# Short Selling Efficiency

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## Abstract

We examine the predictive power of short selling efficiency (SSE) for aggregate stock returns, with SSE measured each month by the slope coefficient of a cross-sectional regression of abnormal short interest on overpricing measure. We find that SSE strongly and negatively predicts the equity risk premium, suggesting that large overpricing exists when short selling is executed in the right stocks. The predictive power of SSE is at least as strong as aggregate short interest and appears stronger when the level of short interest is high. Moreover, low SSE signals relatively efficient market and the CAPM performs well in the subsequent month.

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*JEL Classification*: G11, G23

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## 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. However, their analysis does not distinguish between short sales executed in different stocks. In theory, short sales in overpriced stocks should impose stronger price effects than those in underpriced stocks, since the former is more informative. In this paper, we combine the information of short interest with stock mispricing to examine the role of short selling *efficiency* in the aggregate stock market.

Efficient short selling means that the scare 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., detrended ratio of the number of 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

[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.

interest and overpricing across stocks, 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 short interest as well as stock mispricing and thus differs from aggregate short interest used in prior research (which happens to be the intercept term in the cross-sectional regression). 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 reduce the impact of measurement error and hence provides more powerful stock return prediction.

First, we show that SSE is a strong and robust predictor of stock market returns. Over the sample period 1974–2017, SSE has statistically and economically significant predictive power for the equity risk premium both in-sample and out-of-sample. For example, when we regress future excess stock market returns on SSE at a monthly frequency, we obtain a regression coefficient of -0.61, with a t-value of -3.50 and an R-squared of 1.64%. The predictive power persists over a year. At the annual horizon, the regression coefficient is -0.40, with a t-value of -3.69 and an R-squared of 8.49%. The predictability is not subsumed by existing return predictors including aggregate short interest, suggesting that SSE contains distinct information about future market returns. SSE predicts stock market returns particularly well at short horizons, as efficient allocation of short interest in the cross section signals strong arbitrage forces and thus price correction is likely to follow immediately. 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 mean of stock market returns. The results are robust to a battery of sensitivity tests, such as various forecasting horizons, alternative ways of trend adjustment, and inclusion or exclusion of micro-cap firms.

Second, SSE and aggregate short interest seem to reinforce each other in forecasting stock market returns, in that the predictive power of SSE appears stronger in the presence of a higher level of aggregate short interest, and vice versa. For example, when the level of aggregate short interest is higher (lower) than the median, 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 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.

Finally, 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) of Sharpe (1964) 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 in the subsequent month. 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.

We focus on the short side of arbitrage trading in this paper. Chen, Da and Huang (2019) show that combining the long and the short sides provides a more complete picture about the role of arbitrageurs in affecting stock prices. We compute the arbitrage trading efficiency (ATE) in a similar fashion to SSE (except that we replace abnormal short interest with the net arbitrage trading measure) and find ATE to negatively predict future market returns as well. The quarterly availability of ATE, however, significantly reduces the statistical power of our time series tests. Hence, we investigate monthly SSE primarily in most of our empirical analyses.

Our paper makes several contributes to the literature. First, it relates to the studies of how short sales affect asset prices. Prior research on short selling mostly focuses on the cross-sectional effect of short selling, as well as its constraints, on stock returns, such as Nagel (2005), Cohen, Diether, and Malloy (2007), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009a), Engelberg, Reed, and Ringgenberg (2012), Hanson and Sundram (2014), Drechsler and Drechsler (2016). In particular, a few of these papers (Nagel, 2005; Hanson and Sundram, 2014; Drechsler and Drechsler, 2016) examine the relation between short sales and return anomalies. Our paper complements the existing research by investigating the predictive power of short selling efficiency for aggregate stock returns.

The closest paper to ours is Rapach, Ringgenberg, and Zhou (2016), who show that the level of short interest can predict the equity market premium. In fact, these authors assert that "short interest is arguably *the* strongest predictor of the equity market premium identified to date" (p. 46). Our study of short interest efficiency sharpens the predictor by combining stock mispricing information (i.e., anomalies) with short interest and sheds new light on how short sellers impact stock markets at the aggregate level. Importantly, our study is motivated by the economic insight that how scare resources are allocated across stocks for short selling activity should impact overall market efficiency. To the best of our knowledge, our paper is the first to link short selling efficiency to aggregate price movement in the stock market.

Finally, our study relates to the literature on market return predictability. Given the importance of the equity market premium in practice, there has been decades-long research and debate about this topic.[2] Many previous studies examine the predictive power of factors

[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),

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 arbitrage trading such as short selling contains significant predictive signals for future stock market returns.[3] Therefore, our results contribute to the existing evidence on how arbitrage activity affects asset prices (e.g., Brunnermeier and Nagel, 2004; Chen, Da, and Huang, 2019).

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

$$ASI_{i,t} = a_t + b_t \, MISP_{i,t} + e_{i,t}, \tag{1}$$

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 stock overpricing (underpricing). For our empirical analysis, we adopt the

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Huang, Jiang, Tu, and Zhou (2015), Rapach, Ringgenberg, and Zhou (2016), 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] Over 80% of short selling activity in recent years has been performed by hedge funds. See, e.g., Brunnermeier and Nagel (2004), Ben-David, Franzoni, and Moussawi (2012), Chen, Da, and Huang (2019), Chen, Kelly, and Wu (2019) for discussions and evidence about stock trading behavior of hedge funds as professional arbitrageurs.

comprehensive mispricing percentile ranking measure of Stambaugh, Yu, and Yuan (2015). To ease interpretation of the regression coefficients, we have demeaned MISP cross-sectionally so that it takes the value of 50 (-50) for the most overvalued (undervalued) stocks.

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 in 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 can be seen from the regression, SSE (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 sales are performed to overpriced stocks. In practice, not all short sales are for arbitrage purposes, but some short selling can occur to undervalued stocks. For example, investors sometimes sell short a stock 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 activity to predict stock returns in the cross section. Consequently, our SSE measure of short selling activity contains important information over and above the level of short interest itself. In addition, the emphasis of SSE on overpriced stocks helps reduce the impact of measurement error that arises from short sales for non-arbitrage purposes. Since noises in the forecaster hamper the detection of a predictive relation, mitigating the effect of measurement error will improve the power of the tests. In sum, we expect SSE to possess significant forecasting power for the equity risk premium over and above the previously studied predictor based on 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 coverage on 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). It allows us to compute the abnormal short interest for each stock each month from 1974 to 2017. 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 use 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) 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 is associated with 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.

[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.

In our baseline analysis, we require stocks to have non-missing values of ASI and MISP to be included in regression (1) and we exclude micro-cap stocks and stocks whose price are less than five dollars. As robustness checks, we later include micro-cap stocks in the analysis.

As documented by Rapach, Ringgenberg, and Zhou (2016), there has been an upward trend in short selling since the 1970s, perhaps due to the rise of hedge funds as the main group of short sellers in the US stock market. As a result, both the SSE and the SSL monthly time series display upward trends. Following Rapach, Ringgenberg, and Zhou (2016), we remove the time trends in both SSE and SSL and standardize both variables. While this adjustment is done using the full sample in our baseline analysis, robustness checks confirm that a dynamic adjustment using backward expanding windows produces very similar results.

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. The information in 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. Not surprisingly, SSE and the short selling level (SSL) are positively correlated (with a correlation of 0.6), as the existence of overpricing should motivate arbitrageurs to short more stocks, especially the most overpriced ones. 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.

### 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 personal websites of several researchers.[5] 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 that 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).
7. Three-month T-bill rate (TB3): three-month T-bill rate, as in Campbell (1987) and Hodrick (1992).

[5] 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.

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).

Panel B of Table 1 presents the correlations between SSE and the other return predictors. As discussed previously, there is a fairly high correlation coefficient (0.6) between SSE and SSL, indicating that more short selling is directed to the right stocks when aggregate short interest is also high in the stock market. Meanwhile, SSE bears relatively low correlations with the rest of other predictors, suggesting that SSE covers different information from the predictors constructed from firm fundamentals or macroeconomic conditions.

## 4. The Predictability 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. Next, we explore the predictability of SSE jointly with the short interest level (SSL). Finally, we assess the out-of-sample predictive ability of SSE.

### 4.1 In-sample predictability

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

$$r_{t+s} = \alpha + \beta x_t + \varepsilon_{t+s}, \tag{2}$$

where $x$ is the return predictor at a month frequency. The forecasting horizon $s$ varies from one, three, six, to 12 months. 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. For comparison purposes, we perform the same analysis for the other predictors. The 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, though we verify that our conclusions remain 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 always significantly predicts future excess market returns. For example, for monthly excess market returns 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).

The predictive power of SSE seems to compare 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. We find that SSE performs as least as well as SSL and possesses strong predictive power at all of the four forecasting horizons.

Other predictors, such as cash flow-related ratios and market conditions, show correct signs in forecasting aggregate stock returns, but they are not as statistically significant especially over shorter horizons. As forecasting horizon gets longer, 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 market premium, we perform regressions that include the other predictors, one at each time, as control variables in a multiple regression setting. 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 at the one-month horizon, 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. In general, controlling for the other predictors does not subsume the forecasting power of SSE. We obtain the same inference at the other 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 reported in Panel D. In addition, the adjusted R-squared from this multiple regression including both SSE and SSL, 12.16%, is higher than that from the single regression for SSE at 8.49%.

We draw two conclusions from the results thus far. First, SSE possesses independent predictive power for the equity market premium over and above the existing return predictors. While SSL carries information about the stock market at a long horizon, SSE predicts market returns well at short horizons. The contrast makes sense as efficient allocation of short interest in the cross section signals strong arbitrage forces and immediate correction is likely to follow. Second, as two distinct measures of short selling activity, SSE and SSL can join force with each other to enhance the ability to predict stock market returns. Next, we further explore the joint predicative power by interacting these two measures.

### 4.2 Interacting SSE and SSL

Here, we investigate how SSE interacts with SSL in predicting aggregate stock returns. Specifically, we examine the predictive power of SSE in subsamples that feature high or low SSL relative to the median value from the full sample, and vice versa. The idea is to check whether short selling efficiency (i.e., the allocation of short sales to correct stocks) contains particularly forecasting signals while large aggregate short interest exists across stocks.

Table 4 shows the results. First, we observe stronger forecasting power of SSE when SSL is above the median level. For example, at the three-month horizon, the single regression produces a coefficient on SSE of -0.81 (t-value = -2.80) and an adjusted R-squared of 9.13% when SSL is at a high level. In contrast, when SSL is at a low level, the regression coefficient on SSE is merely -0.53 (t-value = -1.65) with an adjusted R-squared 1.51%. This observation holds across all the forecasting horizons from one to 12 months. Nonetheless, 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.

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 at the three- to 12-month horizons, compared with the one-month horizon.

Taken together, SSE and SSL reinforce each other in forecasting the equity market 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 to 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.

### 4.3 Out-of-sample predictability

Recent research on stock return predictability (e.g., Goyal and Welch, 2008) points out the importance of testing out-of-sample forecasting performance for proposed predictors to help validate the detected in-sample performance. In this subsection, we evaluate the power of SSE in predicting aggregate stock returns in an out-of-sample test setting. Following the literature, we examine whether SSE can outperform the historical mean of stock market returns.

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

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

where $x_{t-1}$ is one-month lagged value of the forecasting variable, and $r_t$ is the excess market return. Then, we use the fitted value $\hat{\mu}_t$ from the estimation as the forecasted equity premium for month t+1, with $\hat{\mu}_t$ computed as follows.

$$\hat{\mu}_t = \hat{\alpha} + \hat{\beta} x_{t-1}. \tag{4}$$

Next, we either increase the sample by one additional observation each time (expanding) or have a rolling sample of ten-year data (rolling), and thereby generate a series of out-of-sample equity premium forecasts, $\hat{\mu}_t, \hat{\mu}_{t+1}, \ldots, \hat{\mu}_{T-1}$. 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 mean.

$$R^2 = 1 - \frac{\sum_{i=s_0}^{T-1}(r_{i+1} - \hat{\mu}_i)^2}{\sum_{i=s_0}^{T-1}(r_{i+1} - \bar{r}_i)^2}, \tag{5}$$

where $\bar{r}_i$ is the historical mean of returns up to month *i* and *T* is the total number of months in our sample. We require $s_0$ to be 120 months for the initial estimation. We consider two approaches. In the first approach, the sample always starts in 1974, with the first estimation using 10 years of data. After that, we expand the sample by one month in each round of estimation. In the second approach, the first estimation remains the same, but the sample uses a backward rolling window of 120 months each time we move forward. In each approach (expanding or rolling), we consider three cases: 1) with no restriction, 2) with sign restrictions, which set the premium estimates to the historical mean when coefficient signs are incorrect, and 3) with premium restrictions, which set premium estimates to zero when the forecasted equity premium is negative. We use the Clark and West (2007) method to compute p-values for the test statistics. In the test, a positive out-of-sample R-squared indicates outperformance of the predictor over the historical mean.

Table 5 presents the results of out-of-sample performance. To remove the effect of the observed upward trend, we filter SSE and other predictors with a simple time trend using the full sample. (For robustness, we use an alternative way to remove the time trend dynamically using information up to month t.) Based on both the expanding sample and the rolling sample, we find consistent evidence that SSE performs significantly better than the historical mean in forecasting the equity premium across all of the 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 1.68% (p-value = 0.02) to 2.10% (p-value = 0.00). Similarly, using the 10-year rolling sample, we observe out-of-sample R-squared varying from 0.92% (p-value = 0.02) to 1.83% (p-value = 0.00).

In contract, the out-of-sample performance of the other predictors is not as strong over our sample period 1974–2017. The result about these predictors broadly resembles Goyal and Welch (2008), who find that many predictors cannot outperform the historical mean out-of-sample. Sentiment and funding liquidity spread, however, show significant outperformance over the historical mean in some cases. In the meantime, none of these predictors including SSL significantly underperform the historical mean judging by their p-values. The finding for SSL is perhaps not surprising, given the earlier evidence that its forecasting power lies in a long horizon while the out-of-sample test focuses on a one-month-ahead horizon.

To summarize, the out-of-sample test suggests that SSE outperforms the historical mean in predicting the equity market premium. Thus, both in-sample and out-of-sample results strongly support the notion that the efficiency of short selling activity contains statistically and economically significant signals about future stock market returns. Since short sellers, as a group of arbitrageurs, attempt to exploit overpricing, their trading can in turn relate to the equilibrium asset prices and market efficiency, which is examined in the next section.

## 5. Short Selling Activity and the CAPM

In this section, we investigate the relation between short selling activity and the performance of the capital asset pricing model (CAPM) of Sharpe (1964). The CAPM predicts that expected returns on individual stocks are positively and linearly related to their sensitivity (i.e., beta) to aggregate market 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 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 the 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. Therefore, 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.

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 (2019) 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 possess and exploit private information, 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 terms 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 various 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 Analysis

In this section, we check the robustness of our results. First, we use an alternative "real time" approach to detrending the predictor SSE. Second, we add back micro-cap stocks to our sample so that the resulting SSE covers nearly all public firms. Finally, we examine the predictive power of a measure of arbitrage trading efficiency by supplementing short selling activity with the long side of arbitrage trading proxied by hedge funds' stock holdings.

### 6.1 "Real time" detrending

Both SSE and SSL exhibit a time trend, indicating the steady increase of short selling activity. In Section 4, we have used the full sample to adjust the time trend for these predictors. The full sample detrending approach is not suitable for real time prediction. Here, an alternative detrending approach, similar to Campbell (1991), is considered to dynamically remove the time trend with information up to month t. Specifically, we begin with the subsample of 1974–1978 to remove the time trend. We normalize the residuals of the time trend regression and keep the last observation that is matched with future one- to 12-month excess market returns. Then, we extend the subsample forward by one month at a time to remove the time trend. We refer to this procedure as the "real time" detrending, which avoids look-ahead biases and suits for real-time forecasting.

Panel A of Table 6 reports the in-sample predictability. With this alternative detrending, SSE continues to exhibit significant predicting power for stock market returns. In a single regression, the coefficient is -0.35 (t-value = -3.27) at the one-month horizon, -0.35 (t-value = -3.18) at the three-month horizon, -0.36 (t-value = -3.48) at the six-month horizon, and -0.23 (t-value = -2.97) at the 12-month horizon. When we include SSL in a multiple regression, the coefficient on SSE remains highly significant, especially at short horizons. The coefficient is -0.49 (t-value = -3.12), -0.41 (t-value = -3.35), -0.36 (t-value = -3.25), and -0.20 (t-value = -1.91) at the one-, three-, six-, and 12-month horizons, respectively. Meanwhile, the forecasting ability of SSL weakens to some extent relative to the full sample detrending.

Panel B of Table 6 presents the out-of-sample performance of SSE from the real time detrending approach. Consistent with the evidence from the full sample detrending method, we find that SSE performs better than the historical mean in predicting stock market returns out-of-sample. In all of the three cases regarding test restrictions (as described in Section 4.3), SSE outperforms the historical mean, based on both the expanding sample and the rolling sample. For example, from the expanding sample, SSE's out-of-sample R-squared is around 1.90% with a p-value about 0.02 in all of the three cases. The result from the rolling sample delivers a similar message.

Thus, the performance of SSE in predicting market returns, both in-sample and out-of-sample, is robust to the alterative real time detrending approach. This suggests that SSE, which combines information of both short selling and stock mispricing, could potentially guide investment decisions in real time.

### 6.2 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 performing the test is that perhaps short sales are heavily executed to such small stocks, since information acquisition is usually not as much on small stocks as on large stocks (e.g., Farboodi, Matray, Veldkamp, and Venkateswaran, 2019) and thus small stocks may have larger and longer-lasting mispricing.

Table 7 repeats the single regression analysis for the expanded sample. SSE continues to exhibit significant forecasting power at all of the forecasting horizons examined. Adding back the subset of micro-cap stocks does not affect the inference about SSL, either. If anything, the magnitude of the regression coefficient gets slightly smaller, perhaps because the subset of stocks does not relate much to the equity risk premium but adds noises.

Table 8 reports the results of multiple regressions using the expanded sample. Again, the inference remains unchanged, in that the reconstructed SSE still significantly predicts future stock market returns in the presence of the control variables. Therefore, our findings are robust to the inclusion of micro-cap stocks.

### 6.3 Incorporating the long side of arbitrage trading

Short selling activity focused on overpriced stocks is the short side of arbitrage trading. However, Chen, Da and Huang (2019) show that combining the long and the short sides provides a more complete picture about the role of arbitrageurs in affecting stock prices. Therefore, in this subsection, we supplement short selling activity with the stock purchases of arbitrageurs as the long side to measure arbitrage trading efficiency (ATE) and investigate its predictive power for the equity risk premium. That is, we use the information of both long and short sides of arbitrage trading, together with the mispricing score, to forecast aggregate market 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 data on hedge fund stock holdings compiled by Cao, Chen, Goetzmann, and Liang (2018) who manually match information from six hedge fund databases to the Securities and Exchange Commission (SEC)'s Form 13F filings.[6] Existing research shows that hedge fund activities influence stock market efficiency in various aspects (e.g., Brunnermeier and Nagel, 2004; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015; Kokkonen and Suominen, 2015; Sias, Turtle, and Zykaj, 2016; Cao, Chen, Goetzmann, and Liang, 2018; Chen, Da, and Huang, 2019; Chen, Kelly, and Wu, 2019). In a recent study, 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).[7] 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 dependence 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 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 9 presents the evidence on the predictive power for aggregate stock returns one-quarter ahead. When including both ATE (the efficiency measure) and NAT (the level measure)

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[6] 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.

[7] 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/.

as the independence variables, we find that the coefficient on ATE is 2.07 (t-value = 2.25). This result echoes 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 multiple regression provides similar results.

Therefore, by adding the long side of arbitrage trading to 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 selling. Hence, focusing on the short side through SSE should be able to capture the main force of arbitrage efficiency.

## 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 simple 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 also provides useful investment guidance in practice.

In addition, 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 returns. 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. The sample period is from January 1974 to December 2017.

Panel A: Summary of the predictors

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

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: Single Regression

This table reports the predictive power of SSE and other return predictors in a single 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). In each panel, Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R2 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 |
| R2 (%) | 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 |
| R2 (%) | 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 |
| R2 (%) | 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 |
| R2 (%) | 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: Multiple Regression

This table reports the predictive power of SSE along with the other return predictors, one at a time, in a multiple 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). In each panel, the top two lines correspond to SSE, 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 R2 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 |
| | R2(%) | 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 |
| | R2(%) | 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 |
| | R2(%) | 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 |
| | R2(%) | 12.16 | 9.93 | 10.46 | 9.62 | 9.83 | 9.47 | 8.76 | 8.75 | 10.28 |

## Table 4 Interacting SSE and SSL

In 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 stock market returns at the one-, three-, six- and 12-month horizons in Panels A through D, respectively. Similarly, in 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. In each panel, Coeff is the regression coefficient in a single regression, t-value is Newey-West t-values with lags equal to the forecast horizon, and R2 is the adjusted R-squared. The coefficients are multiplied by 100.

| | Coefficient on SSE | | Coefficient on SSL | |
|---|---|---|---|---|
| | SSL > Median | SSL < Median | SSE > Median | SSE < Median |
| Panel A: Forecasting one-month return | | | | |
| Coeff | -0.66 | -0.63 | -0.32 | 0.19 |
| t-value | -2.34 | -1.56 | -1.01 | 0.46 |
| R2 (%) | 2.07 | 0.55 | -0.01 | -0.18 |
| Panel B: Forecasting three-month return | | | | |
| Coeff | -0.81 | -0.53 | -0.62 | -0.08 |
| t-value | -2.80 | -1.65 | -2.04 | -0.24 |
| R2 (%) | 9.13 | 1.51 | 3.89 | -0.30 |
| Panel C: Forecasting six-month return | | | | |
| Coeff | -0.75 | -0.48 | -0.71 | -0.27 |
| t-value | -3.32 | -1.95 | -3.15 | -1.23 |
| R2 (%) | 14.86 | 2.58 | 10.80 | 1.51 |
| Panel D: Forecasting 12-month return | | | | |
| Coeff | -0.44 | -0.37 | -0.57 | -0.26 |
| t-value | -3.42 | -1.93 | -4.29 | -1.52 |
| R2 (%) | 10.42 | 3.60 | 16.24 | 3.17 |

## Table 5 Out-of-Sample Predictability

This table reports the out-of-sample predictability. First, we run the following time-series regression:

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

where $x_{t-1}$ is one-month lagged value of the predictor, and $r_t$ is the excess market return. Then, we use the fitted value $\hat{\mu}_t$ from the estimation as the forecasted equity premium for month t+1, with $\hat{\mu}_t$ computed as follows.

$$\hat{\mu}_t = \hat{\alpha} + \hat{\beta} x_{t-1}.$$

Next, we either increase the sample by one additional observation each time (expanding) or have a rolling sample of ten-year data (rolling), and thereby generate a series of out-of-sample equity premium forecasts, $\hat{\mu}_t,\ \hat{\mu}_{t+1}, \ldots, \hat{\mu}_{T-1}$. Following Campbell and Thompson (2008) and Welch and Goyal (2008), the out-of-sample *R*-squared compares the mean-squared errors obtained from the predictor with those from the historical mean.

$$R^2 = 1 - \frac{\sum_{i=s_0}^{T-1}(r_{i+1} - \hat{\mu}_i)^2}{\sum_{i=s_0}^{T-1}(r_{i+1} - \bar{r}_i)^2},$$

where $\bar{r}_i$ is the historical mean of returns up to time *i* and *T* is the number of observations in our sample. We require $s_0$ to be 120 months when we start expanding the sample and use a 10-year rolling window when we roll the sample. In each approach (expanding or rolling), we consider three cases: 1) with no restriction, 2) with sign restrictions, which set premium estimates to the historical mean when coefficient signs are incorrect, and 3) with premium restrictions, which set premium estimates to zero when forecasted premium is negative. We use the Clark and West (2007) method to compute p-values for the test statistics. A positive out-of-sample R-squared indicates outperformance of the predictor over the historical mean. We use a regression to remove time trend for SSE and SSL. The 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).

| | | Case 1 | Case 2 | Case 3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|
| SSE | Expanding | 1.68 | 1.71 | 2.10 | 0.02 | 0.02 | 0.00 |
| | Rolling | 0.92 | 1.16 | 1.83 | 0.02 | 0.02 | 0.00 |
| SSL | Expanding | -0.47 | 0.18 | -0.27 | 0.42 | 0.30 | 0.35 |
| | Rolling | -0.59 | 0.22 | 0.06 | 0.46 | 0.23 | 0.22 |
| SENT | Expanding | -0.10 | 0.03 | -0.02 | 0.59 | 0.39 | 0.47 |
| | Rolling | 0.00 | -0.02 | 0.96 | 0.14 | 0.14 | 0.06 |
| PE10 | Expanding | -3.45 | -3.03 | -1.13 | 0.77 | 0.71 | 0.77 |
| | Rolling | -2.73 | -1.73 | -1.55 | 0.79 | 0.53 | 0.58 |
| PD | Expanding | -2.79 | -2.34 | -1.25 | 0.73 | 0.64 | 0.73 |
| | Rolling | -3.59 | -2.63 | -1.74 | 0.79 | 0.59 | 0.57 |
| CS | Expanding | -2.04 | 0.00 | -1.28 | 0.83 | 0.84 | 0.77 |
| | Rolling | -2.60 | -1.65 | -0.28 | 0.42 | 0.39 | 0.29 |
| TS | Expanding | -0.97 | -0.97 | -0.92 | 0.32 | 0.32 | 0.31 |
| | Rolling | -1.00 | -0.33 | -0.67 | 0.69 | 0.43 | 0.57 |
| TB3M | Expanding | -0.48 | -0.43 | -0.42 | 0.55 | 0.52 | 0.51 |
| | Rolling | -1.13 | -0.41 | -0.25 | 0.45 | 0.29 | 0.24 |
| FLS | Expanding | -0.29 | -0.29 | -0.45 | 0.23 | 0.23 | 0.31 |
| | Rolling | 1.62 | 1.08 | 0.96 | 0.02 | 0.05 | 0.04 |
| CAPR | Expanding | -1.55 | -1.32 | -0.34 | 0.46 | 0.39 | 0.38 |
| | Rolling | -1.85 | -1.15 | -0.86 | 0.44 | 0.23 | 0.32 |

## Table 6 "Real Time" Detrending

In this table, we adjust time trend in SSE and SSL dynamically. We use the sample from 1974 to 1978 as the first subsample to remove the time trend. We normalize the residuals of the time trend regression and keep the last observation that is matched with future one- to 12-month excess market returns. Then, we extend the subsample forward by one month at a time to remove the time trend. We refer this procedure as "real time" detrending. In panel A, we examine the predictive power of SSE and SSL in both single and multiple regressions at the one-, three-, six- and 12-month horizons. Coeff is the regression coefficient, t-value is Newey-West t-values, and R2 is the adjusted R-squared. The coefficients are multiplied by 100. In panel B, we assess the out-of-sample performance of SSE and the other predictors with the real time detrending. In each approach (expanding or rolling), we consider three cases: 1) with no restriction, 2) with sign restrictions, which set premium estimates to the historical mean when coefficient signs are incorrect, and 3) with premium restrictions, which set premium estimates to zero when forecasted premium is negative. We use the Clark and West (2007) method to compute p-values for the test statistics. A positive out-of-sample R-squared indicates outperformance of the predictor over the historical mean. The other 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).

Panel A: In-sample predictability with real time detrending

| | Single regression | | Multiple regression | |
|---|---|---|---|---|
| | SSE | SSL | SSE | SSL |
| Forecasting one-month return | | | | |
| Coeff | -0.35 | -0.05 | -0.49 | 0.17 |
| t-value | -3.27 | -0.58 | -3.12 | 1.35 |
| R2 (%) | 1.30 | -0.15 | 1.47 | |
| Forecasting three-month return | | | | |
| Coeff | -0.35 | -0.11 | -0.41 | 0.08 |
| t-value | -3.18 | -1.21 | -3.35 | 0.73 |
| R2 (%) | 3.84 | 0.52 | 3.85 | |
| Forecasting six-month return | | | | |
| Coeff | -0.36 | -0.17 | -0.36 | 0.00 |
| t-value | -3.48 | -1.67 | -3.25 | -0.02 |
| R2 (%) | 8.16 | 2.99 | 7.97 | |
| Forecasting 12-month return | | | | |
| Coeff | -0.23 | -0.14 | -0.20 | -0.04 |
| t-value | -2.97 | -1.73 | -1.91 | -0.43 |
| R2 (%) | 6.54 | 3.77 | 6.60 | |

Table 6, continued.

Panel B: Out-of-sample predictability with real time detrending

| | | Case 1 | Case 2 | Case 3 | p1 | p2 | p3 |
|---|---|---|---|---|---|---|---|
| SSE | Expanding | 1.90 | 1.90 | 1.93 | 0.02 | 0.02 | 0.01 |
| | Rolling | 1.59 | 1.77 | 1.68 | 0.02 | 0.01 | 0.01 |
| SSL | Expanding | -0.39 | 0.03 | -0.38 | 0.77 | 0.40 | 0.77 |
| | Rolling | -0.27 | 0.30 | 0.07 | 0.47 | 0.20 | 0.30 |
| SENT | Expanding | 0.75 | 0.75 | 1.09 | 0.11 | 0.11 | 0.05 |
| | Rolling | 0.34 | 0.32 | 1.36 | 0.11 | 0.12 | 0.05 |
| PE10 | Expanding | -0.96 | -0.46 | -0.91 | 0.68 | 0.47 | 0.70 |
| | Rolling | -1.74 | -0.76 | -1.02 | 0.48 | 0.22 | 0.35 |
| PD | Expanding | -0.95 | -0.36 | -0.92 | 0.56 | 0.32 | 0.55 |
| | Rolling | -3.28 | -2.16 | -1.52 | 0.63 | 0.39 | 0.44 |
| CS | Expanding | -1.37 | -0.27 | -1.12 | 0.86 | 0.77 | 0.81 |
| | Rolling | -3.23 | -2.09 | -0.28 | 0.42 | 0.39 | 0.27 |
| TS | Expanding | -0.78 | -0.01 | -0.78 | 0.54 | 0.84 | 0.54 |
| | Rolling | -0.77 | -0.84 | -0.35 | 0.64 | 0.92 | 0.46 |
| TB3M | Expanding | -1.33 | -1.26 | -1.33 | 0.71 | 0.68 | 0.71 |
| | Rolling | -0.91 | 0.00 | 0.13 | 0.37 | 0.18 | 0.15 |
| FLS | Expanding | 1.00 | 0.26 | 0.95 | 0.05 | 0.16 | 0.05 |
| | Rolling | 2.11 | 0.86 | 1.32 | 0.02 | 0.08 | 0.04 |
| CAPR | Expanding | -0.75 | -0.34 | -0.61 | 0.54 | 0.32 | 0.55 |
| | Rolling | -2.14 | -1.27 | -1.07 | 0.45 | 0.22 | 0.34 |

## Table 7 Including Micro-Cap Stocks: Single Regression

In this table, we examine the predictive power of SSE and SSL through a single regression by including micro-cap stocks in the sample. We forecast excess stock market returns at the one-, three-, six- and 12-month horizons. In each panel, Coeff is the regression coefficient, t-value is Newey-West t-value with eight lags, and R2 is the adjusted R-squared. The coefficients are multiplied by 100.

| | SSE | SSL |
|---|---|---|
| Panel A: Forecasting one-month return | | |
| Coeff | -0.55 | -0.19 |
| t-value | -3.40 | -1.10 |
| R2 (%) | 1.31 | -0.01 |
| Panel B: Forecasting three-month return | | |
| Coeff | -0.55 | -0.40 |
| t-value | -3.41 | -2.70 |
| R2 (%) | 3.96 | 2.06 |
| Panel C: Forecasting six-month return | | |
| Coeff | -0.43 | -0.51 |
| t-value | -2.97 | -3.53 |
| R2 (%) | 4.67 | 6.70 |
| Panel D: Forecasting 12-month return | | |
| Coeff | -0.27 | -0.43 |
| t-value | -2.34 | -4.15 |
| R2 (%) | 3.69 | 10.39 |

## Table 8 Including Micro-cap Stocks: Multiple Regression

In this table, we examine the predictive power of SSE with the control of other predictors, one at a time, by including micro-cap stocks in the sample. We forecast excess stock market returns at the one-, three-, six- and 12-month horizons. The other 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. Coeff is the regression coefficient on the return predictor, t-value is the Newey-West t-value with eight lags, and R2 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 | -0.58 | -0.55 | -0.55 | -0.52 | -0.54 | -0.54 | -0.56 | -0.57 | -0.53 |
| | t-value | -2.90 | -3.35 | -3.37 | -2.92 | -3.33 | -3.30 | -3.54 | -3.42 | -3.20 |
| Other predictor | Coeff | 0.06 | -0.18 | -0.02 | 1.92 | 27.15 | 33.15 | -5.99 | -3.54 | -9.62 |
| | t-value | 0.30 | -0.72 | -0.70 | 1.51 | 0.42 | 1.18 | -1.04 | -0.44 | -1.14 |
| | R2(%) | 1.14 | 1.26 | 1.22 | 1.68 | 1.20 | 1.42 | 1.36 | 1.22 | 1.28 |
| Panel B: Forecasting three-month return | | | | | | | | | | |
| SSE | Coeff | -0.46 | -0.54 | -0.55 | -0.53 | -0.54 | -0.54 | -0.56 | -0.56 | -0.54 |
| | t-value | -2.61 | -3.39 | -3.40 | -3.15 | -3.27 | -3.27 | -3.51 | -3.54 | -3.31 |
| Other predictor | Coeff | -0.20 | -0.17 | -0.02 | 1.41 | 35.03 | 28.77 | -4.86 | -2.06 | -9.94 |
| | t-value | -1.03 | -0.74 | -0.81 | 1.16 | 0.63 | 1.11 | -0.88 | -0.31 | -1.28 |
| | R2(%) | 4.22 | 4.09 | 4.11 | 4.70 | 4.14 | 4.40 | 4.21 | 3.87 | 4.41 |
| Panel C: Forecasting six-month return | | | | | | | | | | |
| SSE | Coeff | -0.25 | -0.42 | -0.42 | -0.41 | -0.41 | -0.42 | -0.44 | -0.44 | -0.42 |
| | t-value | -1.53 | -2.97 | -2.98 | -2.69 | -2.85 | -2.82 | -3.00 | -3.07 | -2.92 |
| Other predictor | Coeff | -0.40 | -0.22 | -0.02 | 1.10 | 53.50 | 24.68 | -3.95 | -1.84 | -9.88 |
| | t-value | -2.09 | -1.16 | -1.07 | 1.09 | 1.29 | 1.07 | -0.75 | -0.50 | -1.34 |
| | R2(%) | 7.85 | 5.52 | 5.48 | 5.51 | 6.08 | 5.35 | 5.02 | 4.62 | 5.84 |
| Panel D: Forecasting 12-month return | | | | | | | | | | |
| SSE | Coeff | -0.09 | -0.26 | -0.25 | -0.24 | -0.24 | -0.25 | -0.27 | -0.27 | -0.25 |
| | t-value | -0.63 | -2.34 | -2.32 | -1.97 | -2.19 | -2.12 | -2.33 | -2.39 | -2.29 |
| Other predictor | Coeff | -0.40 | -0.21 | -0.03 | 1.11 | 41.23 | 23.18 | -2.49 | -1.77 | -9.09 |
| | t-value | -2.78 | -1.40 | -1.43 | 1.20 | 1.34 | 1.25 | -0.56 | -0.93 | -1.43 |
| | R2(%) | 10.57 | 5.56 | 6.38 | 5.75 | 5.52 | 5.15 | 3.95 | 3.77 | 6.21 |

## Table 9 Forecasting Power of Arbitrage Trading Efficiency

This table reports the forecasting 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 treading, 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 multiple 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 R2 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 |
| | R2(%) | 4.70 | 6.16 | 6.79 | 6.92 | 4.75 | 4.88 | 4.81 | 5.00 | 5.63 |

**Figure 1 Time Variation of SSE and SSL**

This figure plots the time variation of short selling efficiency (SSE) and short selling level (SSL). For each stock in month t, we 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, we regress ASI on the demeaned mispricing ranks in each month to compute SSE (the slope coefficient) and SSL (the intercept). 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.

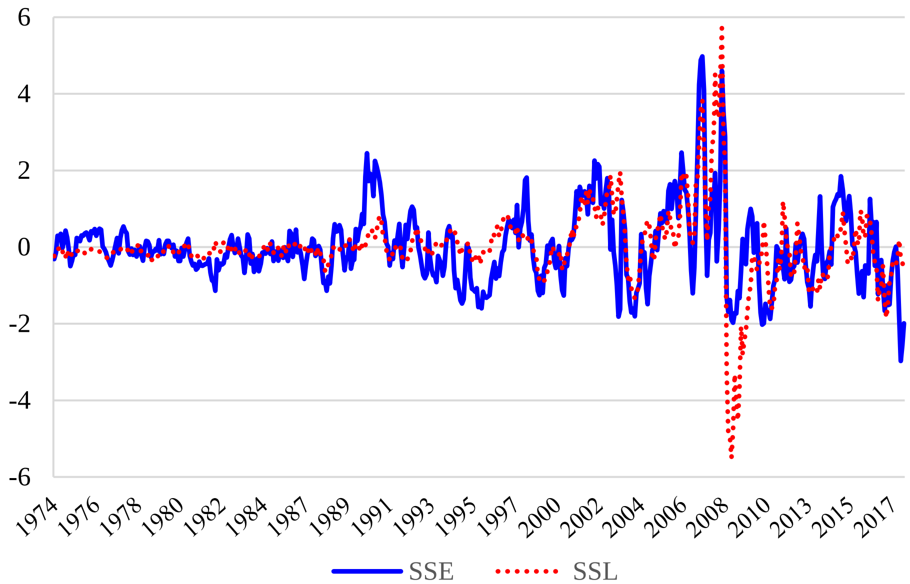
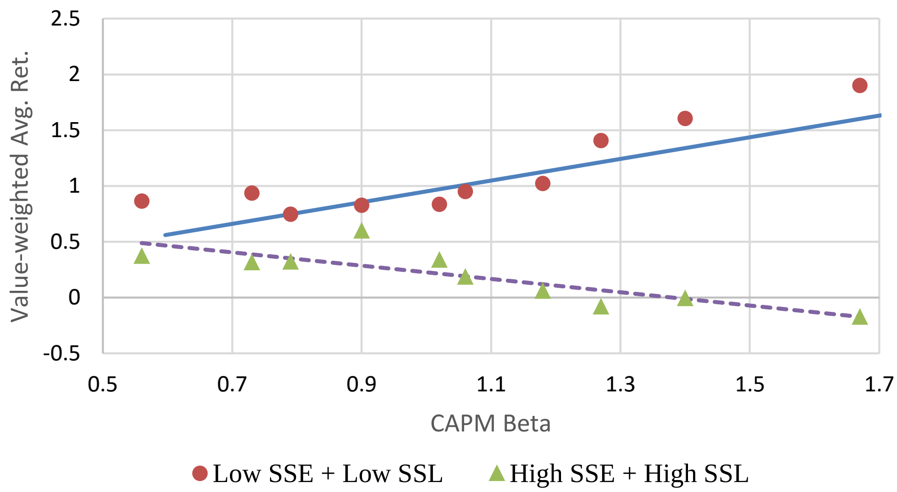


**Figure 2 Returns of Beta and Mispricing Portfolios following Subperiods**

We examine subperiods when both SSE and SSL are below or above their time-series medians, referred to as LL and 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

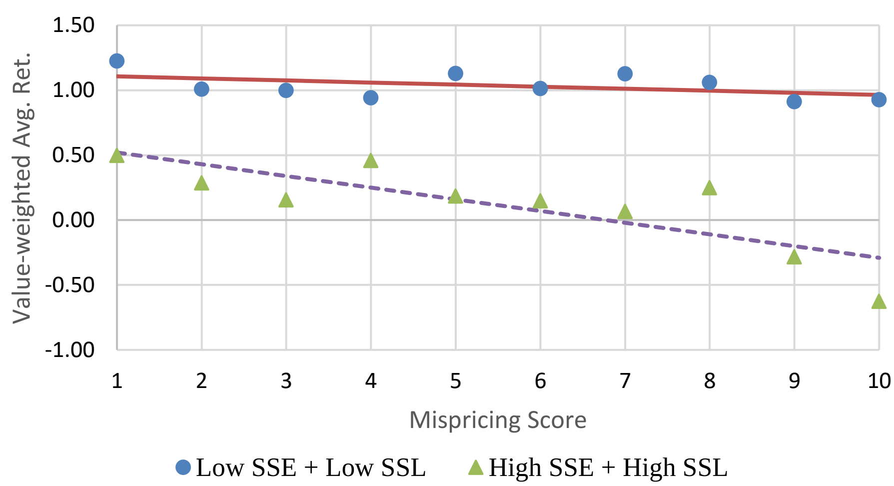
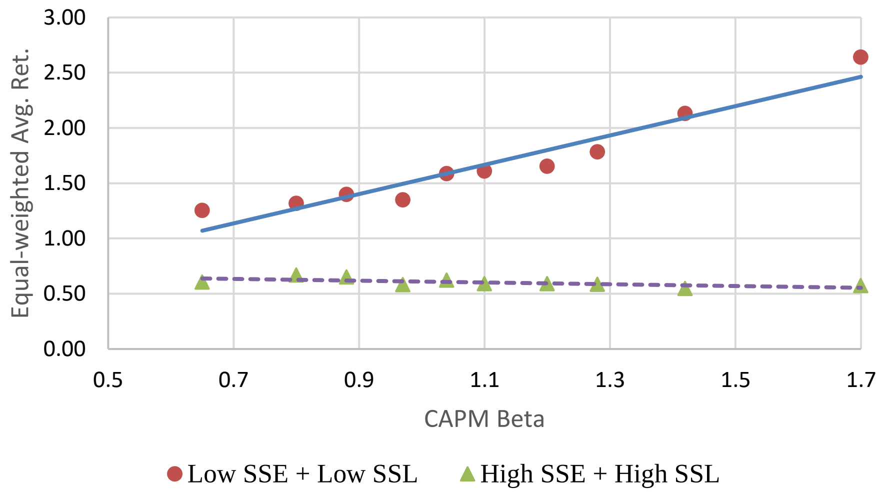


Figure 2, continued.

Panel C: Equal-weighted Average Return and CAPM Beta




Panel D: Equal-weighted Average Return and Mispricing Score