.45 | 0.56 | 0.55 | 0.56 |
| | Rolling | -0.89 | -0.10 | -0.51 | 0.65 | 0.35 | 0.52 |
| TB3M | Expanding | -0.59 | -0.53 | -0.59 | 0.73 | 0.69 | 0.73 |
| | Rolling | -1.14 | -0.33 | -0.27 | 0.44 | 0.27 | 0.25 |
| FLS | Expanding | -1.07 | -0.56 | -0.95 | 0.86 | 0.72 | 0.84 |
| | Rolling | -1.84 | -1.24 | -1.09 | 0.51 | 0.55 | 0.40 |
| CAPR | Expanding | -0.98 | -0.62 | -0.66 | 0.57 | 0.40 | 0.55 |
| | Rolling | -1.94 | -1.31 | -0.96 | 0.48 | 0.29 | 0.36 |

**Table 5 Interacting SSE and SSL**

In Panel A (the left half of the table), we split the sample into two subsamples based on whether SSL is above or below its median. We then examine the forecasting power SSE in each of the two subsamples. We forecast excess stock market returns at the one-, three-, six- and 12-month horizons. In Panel B (the right half of the table), we split the sample into two subsamples based on whether SSE is above or below its median, and then we investigate the forecasting power SSL in each of the two subsamples. Coeff is the regression coefficient in a univariate regression, t-value is Newey-West t-values with lags equal to the forecast horizon, and $R^2$ is the adjusted R-squared. The coefficients are multiplied by 100.

| | Panel A: Coefficient on SSE | | Panel B: Coefficient on SSL | |
|---|---|---|---|---|
| | SSL > Median | SSL < Median | SSE > Median | SSE < Median |
| Forecasting one-month return | | | | |
| Coeff | -0.66 | -0.63 | -0.32 | 0.19 |
| t-value | -2.34 | -1.56 | -1.01 | 0.46 |
| $R^2$ (%) | 2.07 | 0.55 | -0.01 | -0.18 |
| Forecasting three-month return | | | | |
| Coeff | -0.81 | -0.53 | -0.62 | -0.08 |
| t-value | -2.80 | -1.65 | -2.04 | -0.24 |
| $R^2$ (%) | 9.13 | 1.51 | 3.89 | -0.30 |
| Forecasting six-month return | | | | |
| Coeff | -0.75 | -0.48 | -0.71 | -0.27 |
| t-value | -3.32 | -1.95 | -3.15 | -1.23 |
| $R^2$ (%) | 14.86 | 2.58 | 10.80 | 1.51 |
| Forecasting 12-month return | | | | |
| Coeff | -0.44 | -0.37 | -0.57 | -0.26 |
| t-value | -3.42 | -1.93 | -4.29 | -1.52 |
| $R^2$ (%) | 10.42 | 3.60 | 16.24 | 3.17 |

**Table 6 Predictive Power of SSE: Conditional Evidence**

This table reports conditional predictive power of SSE for excess market returns over the next month with respect to market conditions and information environment. Panel A examines the predictive power of SEE during normal times versus recessions. The recessions are based on the NBER recession indicators. We test the predictive power for excess stock market returns following normal times and recessions separately. In Panel B, we examine the predictive power of SSE during the months of high versus low market volatility. We split the sample into subperiods of high and low market volatility, depending on whether the value of VIX in a month exceeds the time-series median. Then, we test the predictive power for excess market returns following high and low volatility months separately. Finally, in Panel C, we examine the predictive power during months with high versus low level of public information. For each quarter, we define high information months as the first two months, since earnings announcements tend to occur in these months. Hence, the last month of each quarter is low information months. We then test the predictive power for excess market returns following high and low information months separately. In all the tests, we use univariate regressions to predict excess stock market returns at the one-month horizon (i.e., month t + 1), based on SSE and the conditional variables measured in month t. Coeff is the regression coefficient on SSE, t-value is Newey-West t-values with lags equal to the forecast horizon, and $R^2$ is the adjusted R-squared. The coefficients are multiplied by 100.

Panel A: NBER recessions

| | Normal times | Recession times |
|---|---|---|
| Coeff | -0.43 | -1.16 |
| t-value | -2.32 | -2.35 |
| $R^2$ (%) | 0.78 | 3.37 |
| # of obs | 457 | 70 |

Panel B: Market volatility

| | Low volatility | High volatility |
|---|---|---|
| Coeff | -0.32 | -1.15 |
| t-value | -1.97 | -2.49 |
| $R^2$ (%) | 0.93 | 3.86 |
| # of obs | 167 | 167 |

Panel C: Public information environment

| | High information | Low information |
|---|---|---|
| Coeff | -0.43 | -1.00 |
| t-value | -2.12 | -2.95 |
| $R^2$ (%) | 0.79 | 3.11 |
| # of obs | 352 | 175 |

**Table 7 Predictive Power of SSE: Robustness Checks**

This table reports several sets of robustness checks for the predictive power of SSE. Panel A report the in-sample evidence of the predictive power of SSE for excess market returns at different horizons using univariate predictive regressions. First, we examine the un-detrended SSE. Second, as an alternative measure of SSE, we examine the spread in the average abnormal short interest between stocks in the top decile and those in the bottom decile of the Stambaugh, Yu, and Yuan (2015) mispricing score. Third, we include micro-cap stocks in the sample. The dependent variable is monthly excess market returns. The independent variables are normalized. In tests (2) and (3), time trend is removed before the normalization as described in Section 4.2. Coeff is the regression coefficient on the SSE, t-value is the Newey-West t-value with eight lags, and $R^2$ is the adjusted R-squared. The regression coefficients are multiplied by 100. Panel B reports the out-of-sample predictive power for one-month-ahead excess market returns. In tests (2) and (3), time trend is removed before the normalization. Finally, Panel C reports the out-of-sample predictive power of SSE for excess stock market returns at longer horizons, where SSE is the original measure as used in Table 4.

Panel A: In-sample predictability of alternative SSE measures

| | (1)<br>Undetrended SSE | (2)<br>Spread SSE | (3)<br>Including microcap |
|---|---|---|---|
| Forecasting one-month return | | | |
| Coeff | -0.47 | -0.54 | -0.55 |
| t-value | -2.21 | -3.48 | -3.40 |
| $R^2$ (%) | 0.89 | 1.25 | -1.31 |
| Forecasting three-month return | | | |
| Coeff | -0.48 | -0.54 | -0.55 |
| t-value | -2.33 | -3.17 | -3.41 |
| $R^2$ (%) | 3.03 | 3.87 | 3.96 |
| Forecasting six-month return | | | |
| Coeff | -0.47 | -0.54 | -0.43 |
| t-value | -2.57 | -3.19 | -2.97 |
| $R^2$ (%) | 5.66 | 7.45 | 4.67 |
| Forecasting 12-month return | | | |
| Coeff | -0.31 | -0.32 | -0.27 |
| t-value | -2.20 | -2.93 | -2.34 |
| $R^2$ (%) | 5.05 | 5.63 | 3.69 |

Panel B: Out-of-sample predictability of alternative SSE measures

| | | Case 1 | Case 2 | Case 3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|
| (1) Undetrended SSE | Expanding | 0.35 | 0.52 | 0.91 | 0.12 | 0.10 | 0.04 |
| | Rolling | 0.68 | 1.00 | 1.68 | 0.04 | 0.03 | 0.01 |
| (2) Spread SSE | Expanding | 0.86 | 0.87 | 0.89 | 0.07 | 0.06 | 0.05 |
| | Rolling | 0.79 | 0.80 | 0.62 | 0.05 | 0.04 | 0.03 |
| (3) Including Microcap | Expanding | 0.80 | 1.12 | 0.81 | 0.05 | 0.02 | 0.05 |
| | Rolling | 0.26 | 1.01 | 0.49 | 0.05 | 0.01 | 0.03 |

Table 7, continued.

Panel C: Out-of-sample predictability of the original SSE measure at longer horizons

| | | Case 1 | Case 2 | Case 3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|
| Forecasting three-month return | | | | | | | |
| SSE | Expanding | 1.53 | 3.34 | 1.35 | 0.06 | 0.01 | 0.06 |
| | Rolling | 2.64 | 4.47 | 1.97 | 0.01 | 0.00 | 0.02 |
| Forecasting six-month return | | | | | | | |
| SSE | Expanding | 5.26 | 6.04 | 4.90 | 0.01 | 0.00 | 0.01 |
| | Rolling | 6.26 | 7.88 | 3.92 | 0.01 | 0.00 | 0.03 |
| Forecasting 12-month return | | | | | | | |
| SSE | Expanding | 1.15 | 2.38 | 1.15 | 0.10 | 0.03 | 0.10 |
| | Rolling | 3.71 | 4.52 | 3.73 | 0.01 | 0.01 | 0.01 |

**Table 8 Predictive Power of Arbitrage Trading Efficiency**

This table reports the predictive power of arbitrage trading efficiency (ATE) that contains information of both the long side and the short side of arbitrage trading. To measure ATE, we replace abnormal short interest in regression (1) with net arbitrage trading, which is the long side of arbitrage trading, proxied by abnormal hedge fund stock holdings, minus the short side of arbitrage trading, proxied by abnormal short interest. The intercept term in the regression is aggregate NAT. The slope coefficient in the regression is ATE. Then, we use ATE to forecast one-quarter ahead excess market returns with the control of the other predictors, one at a time, in a bivariate regression. Both ATE and NAT are filtered with time trend. In the table, the top two lines correspond to ATE, while the next two lines correspond to one other predictor in each column. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and $R^2$ is the adjusted R-squared. The regression coefficients are multiplied by 100. In this table, all predictors are at a quarterly frequency from 1990:Q1 to 2017:Q4.

| | | NAT | SENT | PE | PD | CS | TS | TB3M | FLS | CAPR |
|---|---|---|---|---|---|---|---|---|---|---|
| ATE | Coeff | 2.07 | 1.71 | 2.03 | 1.92 | 2.10 | 2.07 | 2.08 | 2.03 | 2.08 |
| | t-value | 2.25 | 1.80 | 2.30 | 2.11 | 2.34 | 2.35 | 2.35 | 2.46 | 2.27 |
| Other Predictor | Coeff | 0.05 | -1.74 | -0.18 | -0.08 | 50.52 | 48.50 | -12.12 | 15.79 | -31.40 |
| | t-value | 0.03 | -1.47 | -1.53 | -1.69 | 0.20 | 0.53 | -0.43 | 0.31 | -0.97 |
| | $R^2$ (%) | 4.70 | 6.16 | 6.79 | 6.92 | 4.75 | 4.88 | 4.81 | 5.00 | 5.63 |

**Figure 1 Time Series of Short Selling Efficiency**

This figure plots short selling efficiency (SSE) over time. For each stock in month t, we first define abnormal short interest (ASI) as the difference of short interest in the month and the average of short interest in the past 12 months. We require the stocks in our sample to have non-missing values of ASI and the mispricing score. Each month, stocks are ranked from one to 100 based on their mispricing scores, with a large score representing overpricing. We demean these ranks in each cross section. Then, from the regression of ASI on the demeaned mispricing ranks in each month, the slope coefficient is SSE while the intercept is short selling level (SSL). We remove time trend and normalize the values of SSE and SSL. Micro-cap stocks and stocks whose price are less than five dollars are excluded. The sample period is from January 1974 to December 2017.

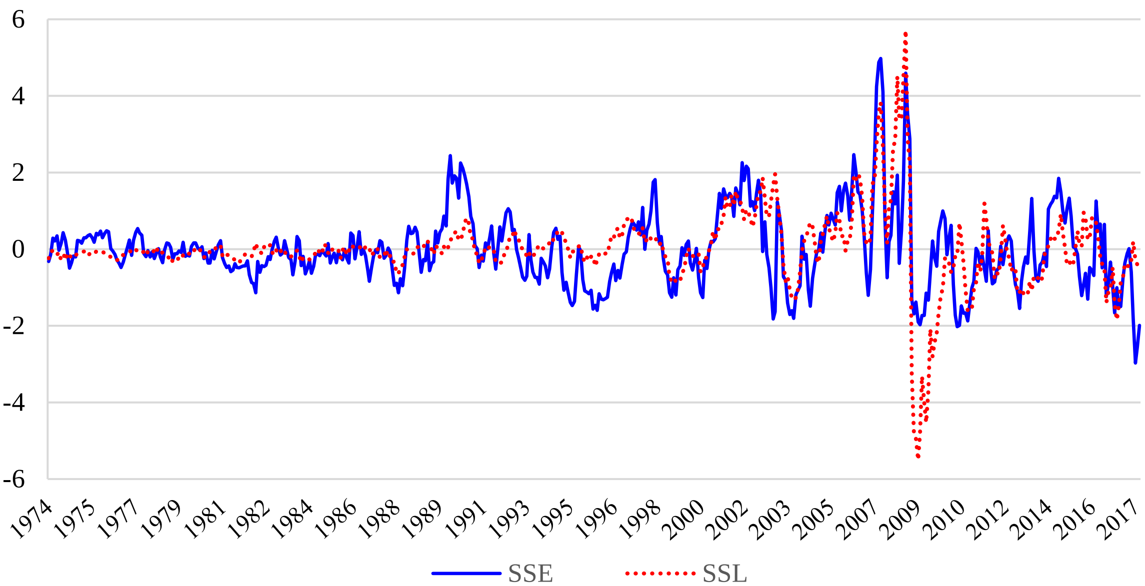
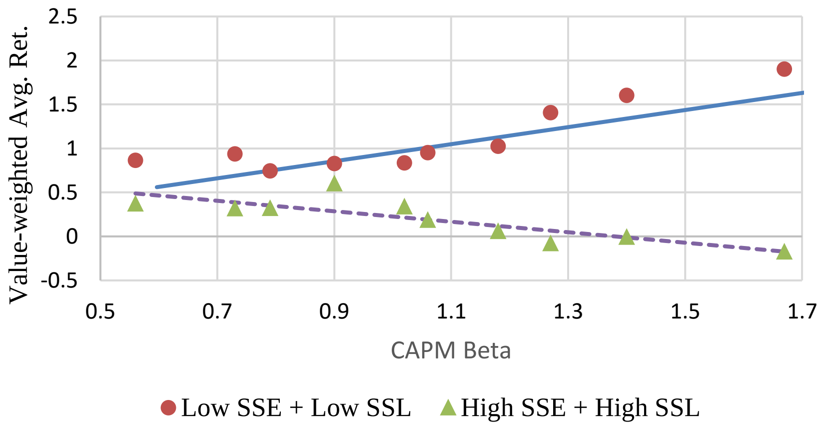


**Figure 2 Returns of Beta and Mispricing Portfolios**

We examine the returns of portfolios sorted by the CAPM beta and the mispricing score following subperiods when both SSE and SSL are below, or above, their time-series medians, referred to as LL or HH subperiods. In Panel A, we form decile stock portfolios based on the CAPM beta and plot the value-weighted average returns on the portfolios. Following each subperiod, we track the average return for each portfolio in the *subsequent* month. In the figure, each dot corresponds to the next-month average return for a beta portfolio following a particular subperiod. In Panel B, we form decile portfolios based on the Stambaugh, Yu, and Yuan (2015) mispricing score and plot the value-weighted average returns on the portfolios. In panel C, we form decile portfolios based on the CAPM beta and plot the equal-weighted average returns on the portfolios. Finally, in Panel D, we form decile portfolios based on the mispricing score and plot the equal-weighted average returns on the portfolios. The average returns are in percent per month.

Panel A: Value-weighted Average Return and CAPM Beta




Panel B: Value-weighted Average Return and Mispricing Score

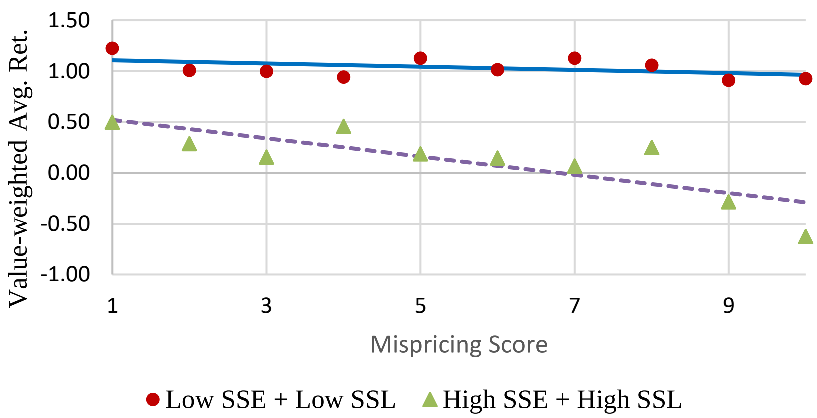
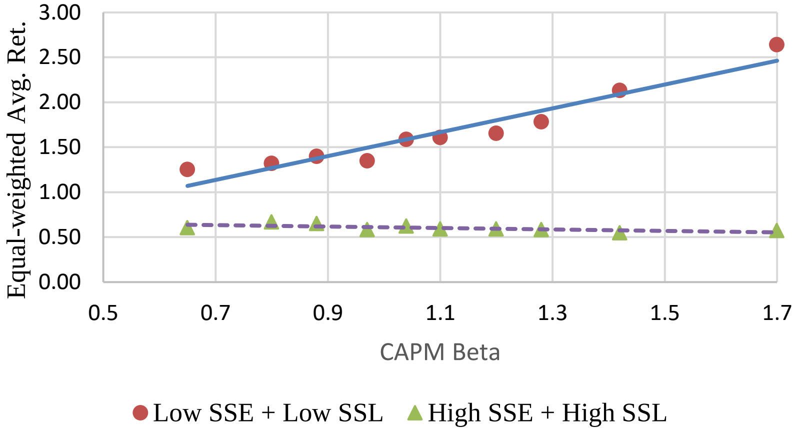


Figure 2, continued.

Panel C: Equal-weighted Average Return and CAPM Beta




Panel D: Equal-weighted Average Return and Mispricing Score

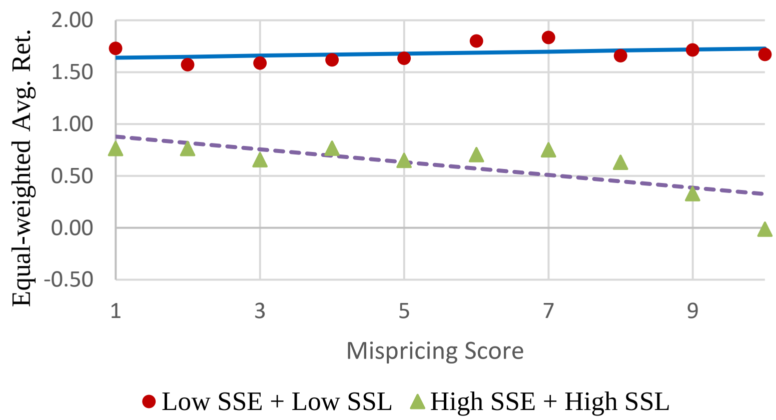


**Figure 3 Predictive Power of SSE: Daily Evidence**

This figure presents daily evidence of the predictive power of SSE. We construct daily SSE using the short selling data obtained from Markit. For each stock in day t, daily abnormal short interest (ASI) is defined as the difference of short interest in the day and the average short interest in the past 30 days. In each cross section, stocks are ranked from one to 100 based on their mispricing scores at the beginning of the month, with a large (small) score indicating overpricing (underpricing). We require the stocks in our sample to have non-missing values of ASI and the mispricing score. We demean the mispricing ranks and then regress ASI on the demeaned mispricing ranks in each day to compute SSE based on the slope coefficient. In the test of forecasting power, the daily SSE is the average in the past five days and then normalized across stocks. We exclude micro-cap stocks and stocks whose price are less than five dollars at the beginning of the month. In the figure, the y-axis is the coefficient from regressing future cumulative excess market returns on the daily SSE. The x-axis is the number of days into the future. The sample period is from July 2006 to March 2011, in which we exclude the shorting ban period July 2008–January 2009.