Short Interest and Aggregate Stock Returns*

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Abstract

We show that short interest is arguably *the* strongest known predictor of aggregate stock returns. It outperforms a host of popular return predictors both in and out of sample, with annual R^2 statistics of 12.89% and 13.24%, respectively. In addition, short interest can generate utility gains of over 300 basis points per annum for a mean-variance investor. A vector autoregression decomposition shows that the economic source of short interest's predictive power stems predominantly from a cash flow channel. Overall, our evidence indicates that short sellers are informed traders who are able to anticipate future aggregate cash flows and associated market returns.

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1. Introduction

The equity market risk premium impacts many fundamental areas of finance, from portfolio theory to capital budgeting. Accordingly, a voluminous literature attempts to predict changes in future aggregate excess stock returns.[1] In this paper, we show that short interest, aggregated across securities, is arguably *the* strongest predictor of the equity risk premium identified to date. Short interest outperforms a host of popular return predictors from the literature in both in-sample and out-of-sample tests. Short interest also generates substantial utility gains and Sharpe ratios that exceed those provided by popular predictors. Furthermore, we provide evidence that the ability of short interest to predict future market returns stems predominantly from a cash flow channel. Taken together, our results suggest that short sellers are informed traders who are able to anticipate changes in future aggregate cash flows and associated changes in future market returns.

We begin by constructing a long monthly time series of aggregate short interest spanning 1973 to 2014. Each month, using data recently made available by Compustat, we calculate the log of the equal-weighted mean of short interest (as a percentage of shares outstanding) across all publicly listed stocks on U.S. exchanges. The resulting series constitutes a measure of total short selling in the economy. The short interest series, which is plotted in Panel A of Fig. 1, displays a strong upward trend over our sample period. Much of the upward trend is likely due to the continued development of the equity lending market, which has made it easier to short sell over time, as well as the increase in the number of hedge funds in existence, which has led to an increase in the amount of capital devoted to short arbitrage. Indeed, we find significant evidence of a linear trend using robust statistical tests; this trend obscures the true information content in aggregate short interest. We thus detrend the short interest series to capture the variation in short interest that is due to changes in the beliefs of short sellers, and not simply secular changes in equity lending conditions and/or the amount of capital devoted to short arbitrage. We standardize the detrended series to create a short interest index (SII, hereafter) that can be viewed as a measure of market

[1] See Pástor and Stambaugh (2009), Henkel, Martin, and Nardari (2011), and Pettenuzzo, Timmermann, and Valkanov (2014) for recent examples. Rapach and Zhou (2013) provide a survey of the literature.

pessimism based on short interest data.

If short interest does contain information about future market returns, we would expect higher values of SII to predict lower future returns. We find that it does. In-sample tests show that a one-standard-deviation increase in SII corresponds to a six to seven percentage point decrease in the future annualized market excess return. SII produces predictive regression R^2 statistics of 1.24% at the monthly horizon and 12.89% at the annual horizon. We also compare the predictive power of SII to that of 14 popular predictor variables from Goyal and Welch (2008). SII substantially outperforms all of the popular predictors at quarterly, semi-annual, and annual horizons and performs as well as or better than all of the predictors at the monthly horizon.

Goyal and Welch (2008) show that, despite significant evidence of in-sample predictive ability, popular predictor variables fail to predict the equity risk premium based on *out-of-sample* tests. Consequently, we also examine the out-of-sample predictive ability of SII.[2] We find positive out-of-sample R^2 statistics (Campbell and Thompson, 2008) of 1.94%, 6.54%, 11.70%, and 13.24% at horizons of one, three, six, and twelve months, respectively, which are statistically significant and larger than those for all of the popular predictors from the literature. Using encompassing tests, we also show that forecasts based on SII have superior information content relative to forecasts based on popular predictors.

In addition, we examine the economic significance of SII's predictive ability via an asset allocation analysis and find that SII generates large utility gains for a mean-variance investor who allocates between equities and risk-free bills. Assuming a relative risk aversion coefficient of three, a mean-variance investor would be willing to pay between 343 and 544 basis points in annualized portfolio management fees at various rebalancing frequencies to have access to excess return forecasts based on SII. These utility gains far outweigh those provided by popular predictor variables. Around the recent Global Financial Crisis, the utility gains accruing to SII are particularly large, with gains of approximately 1,100 basis points or more at all rebalancing frequencies.

[2] We are careful to use only information available at the time of forecast formation when we calculate detrended aggregate short interest for our out-of-sample tests, so that our forecasts do not have a "look-ahead" bias.

Why does SII predict future market returns? We present evidence that SII's predictive ability primarily operates via a cash flow channel. Specifically, we use the Campbell (1991) and Campbell and Ammer (1993) vector autoregression (VAR) approach and the information contained in popular predictors to decompose total stock returns into their expected return, discount rate news, and cash flow news components. We find that the ability of SII to predict future stock returns predominantly results from its ability to predict future cash flow news. If we treat the set of popular predictors as a proxy for the market information set, then our results suggest that short sellers primarily possess information acquisition and/or processing advantages when it comes to anticipating future aggregate cash flows in the economy. This finding is consistent with the existing literature indicating that short sellers are informed traders who earn excess returns in compensation for processing firm-specific information (Boehmer, Jones, and Zhang, 2008; Karpoff and Lou, 2010; Engelberg, Reed, and Ringgenberg, 2012; Akbas, Boehmer, Erturk, and Sorescu, 2013).[3] In our setting, we find that short sellers are also able to predict future overall market movements due to their informed anticipations of future aggregate cash flows. The information content of short selling thus appears more economically important than previously thought.

To the best of our knowledge, there are only a few academic studies that examine the relation between short interest and stock returns at the aggregate level. Seneca (1967) estimates a significantly negative relation between the level of the S&P 500 index (deflated by the wholesale price index) and aggregate short interest in the middle of the previous month. This early study does not directly examine the predictability of the equity risk premium and predates the advent of modern time-series econometrics.[4] In a later paper, Lamont and Stein (2004) investigate aggregate short interest for NASDAQ firms from 1995 to 2002 and examine how limits to arbitrage may have prevented short sellers from correcting aggregate mispricings. However, they do not analyze the predictive ability of short interest for aggregate market returns. Finally, in a recent paper,

[3]These empirical findings are consistent with theoretical models; for example, Diamond and Verrechia (1987) point out that short sellers cannot access the proceeds of a short sale and thus are unlikely to trade for liquidity reasons.

[4]In particular, Seneca (1967) uses the level of the S&P 500 index as the dependent variable in his main specification. Furthermore, he normalizes aggregate short interest by volume (while it is now common practice to normalize by shares outstanding). See Hanna (1968) for a critique of the findings in Seneca (1967).

Lynch, Nikolic, Yan, and Yu (2014) examine daily short sales *volume* from January 2005 to July 2007. They find that short volume exhibits commonality across stocks and that some measures of aggregate short sales volume can predict market returns over the next five to 20 days. Our paper is distinct from these existing works: using a modern time-series approach, we are the first to show that aggregate short interest is arguably the strongest known predictor of the equity risk premium.

We emphasize that the predictive ability of aggregate short interest that we uncover is also distinct from the existing literature on firm-level short selling. The literature on firm-level short selling detects a significant relation between cross-sectional variation in short interest and future returns (e.g., Senchack and Starks, 1993; Desai, Ramesh, Thiagarajan, and Balachandran, 2002; Asquith, Pathak, and Ritter, 2005; Diether, Lee, and Werner, 2009). However, it is known that firm-level relations do not necessarily hold at the aggregate level. For example, in contrast to the positive relation documented at the firm level, Kothari, Lewellen, and Warner (2006) find a negative relation between aggregate earnings surprises and returns. In addition, Hirshleifer, Hou, and Teoh (2009) find a reversal in the accrual-return relation from negative at the firm level to positive at the aggregate level. Indeed, firm-level studies of short selling typically explicitly control for aggregate effects by estimating two-way fixed-effects panel regressions and/or factor models that include the market factor. By construction, such procedures measure the effects of *relative* short interest positions and thus do not shed light on *aggregate* effects. In contrast, our paper is the first to explicitly examine the relation between aggregate short interest and aggregate stock returns.

The rest of the paper is organized as follows. Section 2 describes our data, including the construction of SII. Section 3 reports in-sample and out-of-sample predictive regression results for SII and 14 popular predictor variables, while Section 4 reports results for the asset allocation analysis. Section 5 provides results for the VAR decomposition to analyze the economic underpinnings of SII's predictive ability, and Section 6 discusses possible interpretations of the results. Section 7 concludes.

2. Data

To examine the information content of aggregate short interest, we combine monthly short interest data from Compustat with data on the equity risk premium and popular predictor variables from the existing literature.

2.1. Short interest

We construct an aggregate short interest series using firm-level short interest data from Compustat. Each month, U.S. exchanges publicly report the level of short interest in each stock. The data are typically compiled as of the 15th of each month and publicly reported four business days later.[5] Historically, these data were published in the financial press on the day following their public release from the exchanges. As such, our data were available to investors at each point in time. The Compustat short interest data begin in January of 1973 and our sample extends through December 2014. We note that historical short interest data extending back to 1973 were only added to the Compustat database in 2014; to the best of our knowledge, ours is the first paper to examine such a long time series of short interest data.

The raw short interest numbers from Compustat are reported as the number of shares that are held short in a given firm. We normalize these numbers by dividing the level of short interest by each firm's shares outstanding from CRSP. We filter the data to exclude assets with a stock price below $5 per share, and we drop assets that are below the fifth percentile breakpoint of NYSE market capitalization using the breakpoints provided on Kenneth French's website. The resulting database includes over two million observations at the firm-month level for the 42-year period from January 1973 through December 2014. The data cover a variety of asset classes, including common equities, ADRs, ETFs, and REITs. While many studies often exclude data on ADRs, ETFs, and REITs, it is likely that alternative asset classes, especially ETFs, contain valuable

[5] As of September 2007, short interest data are reported twice a month. For consistency, we use only the mid-month numbers in the post-September 2007 period, so that our entire sample consists of one short interest number each month for each stock.

information about the aggregate economy. In particular, ETFs represent a relatively inexpensive way for investors to achieve a short exposure to a sector or the market in general. Accordingly, we include ADRs, ETFs, and REITs in our calculation of aggregate short interest (although in our robustness analysis in Section 3.4, we examine the effects of removing these assets). Each month, we calculate aggregate short interest as the equal-weighted mean of all asset-level short interest data (EWSI, hereafter).

To relate our findings to the voluminous literature on market return predictability, we compare the predictive ability of aggregate short interest to that of 14 monthly predictor variables from Goyal and Welch (2008),[6] which constitute a set of popular predictors from the literature. Specifically, we include the following predictors:

1. Log dividend-price ratio (DP): log of a twelve-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (S&P 500 index).

2. Log dividend yield (DY): log of a twelve-month moving sum of dividends minus the log of lagged stock prices.

3. Log earnings-price ratio (EP): log of a twelve-month moving sum of earnings on the S&P 500 index minus the log of stock prices.

4. Log dividend-payout ratio (DE): log of a twelve-month moving sum of dividends minus the log of a twelve-month moving sum of earnings.

5. Excess stock return volatility (RVOL): computed using a twelve-month moving standard deviation estimator, as in Mele (2007).[7]

6. Book-to-market ratio (BM): book-to-market value ratio for the Dow Jones Industrial Average.

[6] Updated data for the variables in Goyal and Welch (2008) are available from Amit Goyal's webpage at http://www.hec.unil.ch/agoyal/.

[7] Goyal and Welch (2008) measure stock return volatility using the sum of squared daily excess stock returns during the month. However, this measure produces a severe outlier in October of 1987, while the moving standard deviation estimator avoids this problem and yields more plausible estimation results.

7. Net equity expansion (NTIS): ratio of a twelve-month moving sum of net equity issues by NYSE-listed stocks to the total end-of-year market capitalization of NYSE stocks.

8. Treasury bill rate (TBL): interest rate on a three-month Treasury bill (secondary market).

9. Long-term yield (LTY): long-term government bond yield.

10. Long-term return (LTR): return on long-term government bonds.

11. Term spread (TMS): long-term yield minus the Treasury bill rate.

12. Default yield spread (DFY): difference between Moody's BAA- and AAA-rated corporate bond yields.

13. Default return spread (DFR): long-term corporate bond return minus the long-term government bond return.

14. Inflation (INFL): calculated from the CPI for all urban consumers.[8]

Consistent with the existing literature on predicting aggregate returns, we focus on predicting the excess return on a value-weighted market portfolio. We measure the market excess return as the log return on the S&P 500 index minus the log return on a one-month Treasury bill.[9]

2.2. *Sample properties*

Panel A of Table 1 contains summary statistics for EWSI and the 14 predictor variables from the literature over our 1973:01 to 2014:12 sample period. EWSI has a mean of 2.15% (expressed as a percent of shares outstanding), a median of 1.31%, and a maximum value of 8.93% in July of 2008 (unreported).

In Panel B of Table 1, we show the mean value of EWSI in each of four subsamples broken out by time; from the subsamples, it is apparent that EWSI exhibits a strong upward trend over

[8] We account for the delay in CPI data releases when testing the predictive ability of inflation.
[9] These data are also from Amit Goyal's webpage.

the last four decades. Specifically, the mean of EWSI monotonically increases from 0.31% in the first decade of our sample to a mean of 4.98% over the last decade. Similarly, Panel A of Fig. 1 plots the log of EWSI and clearly shows the secular increase in aggregate short interest over our 1973:01 to 2014:12 sample period.

The strong upward trend in aggregate short interest is likely due to several factors. Anecdotal evidence suggests that the equity lending market has expanded significantly over the last few decades; as a result, short sale constraints have likely been reduced.[10] There has also been a significant increase in the amount of capital devoted to short arbitrage over our sample period. An industry report by the Managed Funds Association (2012) indicates that assets under management for the hedge fund industry more than tripled between 2002 and 2012, and the number of hedge funds increased from less than 1,000 funds in 1990 to more than 7,000 funds in 2012. As a consequence, it is likely that much of the increase in short interest over our sample period relates to secular increases in short selling due to the development of the equity lending market and growth of the hedge fund industry; such secular increases are unrelated to the information set of short sellers.

Statistical evidence confirms the existence of a significant trend in aggregate short interest. Consider the linear time trend model:

$$\log(\mathrm{EWSI}_t) = a + b \cdot t + u_t \quad \text{for} \quad t = 1, \ldots, T, \tag{1}$$

where EWSI_t is equal-weighted short interest for month t. Because, like many predictor variables from the literature, the log of EWSI appears quite persistent in Fig. 1, Panel A, we use the Harvey, Leybourne, and Taylor (2007) procedure to test the significance of b in Eq. (1) for our 1973:01 to 2014:12 sample period. The conventional t-statistic for testing the significance of b can lead to inaccurate inferences when u_t is highly persistent. Harvey, Leybourne, and Taylor (2007) develop

[10] Because the equity lending market is an over-the-counter market, there are no detailed data on the size of the market in the 1970s, 1980s, and 1990s. Since the mid 2000s, Data Explorers has collected and distributed a proprietary database on the supply and demand of shares in the lending market. Using the Data Explorers database, Prado, Saffi, and Sturgess (2014) document a significant increase in the supply of shares available to be borrowed from 2005 to 2010.

a test that is robust to the degree of persistence in u_t (unit root, local-to-unit root, or stationary), and their test clearly indicates that b is significant in Eq. (1).[11]

In light of the robust evidence for a trend in the log of EWSI, we remove the secular increase in aggregate short interest to isolate the economically relevant variation in short selling that reflects the changing beliefs of short sellers. Specifically, we estimate Eq. (1) using ordinary least squares (OLS) for 1973:01 to 2014:12 and take the fitted residual, $\hat{u}_t$, as our detrended measure of aggregate short interest.[12] By construction, $\hat{u}_t$ has a mean of zero, and we standardize the series to have a standard deviation of one. We treat the standardized series as our short interest index, SII, which can be interpreted as a measure of market pessimism based on short interest data. In our out-of-sample analysis, we compute SII recursively using only data available at time t to forecast the return for time $t+1$.

Panel B of Fig. 1 depicts the SII series. SII exhibits significant fluctuations in Fig. 1, Panel B, often around business-cycle turning points. Most notably, SII increases in a reasonably steady manner during the mid 2000s in the run-up to the recent Global Financial Crisis and concomitant Great Recession; it then increases substantially in the middle of 2008 just before the worst part of the crisis and subsequently falls sharply during the later stages of the crisis and Great Recession.[13]

2.3. *Relation to other predictors*

Table 2 displays Pearson correlation coefficients for the 14 popular predictor variables from Goyal and Welch (2008) and SII. While many of the popular predictors from the literature exhibit

[11]The Harvey, Leybourne, and Taylor (2007) $z_{\lambda}^{m\delta}$ statistics are 4.12, 3.89, and 3.57 at the 10%, 5%, and 1% levels, respectively, all of which are significant. The $z_{\lambda}^{m\delta}$ statistic is different for each significance level due to the calibration of a scaling factor that is unique to the significance level.

[12]We consider alternative detrending methods in Section 3. Note that Ng and Perron (2001) unit root tests with good size and power indicate that the log of EWSI is a stationary process around a linear trend: their MZ_{α}^{GLS} (ADF^{GLS}) statistic is -20.32 (-2.82), which is significant at the 5% (10%) level.

[13]The SEC banned short selling in selected U.S. equities from September 19, 2008 through October 8, 2008. Because we measure short interest at the monthly horizon using data compiled by the exchanges on September 15, 2008 and October 15, 2008, our short interest data are not impacted by the short sales ban. Similarly, equity lending market conditions do not significantly impact our short interest data. While equity loan fees, in aggregate, do increase in the last few days of September 2008, they are at normal levels on September 15th and October 15th, when we measure short interest.

strong correlations with each other, our SII measure appears largely unrelated to these predictors. The strongest correlation (in magnitude) between SII and one of the popular predictors occurs with NTIS, which has a correlation of only -0.28. In other words, our SII measure appears to contain substantially different information from many of the stock return predictors used in the existing literature.[14]

3. Predictive regression analysis

3.1. *In-sample tests*

A predictive regression model is the standard framework for analyzing aggregate stock return predictability:

$$r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h} \text{ for } t = 1, \ldots, T-h, \tag{2}$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t, and x_t is a predictor variable. We are interested in testing the significance of β in Eq. (2). For a more powerful test of predictability, Inoue and Kilian (2005) recommend using a one-sided alternative hypothesis, as theory often suggests the sign of β under predictability. It is well known that statistical inferences in Eq. (2) are complicated by the Stambaugh (1999) bias, as well as the use of overlapping observations when $h > 1$ (e.g., Hodrick, 1992; Goetzmann and Jorion, 1993; Nelson and Kim, 1993). To address these complications and make more reliable inferences, we use a heteroskedasticity- and autocorrelation-robust t-statistic and compute a wild bootstrapped p-value to test $H_0 : \beta = 0$ against H_A: $\beta > 0$ in Eq. (2).

We estimate Eq. (2) via OLS for each of the 14 Goyal and Welch (2008) predictor variables and our SII measure. To facilitate comparisons across predictors, we standardize each predictor to have

[14]Using updated data through 2010:12 available from Jeffrey Wurgler's webpage at http://people.stern.nyu.edu/jwurgler/, we find that SII is only weakly correlated (-0.13) with the Baker and Wurgler (2007) sentiment index.

a standard deviation of one. We also take the negative of NTIS, TBL, LTY, INFL, and SII before estimating Eq. (2) for these predictors (as indicated by the negative sign in parentheses in the first column of Table 3), so that H_A: $\beta > 0$ is the relevant alternative hypothesis for each predictor. For our 1973:01 to 2014:12 sample period, after accounting for lags and overlapping observations, we have 503, 501, 498, and 492 usable observations for estimating Eq. (2) at monthly ($h = 1$), quarterly ($h = 3$), semi-annual ($h = 6$), and annual ($h = 12$) horizons, respectively.

Table 3 reports the OLS estimate of β in Eq. (2) and its corresponding t-statistic for each predictor and horizon. At the monthly horizon, four of the 14 Goyal and Welch (2008) predictors display significant predictive ability at conventional levels in the second column of Table 3: RVOL, LTR, TMS, and DFR. Among these predictors, DFR has the largest $\hat{\beta}$ estimate (0.50). SII also exhibits significant predictive ability in the second column (at the 1% level), and its $\hat{\beta}$ estimate (0.50) matches that of DFR and is larger than the estimates for the remaining predictors. The $\hat{\beta}$ estimate for SII has the expected sign (recall that we take the negative of SII in Table 3) and is economically large: a one-standard-deviation increase in SII is associated with a 50 basis point decrease in next month's equity market excess return (corresponding to a six percentage point decrease in annualized excess return).

Because monthly returns inherently contain a large unpredictable component, the R^2 statistics in the third column of Table 3 will necessarily be small. Nevertheless, Campbell and Thompson (2008) and Zhou (2010) argue that a monthly R^2 statistic of approximately 0.5% represents an economically meaningful degree of return predictability. The monthly R^2 statistics for the significant predictors are very near or well above this threshold. SII and DFR deliver the highest monthly R^2 statistic (1.24%). Overall, the second and third columns of Table 3 demonstrate that the predictive power of SII at the monthly horizon is clearly on par with the best individual predictors from the literature.

At the quarterly, semi-annual, and annual horizons, SII displays substantially stronger predictive ability than the 14 popular predictors. The quarterly $\hat{\beta}$ estimate for SII is 0.56 in the fourth column of Table 3. This estimate is significant, well above the $\hat{\beta}$ estimates for the remaining predictors, and implies that a one-standard-deviation increase in SII corresponds to a 6.72 percentage point decrease in future annualized excess return. Among the remaining predictors, only RVOL and TMS have significant $\hat{\beta}$ estimates. The quarterly R^2 statistic for SII is a sizable 4.37% in the fifth column, which is well over twice as large as the next highest quarterly R^2 statistic (1.53% for RVOL).

The semi-annual and annual $\hat{\beta}$ estimates for SII remain sizable in the sixth and eighth columns, respectively, of Table 3. These estimates are again significant and well above the $\hat{\beta}$ estimates for the other predictors. Among the other predictors, only five (three) are significant at the semi-annual (annual) horizon. The semi-annual (annual) R^2 statistic for SII is 8.07% (12.89%) in the seventh (ninth) column of Table 3. These R^2 statistics are approximately two to four times larger than the highest R^2 statistics for the remaining predictors.[15]

The last row of Table 3 report the OLS estimate of β_{SII} and corresponding t-statistic for the following predictive regression:

$$r_{t:t+h} = \alpha + \beta_{\text{SII}}\text{SII}_t + \sum_{j=1}^{3} \beta_{f,j}\hat{f}_{j,t} + \varepsilon_{t:t+h}, \tag{3}$$

where $\hat{f}_{1,t}$, $\hat{f}_{2,t}$, and $\hat{f}_{3,t}$ are the first three principal components extracted from the entire set of Goyal and Welch (2008) variables. Ludvigson and Ng (2007) show that principal components provide an effective strategy for incorporating the information from a large number of economic variables in predictive regression models for stock returns. This specification allows us, in a reasonably parsimonious manner, to test the predictive power of SII after controlling for the entire group of popular predictor variables taken together. The last row of Table 3 also reports the partial R^2 statistic corresponding to SII for Eq. (3).

Comparing the "SII $(-)$" and "SII $(-)|$PC" rows of Table 3, we see that including the principal

[15]Other papers have documented similarly large R^2 statistics for long-horizon predictive regressions. For example, Fama and French (1988) report predictive regression R^2 statistics for dividend yields of 7%, 10%, 13%, and 13% for horizons of one, two, three, and four years, respectively, for 1927 to 1986, while Hirshleifer, Hou, and Teoh (2009) report an annual R^2 statistic for accruals of 20% for 1965 to 2005. Using data from Compustat for our 1973:01 to 2014:12 sample period, we find that SII evinces substantially stronger predictive power than aggregate earnings surprises and accruals at quarterly, semi-annual, and annual horizons.

components in the predictive regression has very little effect on the predictive ability of SII. The estimated slope coefficients for SII remain sizable when the principal components are included in the predictive regression, and the partial R^2 statistics indicate that SII retains substantial marginal predictive power in the presence of the principal components. In sum, directly controlling for numerous popular predictors from the literature via principal components does not affect the predictive ability of SII. In accord with the discussion in Section 2.3, SII contains information that is quite different from that contained in a variety of popular predictors, and this differential information is useful for predicting returns.

3.2. Alternative detrending

As explained in Section 2.2, we use linear detrending to construct our SII measure. To examine the sensitivity of SII's predictive ability to alternative specifications of the time trend in the log of EWSI, we generalize Eq. (1) to allow for higher-order polynomial terms:

$$\log(\mathrm{EWSI}_t) = a + b_1 t + b_2 t^2 + b_3 t^3 + u_t. \tag{4}$$

Eq. (4) allows for a cubic time trend in the log of EWSI and specifies a quadratic time trend model when $b_3 = 0$. Using either a quadratic or cubic trend specification, we estimate Eq. (4) via OLS and again take the fitted residual as our SII measure (where we again standardize SII to have a standard deviation of one). We also consider "stochastic detrending" based on a five-year window, where SII for month t is the difference between log(EWSI) for month t minus the average of log(EWSI) from month $t-59$ to month t. For stochastic detrending, SII observations are available starting in 1977:12.[16]

Table 4 reports estimation results for the predictive regression Eq. (2) based on SII for the different trend specifications.[17] The results show that the predictive power of SII is very robust

[16]Stochastic detrending is frequently applied to the Treasury bill yield in predictive regressions (e.g., Campbell, 1991). We obtain similar results when we use windows of three or four years for stochastic detrending.

[17]To facilitate comparisons, Table 4 also reports the prediction regression estimation results for SII based on linear detrending from Table 3.

to different detrending methods: the $\hat{\beta}$ estimates are statistically and economically significant for all detrending specifications at all horizons (with the exception of cubic detrending at the annual horizon, where the unreported wild bootstrapped p-value is 0.11).

3.3. *Out-of-sample tests*

To examine the robustness of the in-sample results, Table 5 reports results for out-of-sample tests of return predictability. Such tests are important in light of Goyal and Welch (2008), who show that the in-sample predictive ability of a variety of plausible return predictors generally does not hold up in out-of-sample tests.

3.3.1. *Out-of-sample R^2*

Corresponding to each predictor, we compute a predictive regression forecast as

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t, \tag{5}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β, respectively, in Eq. (2) based on data from the beginning of the sample through month t.[18] The prevailing mean forecast, the average excess return from the beginning of the sample through month t, serves as a natural benchmark. This forecast corresponds to the constant expected excess return model, Eq. (2) with $\beta = 0$, and implies that returns are not predictable, as in the canonical random walk with drift model for the log of stock prices.

The second through fifth columns of Table 5 report the proportional reduction in mean squared forecast error (MSFE) for the predictive regression forecast vis-á-vis the prevailing mean benchmark forecast—what Campbell and Thompson (2008) label the out-of-sample R^2 statistic (R^2_{OS})—over the 1990:01 to 2014:12 forecast evaluation period.[19] To ascertain whether the

[18] Note that we only use data from the beginning of the sample through month t to estimate the linear trend used to define SII when computing Eq. (5), so that there is no "look-ahead" bias in the predictive regression forecast based on SII.

[19] Starting the out-of-sample period in 1990:01 provides a reasonably long initial in-sample period for reliably

predictive regression forecast delivers a statistically significant improvement in MSFE, we use the Clark and West (2007) statistic to test the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE (corresponding to H_0: $R^2_{OS} \leq 0$ against H_A: $R^2_{OS} > 0$).[20]

As indicated by the negative R^2_{OS} statistics in the second column of Table 5, all 14 of the popular predictors fail to outperform the prevailing mean benchmark in terms of MSFE at the monthly horizon, confirming the findings of Goyal and Welch (2008). In contrast, the monthly R^2_{OS} statistic for SII is positive (1.94%) and significant according to the Clark and West (2007) statistic, so that, unlike the 14 popular predictors, SII outperforms the prevailing mean benchmark and clears the out-of-sample hurdle. A similar situation prevails at the quarterly horizon: SII is the only predictor with a lower MSFE than the benchmark, and the R^2_{OS} statistic for SII is sizable (6.54%) and significant.

SII continues to outperform the benchmark at the semi-annual and annual horizons, with R^2_{OS} statistics of 11.70% and 13.24%, respectively, both of which are significant. INFL is the only other predictor that outperforms the benchmark at the semi-annual horizon, but its significant R^2_{OS} statistic of 1.95% is still well below that of SII. TMS and INFL are the only popular predictors that outperform the benchmark at the annual horizon. The annual R^2_{OS} statistic for INFL is 3.24%, which is insignificant, while the annual R^2_{OS} statistic for TMS is reasonably large (3.35%) and significant but again well below that of SII.[21]

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estimating the parameters used to generate the initial predictive regression forecasts. This is especially relevant when generating forecasts based on SII, as we also need to estimate the trend for the log of EWSI to construct SII.

[20]The popular Diebold and Mariano (1995) and West (1996) statistic for comparing predictive accuracy has a nonstandard distribution when comparing forecasts from nested models (Clark and McCracken, 2001; McCracken, 2007). Clark and West (2007) modify this statistic so that it has an approximately standard distribution when comparing forecasts from nested models. Note that we account for the serial correlation in the overlapping forecasts when computing the Clark and West (2007) statistic for $h > 1$.

[21]Analogously to the in-sample results in Table 4, we checked the robustness of the out-of-sample predictive ability of SII to different detrending specifications. For quadratic and stochastic detrending, the R^2_{OS} statistics for SII are qualitatively similar to those based on linear detrending at the monthly, quarterly, semi-annual, and annual horizons. For cubic detrending, the R^2_{OS} statistics for SII are qualitatively similar at the monthly, quarterly, and semi-annual horizons. The complete results are reported in Table A1 of the online Appendix.

3.3.2. Forecast encompassing tests

Next, we use forecast encompassing tests to directly compare the information content of the predictive regression forecast based on SII to that of the individual predictive regression forecasts based on the 14 popular predictors. We start by forming an optimal combination forecast as a convex combination of a predictive regression forecast based on one of the popular predictors and the predictive regression forecast based on SII:

$$\hat{r}^{*}_{t:t+h} = (1-\lambda)\hat{r}^{i}_{t:t+h} + \lambda \hat{r}^{\text{SII}}_{t:t+h}, \tag{6}$$

where $\hat{r}^{i}_{t:t+h}$ ($\hat{r}^{\text{SII}}_{t:t+h}$) is the predictive regression forecast based on one of the popular predictors (SII) and $0 \leq \lambda \leq 1$. If $\lambda = 0$, then the optimal combination forecast given by Eq. (6) excludes the forecast based on SII, so that the predictive regression forecast based on the popular predictor encompasses the predictive regression forecast based on SII; in this case, SII does not contain information that is useful for forecasting excess returns beyond the information already found in the popular predictor. Alternatively, if $\lambda > 0$, then the optimal combination forecast includes the forecast based on SII, so that the predictive regression forecast based on the popular predictor does not encompass the predictive regression forecast based on SII; in other words, SII provides information that is useful for forecasting excess returns beyond the information already contained in the popular predictor.

The sixth through ninth columns of Table 5 report the estimate of λ in Eq. (6) corresponding to each popular predictor and indicate whether the estimate is significant using the approach of Harvey, Leybourne, and Newbold (1998). The $\hat{\lambda}$ estimates in Table 5 are all sizable and significant, so that none of the forecasts based on the popular predictors encompasses the SII-based forecast. Interestingly, the vast majority of $\hat{\lambda}$ estimates equal one, and the remaining estimates are reasonably close to one; when $\lambda = 1$, the optimal combination forecast in Eq. (6) is simply $\hat{r}^{\text{SII}}_{t:t+h}$, meaning that the optimal forecast only incorporates information from SII. Indeed, using the Harvey, Leybourne, and Newbold (1998) procedure, we cannot reject the null hypothesis that the weight on $\hat{r}^{i}_{t:t+h}$ equals zero in Eq. (6) for any of the popular predictors at any horizon, so that the predictive regression forecasts based on SII always encompass the forecasts based on the popular predictors. In sum, we have strong evidence that $\lambda = 1$ regardless of the popular predictor included in Eq. (6), which points to the superior information content of SII relative to numerous popular predictors from the literature with respect to out-of-sample forecasting.

3.4. Robustness

Our results are robust to a variety of alternative specifications. In what follows, we discuss several robustness checks which confirm the main findings of the paper.[22] The complete results are reported in Tables A2 through A5 of the online Appendix.

3.4.1. Persistence

First, the monthly autocorrelation coefficient for SII is 0.95, so that—like many popular return predictors from the literature—it is highly persistent. It is well known that highly persistent regressors raise econometric concerns (e.g., Cavanagh, Elliott, and Stock, 1995; Torous, Valkanov, and Yan, 2004). To address these concerns, Kostakis, Magdalinos, and Stamatogiannis (2015) develop a powerful Wald test that is robust to the regressor's degree of persistence (unit root, local-to-unit root, near stationary, or stationary). We use their IVX-Wald statistic to test H_0: $\beta = 0$ against H_A: $\beta \neq 0$ for SII in Eq. (2). The IVX-Wald statistics are significant at all horizons, so that we have robust evidence that the predictive power of SII in Table 3 is not a statistical artifact of SII's persistence.

3.4.2. Temporal stability

Second, we do not find significant evidence of structural instability in the $\hat{\beta}$ estimates for SII in Table 3 according to the Elliott and Müller (2006) test. Their test is particularly useful for

[22]We thank an anonymous referee for these and other insightful suggestions that helped to substantially improve the paper.

analyzing the temporal stability of predictive regressions: it is asymptotically efficient for a wide variety of breaking processes, and Paye and Timmermann (2006) show via simulations that the test has excellent finite-sample properties for predictive regressions with highly persistent predictors. Using the Elliott and Müller (2006) $\widehat{\mathrm{qLL}}$ statistic to test H_0: $\beta_t = \beta$ for all t, none of the $\widehat{\mathrm{qLL}}$ statistics is significant at any horizon for the $\hat{\beta}$ estimates for SII in Table 3. In other words, we do not find evidence that the predictive ability of SII changes over our 1973:01 to 2014:12 sample period. Although we do not find evidence of temporal instability, we also examine predictive regressions for decadal subsamples. The estimated slope coefficients are significant for both the first (1973:01 to 1982:12) and fourth (2003:01 to 2014:12) subsamples at all horizons, despite the substantial reductions in sample size, while the estimated slope coefficients are insignificant for the second (1983:01 to 1992:12) and third (1993:01 to 2002:12) subsamples. As discussed in Section 4, this pattern is consistent with the extant literature that finds that return predictability in general is concentrated in subsamples with deep recessions. Overall, the evidence indicates that SII reliably predicts market returns only during periods that include severe macroeconomic crises.

3.4.3. Equal-weighted market returns

Third, our results are robust to alternative measures of market returns. We have shown that our SII measure, which is based on equal-weighted short interest, strongly predicts value-weighted market returns. As previously discussed, we focus on predicting value-weighted returns so that our results are comparable to the extant literature, even though it is natural to examine the relation between equal-weighted short interest and *equal*-weighted returns. In fact, we also find that SII strongly predicts equal-weighted market portfolio returns. Specifically, SII is a statistically and economically significant predictor of the equal-weighted CRSP market excess return (as well as the equal-weighted S&P 500 excess return) at the monthly, quarterly, semi-annual, and annual horizons. When r_t is the equal-weighted CRSP log excess return in Eq. (2), the $\hat{\beta}$ estimates for SII and R^2 statistics are larger than the corresponding values in Table 3. To summarize, our SII measure based on EWSI is a powerful predictor of *both* equal- and value-weighted market excess returns.

3.4.4. *Short interest constituents*

Fourth, our results are also robust to the universe of assets underlying SII. Our baseline SII measure includes short interest positions in common equities, ADRs, ETFs, and REITs. SII continues to exhibit statistically and economically significant predictive ability when it is comprised of short positions in common equities only or ADRs, ETFs, and REITs only. However, our baseline SII measure that includes common equities, ADRs, ETFs, and REITs evinces the strongest predictive power.

3.4.5. *Why equal-weighted short interest?*

Finally, we note that our goal is to extract a signal from short interest data that measures the changing beliefs of short sellers in the aggregate. Since we focus on predicting the return on the value-weighted market portfolio (following the aggregate return predictability literature), it seems natural to use a value-weighted average of short interest as well. However, as pointed out by Desai, Ramesh, Thiagarajan, and Balachandran (2002) and Asquith, Pathak, and Ritter (2005), short selling is less important in large-capitalization stocks. Indeed, in our sample, large-cap stocks display relatively little variation in short interest, while the variation is much higher for mid-cap stocks. For example, the variance of short interest peaks in the sixth decile of stocks at 7.26 and declines monotonically to 1.05 for the largest market capitalization decile. Given that market capitalization is highly right skewed, a value-weighted measure would necessarily emphasize the actions of short sellers in a segment of the market where they are relatively inactive, while an equal-weighted measure places greater emphasis on more active segments of the short selling market.

Furthermore, because we want to extract an aggregate signal, we want to emphasize beliefs that are held broadly in common across a wide variety of firms. Intuitively, the number of stocks shorted reflects the amount of negative news across the market: to a certain extent, the greater the number of stocks shorted, the more pervasive the negative news, and hence the more likely the market is going to fall. By placing relatively more emphasis on the number of firms shorted, equal weighting likely provides a more informative aggregate signal.

An alternative way to mitigate these concerns is to use quasi-value weighting, where we weight short interest by the log of market capitalization, instead of raw market capitalization. The quasi-value-weighting approach reduces the impact of right skewness in market capitalization, emphasizes mid-cap firms which have an active short selling market, and emphasizes the number of firms with high short interest. As a consequence, it is similar to EWSI in that it is more likely to provide an informative aggregate signal. Indeed, we find that quasi-value-weighted short interest generates $\hat{\beta}$ estimates and R^2 statistics that are very similar to those based on EWSI in Table 3.

Our SII measure based on EWSI predicts both equal- and value-weighted market returns, consistent with the idea that SII predicts the systematic component of returns that is common across stocks of all sizes.[23] There is an interesting open issue: short sellers largely focus on mid-cap stocks, even though large-cap stocks are likely less expensive to short. One possible explanation for this is that mid-cap stocks are more exposed to systematic shocks than large-cap stocks (i.e., they typically have larger betas); as a result, when short sellers have a bearish signal about systematic return movements, they might find it optimal to focus on mid-cap stocks to increase downside exposure. Another possibility is that the link between mid-cap short interest and future returns broadly across market segments relates to the types of information frictions identified by Hou and Moskowitz (2005), Hou (2007), Hong, Torous, and Valkanov (2007), Cohen and Frazzini (2008), and Menzly and Ozbas (2010). While beyond the scope of the present paper, it would be informative to pursue this interesting open issue in future research.

[23]Indeed, the correlation between S&P 500 value-weighted (i.e., large-cap) returns and CRSP equal-weighted returns is 0.79.

3.5. *An end to the trend?*

Our results show that detrended short interest is a powerful predictor of aggregate returns, both in and out of sample. While aggregate short interest displays a strong upward trend over our sample period, this trend may level off in the future. A straightforward method for accommodating a flattening of the secular trend is to fit a quadratic or cubic time trend to the log of EWSI, or to use stochastic detrending. We have shown that the predictive power of SII is robust to quadratic, cubic, and stochastic detrending over our sample period. To the extent that the secular trend in the log of EWSI flattens in the future, quadratic, cubic, and/or stochastic detrending should work even better going forward. Another strategy for accommodating a flattening of the secular trend entails testing for a break in the linear trend. As reported in Section 2.2, the log of EWSI clearly exhibits a significant linear trend according to the Harvey, Leybourne, and Taylor (2007) test. Harvey, Leybourne, and Taylor (2009) subsequently develop a test for a break in a linear trend that delivers reliable inferences for persistent processes. When we apply their test to the log of EWSI for our sample period, there is not significant evidence of a break in the linear trend.[24] If significant evidence of a trend break emerges in the future, EWSI can be appropriately detrended to continue to track the changing beliefs of short sellers.

4. Asset allocation

In this section, we measure the economic value of SII's predictive ability from an asset allocation perspective. Specifically, as in Campbell and Thompson (2008), Rapach, Strauss, and Zhou (2010), and Ferreira and Santa-Clara (2011), we consider a mean-variance investor who allocates between equities and risk-free bills using a predictive regression forecast of excess stock returns. At the end of month t, the investor optimally allocates the following share of her portfolio

[24]The Harvey, Leybourne, and Taylor (2009) t_λ statistics are 2.12, 2.16, and 2.26 at the 10%, 5%, and 1% levels, respectively, none of which is significant. Because a unique scaling factor is calibrated for the significance level, the t_λ statistic is different for each significance level.

to equities during the subsequent month:

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{t+1}}{\hat{\sigma}_{t+1}^2}, \tag{7}$$

where γ is the investor's coefficient of relative risk aversion, $\hat{r}_{t+1}$ is a predictive regression excess return forecast,[25] and $\hat{\sigma}_{t+1}^2$ is a forecast of the excess return variance. Similarly to Campbell and Thompson (2008), we generate the volatility forecast using a ten-year moving window of past returns. We also restrict w_t to lie between -0.5 and 1.5, which imposes realistic portfolio constraints and produces better-behaved portfolio weights given the well-known sensitivity of mean-variance optimal weights to return forecasts.

The investor who allocates using Eq. (7) realizes an average utility or certainty equivalent return (CER) of

$$\text{CER} = \bar{R}_p - 0.5\gamma\sigma_p^2, \tag{8}$$

where $\bar{R}_p$ and σ_p^2 are the mean and variance, respectively, of the portfolio return over the forecast evaluation period. The CER is the risk-free rate of return that an investor would be willing to accept in lieu of holding the risky portfolio. We also compute the CER for the investor when she uses the prevailing mean excess return forecast instead of the predictive regression forecast in Eq. (7). The CER gain is then the difference between the CER for the investor when she uses the predictive regression forecast to guide asset allocation and the CER when she uses the prevailing mean benchmark forecast. We annualize the CER gain so that it can be interpreted as the annual portfolio management fee that the investor would be willing to pay to have access to the predictive regression forecast in place of the prevailing mean forecast. In this way, we measure the direct economic value of return predictability.[26]

To analyze the economic value of return predictability at longer horizons, we assume that the

[25] Note that we forecast the simple excess return—and not the log excess return—for the asset allocation analysis.

[26] We always use the ten-year moving window variance forecast in Eq. (7), so that the portfolio weights only differ because of the excess return forecasts.

investor rebalances at the same frequency as the forecast horizon. For the quarterly horizon, at the end of the quarter, the investor uses a predictive regression or prevailing mean forecast of the excess return over the next three months ($h = 3$) and the allocation rule Eq. (7) to determine the equity weight for the next three months; at the end of the next quarter, the investor updates the quarterly predictive regression or prevailing mean forecast and determines the new weight (so that the investor uses nonoverlapping return forecasts). The investor follows analogous procedures for semi-annual and annual return forecasts and rebalancing.

The second through fifth columns of Table 6 show the CER gains accruing to predictive regression forecasts based on each of the 14 popular predictor variables from Goyal and Welch (2008) and SII for the 1990:01 to 2014:12 forecast evaluation period. We assume a relative risk aversion coefficient of three.[27] The performance of SII clearly stands out. At the monthly horizon, SII provides a hefty CER gain of 417 basis points. Among the 14 popular predictors, only TBL, TMS, and DFR generate positive CER gains (66, 25, and 108 basis points, respectively), but the gains are well below those of SII. SII continues to generate very sizable CER gains of 465, 544, and 343 basis points at the quarterly, semi-annual, and annual horizons, respectively, all of which are higher than any of the gains for the popular predictors. Only four (three) of the 14 popular predictors also produce positive CER gains at the quarterly and annual (semi-annual) horizons, but the gains remain well below those of SII. The last row of Table 6 shows that a buy-and-hold portfolio that passively holds the market portfolio produces CER gains well below those of SII, so that SII also easily outperforms a buy-and-hold strategy.

The sixth through ninth columns of Table 6 report CER gains for the 1990:01 to 2006:12 forecast evaluation period predating the Global Financial Crisis, while the last four columns report gains for the 2007:01 to 2014:12 period surrounding the recent crisis. For the former period, SII provides reasonably sizable CER gains of 88, 73, and 57 basis points at the monthly, quarterly, and semi-annual horizons, respectively, and a negative gain of 38 basis points at the annual horizon. These gains are typically well above those provided by the individual predictors (most of which

[27] This value is consistent with estimates of relative risk aversion from the literature (e.g., Bliss and Panigirtzoglou, 2004). The results are similar for other reasonable relative risk aversion coefficient values.

are negative), close to those produced by the best individual predictors, and below those of the buy-and-hold strategy. After providing moderate gains for the 1990:01 to 2006:12 period, SII generates stunning CER gains of 1,118, 1,308, 1,591, and 1,123 basis points at the monthly, quarterly, semi-annual, and annual horizons, respectively, for the 2007:01 to 2014:12 period corresponding to the Global Financial Crisis. More of the popular predictors from the literature provide positive and sizable CER gains in the last four columns compared to the sixth through ninth columns. However, the gains accruing to SII are approximately two to ten times higher than those accruing to the best of the popular predictors. SII also generates much higher CER gains than a buy-and-hold strategy around the crisis. The especially strong performance of SII during the Global Financial Crisis is consistent with the recent findings of Rapach, Strauss, and Zhou (2010), Henkel, Martin, and Nardari (2011), Rapach and Zhou (2013), and Neely, Rapach, Tu, and Zhou (2014), who show that aggregate stock return predictability and the associated utility gains tend to be particularly sizable around periods of severe economic recessions. The 1990:01 to 2006:12 period covers much of the so-called Great Moderation and contains two relatively mild recessions in the early 1990s and early 2000s, while the 2007:01 to 2014:12 period surrounding the Global Financial Crisis contains the Great Recession, which is by most measures the most severe recession since the Great Depression. In sum, SII offers modest gains during "normal" times and striking gains during periods that include acute macroeconomic stress.

Table 7 reports Sharpe ratios for the portfolios, which allows us to compare portfolio performance independently of relative risk aversion. The second through fifth columns of Table 7 report annualized Sharpe ratios for the entire 1990:01 to 2014:12 forecast evaluation period. The ratios for the portfolio based on the prevailing mean benchmark forecast range from 0.31 to 0.39 at the various horizons. The 14 predictors from the literature rarely outperform the prevailing mean in terms of the Sharpe ratio. Turning to SII, it produces Sharpe ratios that are approximately 1.5 to two times larger than those of the prevailing mean, and the Sharpe ratios for SII are always greater than those for the popular predictors (as well as the buy-and-hold strategy).

Following the pattern in Table 6, the performance of SII for the 1990:01 to 2006:12 period as gauged by the Sharpe ratio is similar to the best individual predictors and somewhat below that of the buy-and-hold strategy, while SII's performance is especially impressive for the 2007:01 to 2014:12 period encompassing the Global Financial Crisis. For the latter period, the prevailing mean generates Sharpe ratios between 0.19 and 0.40, and the predictors from the literature often produce Sharpe ratios in this range. The largest Sharpe ratios among the popular predictors are 0.54 for EP at the monthly horizon and 0.59 for INFL at the annual horizon. The buy-and-hold portfolio produces Sharpe ratios between 0.39 and 0.46 at each horizon. In sharp contrast, SII generates substantial Sharpe ratios ranging from 0.93 to 1.22 for the period including the recent crisis.

Fig. 2 provides additional perspective on the behavior of the monthly portfolio based on SII. Panel A depicts equity weights for the monthly portfolios based on SII and the prevailing mean over the 1990:01 to 2014:12 forecast evaluation period. Because the prevailing mean benchmark forecast is very smooth, the equity weight for the portfolio based on the prevailing mean is relatively stable throughout the out-of-sample period, typically reasonably close to 0.75. In contrast, the equity weight for the portfolio based on SII exhibits substantial fluctuations. The equity weights diverge most dramatically during the run-up to the Global Financial Crisis through the "recovery" from the Great Recession. Specifically, in the early stages of the Global Financial Crisis and Great Recession, the portfolio based on SII takes a short equity position; the portfolio then moves abruptly to an aggressive long position in late 2008 and remains aggressively long through the end of 2014.

Panel B of Fig. 2, which shows the log cumulative wealth for the two portfolios, reveals that the large shifts in the equity weight for the SII portfolio in Panel A represent adept market timing. The SII portfolio's short position in the early stages of the crisis enables it to make money during the Great Recession, and its subsequent long position enables it to ride the bull market from 2009 to 2014, so that cumulative wealth grows substantially from the end of 2007 to the end of 2014. In contrast, the prevailing mean portfolio—which ignores the information in SII—suffers a major drawdown during the Great Recession, and cumulative wealth at the end of 2014 barely returns to its level at the end of 2007.

The results in this section indicate that the information in SII has substantial economic value for a risk-averse investor. This is especially true around the Global Financial Crisis, where SII signals the investor to move to an aggressive short (long) position in the early (late) stages of the crisis. Reiterating the results in Section 3, the information contained in SII appears considerably more valuable than that found in a myriad of popular predictors from the literature.

5. Stock return decomposition

To glean insight into the economic underpinnings of SII's predictive ability, we analyze whether short sellers are able to anticipate future stock returns by anticipating discount rate and/or cash flow news, where we measure the news components using the VAR methodology of Campbell (1991) and Campbell and Ammer (1993). We begin with the the definition of the log stock return, $r_{t+1} = \log[(P_{t+1} + D_{t+1})/P_t]$, where P_t (D_t) is the month-t stock price (dividend). The Campbell and Shiller (1988) log-linear approximation of r_{t+1} is given by

$$r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t, \tag{9}$$

where

$$\rho = \frac{1}{1+\exp(\overline{d-p})}, \tag{10}$$

$$k = -\log(\rho) - (1-\rho)\log[(1/\rho)-1], \tag{11}$$

p_t (d_t) is the log stock price (dividend), and $\overline{d-p}$ is the mean of $d_t - p_t$. We can rewrite Eq. (9) as

$$p_t \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - r_{t+1}. \tag{12}$$

Solving Eq. (12) forward and imposing the no-bubble transversality condition ($\lim_{j\to\infty} \rho^j p_{t+j} = 0$), the canonical Campbell and Shiller (1988) stock price decomposition is given by

$$p_t = \sum_{j=0}^{\infty} \rho^j (1-\rho) d_{t+1+j} - \sum_{j=0}^{\infty} \rho^j r_{t+1+j} + \frac{k}{1-\rho}. \tag{13}$$

Letting E_t denote the expectation operator conditional on information through month t, Eqs. (9) and (13) imply the following decomposition for the log stock return innovation:[28]

$$r_{t+1} - E_t r_{t+1} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j}. \tag{14}$$

According to Eq. (14), the stock return innovation can be decomposed into cash flow news and discount rate news components:

$$\eta_{t+1}^{r} = \eta_{t+1}^{\mathrm{CF}} - \eta_{t+1}^{\mathrm{DR}}, \tag{15}$$

where

$$\eta_{t+1}^{r} = r_{t+1} - E_t r_{t+1} \text{ (stock return innovation)}, \tag{16}$$

$$\eta_{t+1}^{\mathrm{CF}} = (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^j \Delta d_{t+1+j} \text{ (cash flow news)}, \tag{17}$$

$$\eta_{t+1}^{\mathrm{DR}} = (E_{t+1} - E_t) \sum_{j=1}^{\infty} \rho^j r_{t+1+j} \text{ (discount rate news)}. \tag{18}$$

Intuitively, unexpected stock returns (stock return innovations) represent revisions in expectations of current and future cash flows (cash flow news) and/or revisions in expectations of future discount rates (discount rate news).

Campbell (1991) and Campbell and Ammer (1993) use a VAR framework to extract the cash flow and discount rate news components of stock return innovations. Consider the following

[28] In deriving Eq. (14), we assume that p_t is in the month-t information set, so that $E_t p_t = p_t$.

VAR(1) model:

$$y_{t+1} = Ay_t + u_{t+1}, \tag{19}$$

where $y_t = (r_t\,, d_t - p_t\,, z_t')'$, z_t is an n-vector of predictor variables, A is an $(n+2)$-by-$(n+2)$ matrix of VAR slope coefficients, and u_t is an $(n+2)$-vector of zero-mean innovations.[29] Letting e_1 denote an $(n+2)$-vector with one as its first element and zeros for the remaining elements, the stock return innovation and discount rate news component can be expressed as

$$\eta^r_{t+1} = e_1' u_{t+1} \tag{20}$$

and

$$\eta^{\text{DR}}_{t+1} = e1'\rho A(I - \rho A)^{-1} u_{t+1}, \tag{21}$$

respectively. The cash flow news component is then residually defined using Eq. (15) as

$$\eta^{\text{CF}}_{t+1} = \eta^r_{t+1} + \eta^{\text{DR}}_{t+1}. \tag{22}$$

In terms of Eq. (19), the expected stock return for $t+1$ based on information through t is given by

$$E_t r_{t+1} = e_1' A y_t. \tag{23}$$

Using $r_{t+1} = E_t r_{t+1} + \eta^r_{t+1}$ and Eq. (15), the log stock return can then be decomposed as

$$r_{t+1} = E_t r_{t+1} + \eta^{\text{CF}}_{t+1} - \eta^{\text{DR}}_{t+1}. \tag{24}$$

With sample observations for y_t for $t = 1, \ldots, T$, we can use OLS to estimate A and u_{t+1} ($t =$

[29]We omit a constant term from Eq. (19) for notational convenience.

$1,\ldots,T-1$) for the VAR model Eq. (19); denote the OLS estimates by $\hat{A}$ and $\hat{u}_{t+1}$, respectively. We can also estimate ρ using Eq. (10) and the sample mean of the log dividend-price ratio; denote the estimate by $\hat{\rho}$. Plugging $\hat{A}$, $\hat{u}_{t+1}$, and $\hat{\rho}$ into Eqs. (20), (21), (22), and (23) yields $\hat{\eta}^{r}_{t+1}$, $\hat{\eta}^{\mathrm{DR}}_{t+1}$, $\hat{\eta}^{\mathrm{CF}}_{t+1}$, and $\hat{E}_t r_{t+1}$, respectively, for $t=1,\ldots,T-1$.

We analyze the source of SII's predictive power for future stock returns by examining its ability to predict the individual components comprising the total stock return. We begin with a predictive regression model for the log stock return based on SII:

$$r_{t+1} = \alpha + \beta \mathrm{SII}_t + \varepsilon_{t+1} \quad \text{for} \quad t = 1,\ldots,T-1. \tag{25}$$

We then consider the following predictive regression models for the estimates of the individual components on the right-hand-side of Eq. (24):

$$\begin{aligned}
\hat{E}_t r_{t+1} &= \alpha_{\hat{E}} + \beta_{\hat{E}} \mathrm{SII}_t + \varepsilon^{\hat{E}}_{t+1}, && (26)\\
\hat{\eta}^{\mathrm{CF}}_{t+1} &= \beta_{\mathrm{CF}} \mathrm{SII}_t + \varepsilon^{\mathrm{CF}}_{t+1}, && (27)\\
\hat{\eta}^{\mathrm{DR}}_{t+1} &= \beta_{\mathrm{DR}} \mathrm{SII}_t + \varepsilon^{\mathrm{DR}}_{t+1}, && (28)
\end{aligned}$$

for $t=1,\ldots,T-1$.[30] The properties of OLS imply the following relation between the OLS estimate of β in Eq. (25) and those of $\beta_{\hat{E}}$, β_{CF}, and β_{DR} in Eqs. (26), (27), and (28), respectively:

$$\hat{\beta} = \hat{\beta}_{\hat{E}} + \hat{\beta}_{\mathrm{CF}} - \hat{\beta}_{\mathrm{DR}}. \tag{29}$$

By comparing the estimated slope coefficients in Eqs. (25) through (28), we can ascertain the extent to which SII's ability to predict total stock returns relates to its ability to anticipate the individual components on the right-hand-side of Eq. (24). Taking the set of popular predictors as a proxy for the market information set, this analysis provides a deeper understanding of the sources of the unique information in SII.

[30] We exclude an intercept term from Eqs. (27) and (28) because the cash flow and discount rate news components (as well as SII) have zero means by construction.

Table 8 reports OLS estimates of $\beta_{\hat{E}}$, β_{CF} and β_{DR} when the expected return, cash flow news, and discount rate news components are estimated based on individual VARs comprised of the S&P 500 log return, log dividend-price ratio, and one of the 14 popular predictors from Goyal and Welch (2008). We always include the log dividend-price ratio in the VAR, as Engsted, Pedersen, and Tanggaard (2012) show that it is important to include this variable in the VAR to properly estimate the cash flow and discount rate news components.[31] Table 8 also reports results for a return decomposition based on a VAR comprised of the log return, log dividend-price ratio, and the first three principal components extracted from the entire set of popular predictors. As discussed in Section 3.1, principal components allow us to incorporate the information from the entire set of popular predictors in a tractable manner.

For our 1973:01 to 2014:12 sample period, the OLS estimate of β in Eq. (25) is -0.51 (with a heteroskedasticity- and autocorrelation-robust t-statistic of -2.53). Because log excess return fluctuations are dominated by changes in log returns, this estimate is very similar to the corresponding estimate (-0.50) in the second column of Table 3. The relation given by Eq. (29) holds for $\hat{\beta} = -0.51$ and each set of $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{\text{CF}}$, and $\hat{\beta}_{\text{DR}}$ estimates in Table 8 (apart from rounding).[32]

Nearly all of the $\hat{\beta}_{\hat{E}}$ estimates are significant in the second and sixth columns of Table 8. However, they are limited in magnitude and thus contribute little to the size of $\hat{\beta}$. The $\hat{\beta}_{\text{DR}}$ estimates in the fourth and eighth columns are typically larger in magnitude (and most are significant), but the estimates again account for a relatively limited share of $\hat{\beta}$. In contrast, the $\hat{\beta}_{\text{CF}}$ estimates in the third and seventh columns are much more sizable (and all are significant), so that the ability of SII to anticipate cash flow news is clearly the most economically important source of SII's predictive power for stock returns. Overall, the results in Table 8 reiterate the notion that SII contains substantially different information from that found in popular return predictors; furthermore, the differential information in SII is particularly relevant for future aggregate cash flows.

[31] Of course, the first VAR in Table 8 only includes two endogenous variables, since the log dividend-price ratio is always included in the VAR.

[32] The properties of OLS permit the decomposition of the estimated slope coefficient in Eq. (25) given by Eq. (29). However, because the discount rate and cash flow news components are generally correlated, an analogous "clean" decomposition of the R^2 statistic into expected return, cash flow news, and discount rate news components is not available.

6. Interpretation of results

When we treat the information in popular predictor variables as the market information set, Section 5 shows that the predictive power of SII primarily stems from the cash flow channel. In what follows, we discuss several possible interpretations of the predictive power of SII.

6.1. *Short sellers as informed traders*

The natural interpretation of the VAR results is that short sellers possess an information advantage regarding future aggregate cash flows; in other words, short sellers are informed traders. There is an extant literature that shows that short sellers are skilled at processing firm-specific information (Boehmer, Jones, and Zhang, 2008; Karpoff and Lou, 2010; Engelberg, Reed, and Ringgenberg, 2012; Akbas, Boehmer, Erturk, and Sorescu, 2013). Interestingly, our results extend this literature by showing that short sellers are also skilled at processing aggregate information.[33] Taken together with the existing firm-level literature, our results identify short sellers as informed traders with respect to both the idiosyncratic and systematic determinants of equity valuations.

Why do short sellers possess information about future aggregate cash flows that is not reflected in current market prices? In line with Grossman and Stiglitz (1980), one explanation is that short sellers receive compensation for acquiring and interpreting information. However, given that short interest is publicly released by the exchanges, this raises another question: why don't other investors exploit the information in aggregate short interest? Until recently, the short interest data used in this study were not available in electronic form; as such, constructing our short interest index and exploiting its predictive power would have required significant processing costs. In sum, one explanation for the predictive ability of SII is that short sellers earn compensation for their

[33] We note that the extant literature on firm-level short selling does not imply that short sellers are skilled at processing information at the aggregate level. The literature on firm-level short selling documents a significant relation between cross-sectional variation in short interest and future returns; however, as discussed in Section 1, a cross-sectional relation measures the effects of relative short interest positions and ignores the information in aggregate short selling.

skill at acquiring and interpreting information about future aggregate cash flows.

It is also possible that the returns to short sellers' information advantage are compensation for arbitrage risk, in the spirit of Shleifer and Vishny (1997). Engelberg, Reed, and Ringgenberg (2015) show that short sellers, who must borrow shares in the equity lending market to initiate their trades, bear many unique risks, including the risks of loan recalls and substantial changes in loan fees. Moreover, there are important institutional frictions that prevent investors from exploiting the information in our SII measure. For example, many mutual funds are prohibited from shorting. Furthermore, regulations require short sellers to post significant capital, which makes short selling costly.

6.2. Time-varying equilibrium aggregate risk premium

An alternative explanation is that the predictive ability of SII relates to the time-varying equilibrium aggregate risk premium. Under this interpretation, the VAR in Section 5 is misspecified: by excluding SII from the variables appearing in the VAR, we effectively exclude SII from the market information set and the VAR's estimate of the expected return. This interpretation implies that short sellers do not possess an information advantage concerning future aggregate cash flows and/or discount rates, as including SII in the VAR model will make SII uncorrelated with future cash flow news and discount rate news (by construction). However, we then need to explain why fluctuations in SII relate to time variation in the equilibrium aggregate risk premium. Providing such an explanation is not straightforward, as SII is largely orthogonal to popular predictor variables thought to be related to the time-varying equilibrium aggregate risk premium. Of course, because we do not directly observe the equilibrium aggregate risk premium, determining the ultimate source of SII's predictive ability is necessarily subject to the joint hypothesis problem.

6.3. *Why hasn't the predictive power of SII declined?*

As discussed in Section 2.2, short selling has become easier and more common over time, and it is natural to expect that this would lead to a decline in SII's predictive ability.[34] Nevertheless, as shown in Section 3.4.2, the predictive power of SII endures over our 1973:01 to 2014:12 sample period. Under the time-varying equilibrium aggregate risk premium interpretation of Section 6.2, we would not necessarily expect SII's predictive ability to decline over time (e.g., Cochrane, 2011). Another explanation, consistent with the "limits to arbitrage" discussion above, is that short selling costs and risks are significant enough to prevent short selling from increasing to the point that it eliminates aggregate mispricing. Indeed, even though short selling has increased significantly over our sample period, the data suggest that it is still relatively rare. At its peak in July 2008, short interest was only 8.93% of all shares outstanding. Thus, one interpretation of our results is that limits to arbitrage have kept short selling relatively rare, so that the returns to shorting have remained relatively constant over our sample period. This interpretation is consistent with Lamont and Stein (2004), who find that short sellers could not correct aggregate mispricing during the dot-com boom, noting that "remarkably little short selling takes place *at any point* in the cycle" (p. 30, emphasis theirs).

Furthermore, the extant firm-level literature continues to find a significant relation between cross-sectional variation in short interest and future returns. It thus seems difficult in general for investors to exploit the available data on short interest to the point of eliminating mispricing. Investors either are unable to exploit the information in short interest—potentially due to limits to arbitrage and the costs of acquiring and analyzing data—or they are insufficiently aware of it. In fact, evidence suggests that investors are not always aware of arbitrage opportunities based on publicly available data. Schwert (2003) and McLean and Pontiff (2015) present evidence that investors often learn about anomalies after studies are published, which subsequently weakens or eliminates mispricings. From this perspective, it is possible that the predictive ability of short interest will diminish in the future as firm-level and our aggregate results become more widely

[34] We thank an anonymous referee for raising this important question.

known. However, Schwert (2003) also finds that the momentum anomaly persists, despite publication of the result, so that it is also possible that the predictive ability of our SII measure will persist. Along this line, McLean and Pontiff (2015) find that long-short portfolios based on strategies that are more costly to arbitrage experience smaller reductions in returns after publication. It will be interesting to see whether SII's predictive ability will decline in the future or whether it will persist due to limits to arbitrage and/or time variation in the equilibrium aggregate risk premium.

7. Conclusion

In this paper, we find that short interest, when aggregated across firms and appropriately detrended, is a statistically and economically significant predictor of future market excess returns over our 1973:01 to 2014:12 sample period. In fact, our short interest index is arguably *the* strongest known predictor of the equity risk premium. In-sample results show that SII is a statistically and economically significant predictor of S&P 500 excess returns at horizons of one, three, six, and twelve months. SII consistently exhibits stronger in-sample predictive power than 14 popular predictor variables from Goyal and Welch (2008). In out-of-sample tests for the 1990:01 to 2014:12 forecast evaluation period, a predictive regression forecast based on SII outperforms the constant expected excess return benchmark forecast by a statistically and economically significant margin at all horizons. Furthermore, the information contained in the SII-based forecast dominates the information found in forecasts based on popular predictors. SII also generates substantial utility gains for a mean-variance investor with a relative risk aversion coefficient of three, and the gains are especially large during the recent Global Financial Crisis.

Our results show that the information content of short selling is more important economically than previously believed. While a number of papers find that short sellers are skilled at processing information about firm fundamentals, we provide the first evidence that short sellers are also skilled at processing information about macroeconomic conditions. In doing so, we add to the growing literature on informed trading by short sellers. Specifically, we find that after controlling for the information in popular return predictors from the literature, SII anticipates future aggregate cash flows, consistent with informed trading by short sellers at the macroeconomic level.

Overall, we show that aggregate short interest—after accounting for its strong secular trend—constitutes a powerful predictor of stock market returns based on the conscious decisions of short sellers in accord with their beliefs. Our results identify short sellers as informed traders who are able to anticipate changes in future aggregate cash flows and associated changes in future market returns.

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Table 1
Summary statistics, 1973:01–2014:12.

The database contains 504 monthly observations for January 1973 to December 2014. The table displays summary statistics for 14 predictor variables from Goyal and Welch (2008) and aggregate short interest. DP is the log dividend-price ratio, DY is the log dividend yield, EP is the log earnings-price ratio, DE is the log dividend-payout ratio, RVOL is the volatility of excess stock returns, BM is the book-to-market value ratio for the Dow Jones Industrial Average, NTIS is net equity expansion, TBL is the interest rate on a three-month Treasury bill, LTY is the long-term government bond yield, LTR is the return on long-term government bonds, TMS is the long-term government bond yield minus the Treasury bill rate, DFY is the difference between Moody's BAA- and AAA-rated corporate bond yields, DFR is the long-term corporate bond return minus the long-term government bond return, and INFL is inflation calculated from the CPI for all urban consumers. EWSI is the equal-weighted mean across all firms of the number of shares held short in a given firm (from Compustat) normalized by each firm's shares outstanding. EWSI includes common equities, ADRs, ETFs, and REITs. SII is the detrended log of EWSI, constructed by removing a linear trend from the log of EWSI; SII is standardized to have a standard deviation of one. See Section 2 for more details on the sample construction.

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Summary statistics					
Variable	Mean	Median	1st percentile	99th percentile	Std. dev.
DP	−3.62	−3.57	−4.47	−2.84	0.44
DY	−3.61	−3.57	−4.47	−2.83	0.44
EP	−2.82	−2.83	−4.60	−1.97	0.49
DE	−0.80	−0.86	−1.24	1.03	0.35
RVOL (ann.)	0.15	0.14	0.06	0.31	0.05
BM	0.49	0.38	0.13	1.14	0.29
NTIS	0.01	0.01	−0.05	0.04	0.02
TBL (%, ann.)	5.05	5.05	0.02	14.98	3.44
LTY (%, ann.)	7.17	7.07	2.26	13.94	2.73
LTR (%)	0.74	0.82	−6.78	9.29	3.13
TMS (%, ann.)	2.11	2.35	−2.18	4.37	1.51
DFY (%, ann.)	1.10	0.96	0.56	2.86	0.47
DFR (%)	−0.01	0.05	−4.84	3.91	1.47
INFL (%)	0.34	0.29	−0.50	1.33	0.34
EWSI (%)	2.15	1.31	0.22	7.86	1.98
SII	0.00	−0.09	−2.13	2.45	1.00
Panel B: Mean of EWSI across time					
Variable	1973–1982	1983–1992	1993–2002	2003–2014	
EWSI (%)	0.31	0.91	1.82	4.98	

Table 2
Predictor variable correlations, 1973:01–2014:12.

The table displays Pearson correlation coefficients for 14 predictor variables from Goyal and Welch (2008) as well as the short interest index (SII). See the notes to Table 1 for the variable definitions. 0.00 indicates less than 0.005 in absolute value.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Variable	DP	DY	EP	DE	RVOL	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	SII
DP	1.00														
DY	0.99	1.00													
EP	0.73	0.73	1.00												
DE	0.25	0.25	−0.48	1.00											
RVOL	0.01	0.02	−0.25	0.37	1.00										
BM	0.90	0.90	0.82	0.00	0.04	1.00									
NTIS	0.04	0.04	0.10	−0.09	−0.10	0.14	1.00								
TBL	0.67	0.67	0.65	−0.07	−0.06	0.69	0.09	1.00							
LTY	0.76	0.76	0.61	0.11	0.01	0.71	0.13	0.91	1.00						
LTR	0.03	0.04	0.02	0.00	0.01	0.01	−0.07	0.00	−0.02	1.00					
TMS	−0.15	−0.14	−0.38	0.35	0.15	−0.29	0.04	−0.64	−0.26	−0.04	1.00				
DFY	0.48	0.48	0.12	0.45	0.44	0.46	−0.32	0.25	0.36	0.10	0.08	1.00			
DFR	0.02	0.04	−0.08	0.14	0.13	0.01	0.03	−0.04	0.01	−0.44	0.12	0.10	1.00		
INFL	0.45	0.45	0.52	−0.15	−0.02	0.55	0.16	0.51	0.41	−0.07	−0.43	0.01	−0.08	1.00	
SII	−0.13	−0.14	−0.23	0.16	−0.13	−0.23	−0.28	−0.03	−0.06	−0.03	−0.05	−0.07	−0.06	−0.02	1.00

Table 3
In-sample predictive regression estimation results, 1973:01–2014:12.

The table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model,

$$r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h} \quad \text{for} \quad t = 1, \ldots, T-h,$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t, x_t is the predictor variable in the first column, and $(-)$ indicates that we take the negative of the predictor variable. See the notes to Table 1 for the variable definitions. Each predictor variable is standardized to have a standard deviation of one. Brackets below the $\hat{\beta}$ estimates report heteroskedasticity- and autocorrelation-robust t-statistics for testing H_0: $\beta = 0$ against H_A: $\beta > 0$; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to wild bootstrapped p-values; 0.00 indicates less than 0.005 in absolute value. The "SII $(-)$|PC" row corresponds to a multiple predictive regression that includes an intercept, SII, and the first three principal components extracted from the non-SII predictors in the first column. For this multiple predictive regression, the table reports the estimated slope coefficient and partial R^2 statistic corresponding to SII.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$h=1$		$h=3$		$h=6$		$h=12$	
Predictor	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
DP	0.15	0.12	0.17	0.39	0.19	0.93	0.20	2.06
	[0.75]		[0.94]		[1.06]		[1.12]	
DY	0.18	0.15	0.18	0.44	0.19	1.00	0.21	2.18
	[0.86]		[0.99]		[1.10]		[1.15]	
EP	0.09	0.04	0.06	0.05	0.06	0.09	0.08	0.34
	[0.37]		[0.27]		[0.25]		[0.43]	
DE	0.06	0.02	0.12	0.22	0.16	0.68	0.14	1.03
	[0.23]		[0.57]		[0.88]		[1.21]	
RVOL	0.35	0.62	0.33	1.53	0.27	1.90	0.18	1.58
	[1.90]**		[2.12]**		[1.95]**		[1.26]	
BM	−0.01	0.00	0.01	0.00	0.04	0.05	0.05	0.14
	[−0.05]		[0.06]		[0.23]		[0.29]	
NTIS (−)	0.07	0.02	0.00	0.00	−0.01	0.00	0.02	0.02
	[0.27]		[0.00]		[−0.02]		[0.07]	
TBL (−)	0.26	0.34	0.22	0.67	0.19	0.91	0.17	1.38
	[1.28]		[1.20]		[0.99]		[0.99]	
LTY (−)	0.15	0.10	0.10	0.15	0.08	0.15	0.00	0.00
	[0.71]		[0.57]		[0.40]		[0.03]	
LTR	0.33	0.55	0.14	0.27	0.23	1.41	0.15	1.14
	[1.67]**		[0.92]		[2.48]***		[2.90]***	
TMS	0.33	0.56	0.31	1.33	0.28	2.14	0.36	6.52
	[1.66]**		[1.72]*		[1.62]*		[2.27]**	
DFY	0.15	0.11	0.16	0.37	0.24	1.51	0.19	1.75
	[0.55]		[0.66]		[1.24]		[1.18]	
DFR	0.50	1.24	0.23	0.72	0.16	0.71	0.06	0.17
	[1.58]*		[1.26]		[1.38]*		[0.89]	
INFL (−)	0.06	0.02	0.17	0.43	0.26	1.81	0.27	3.64
	[0.21]		[0.90]		[1.62]*		[2.04]*	
SII (−)	0.50	1.24	0.56	4.37	0.57	8.07	0.53	12.89
	[2.50]***		[2.88]***		[2.73]**		[2.70]**	
SII (−)|PC	0.51	1.27	0.58	4.54	0.59	8.64	0.55	13.69
	[2.64]***		[3.02]***		[2.79]**		[2.73]**	

Table 4
Predictive regression estimation results for alternative detrending methods, 1973:01–2014:12.

The table reports the ordinary least squares estimate of β and R^2 statistic for the predictive regression model,

$$r_{t:t+h} = \alpha + \beta \mathrm{SII}_t + \varepsilon_{t:t+h} \text{ for } t = 1, \ldots, T-h,$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \cdots + r_{t+h})$, r_t is the S&P 500 log excess return for month t, SII_t is the short interest index, and $(-)$ indicates that we take the negative of SII_t. SII is computed as the deviation in the log of EWSI from a linear, quadratic, or cubic time trend (as indicated in the first column), where EWSI is the equal-weighted mean across all firms of the number of shares held short in a given firm normalized by each firm's shares outstanding. "Stochastic" indicates that SII is computed as the deviation in the log of EWSI from a 60-month backward-looking moving average; the sample for SII based on stochastic detrending starts in 1977:12. SII is standardized to have a mean of zero and a standard deviation of one. Brackets below the $\hat{\beta}$ estimates report heteroskedasticity- and autocorrelation-robust t-statistics for testing H_0: $\beta = 0$ against H_A: $\beta > 0$; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, according to wild bootstrapped p-values.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$h=1$		$h=3$		$h=6$		$h=12$	
Detrending method	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Linear $(-)$	0.50	1.24	0.56	4.37	0.57	8.07	0.53	12.89
	[2.50]***		[2.88]***		[2.73]**		[2.70]**	
Quadratic $(-)$	0.56	1.57	0.62	5.38	0.62	9.79	0.56	15.51
	[2.74]***		[3.12]***		[2.92]***		[2.87]**	
Cubic $(-)$	0.40	0.79	0.46	3.06	0.46	5.72	0.40	8.35
	[1.68]*		[2.07]**		[1.99]*		[1.76]	
Stochastic $(-)$	0.42	0.91	0.49	3.50	0.51	7.44	0.45	11.02
	[1.98]**		[2.56]***		[2.74]**		[2.83]**	

Table 5

Out-of-sample test results, 1990:01–2014:12.

The second through fifth columns report the proportional reduction in mean squared forecast error (MSFE) at the h-month horizon for a predictive regression forecast of the S&P 500 log excess return based on the predictor variable in the first column vis-á-vis the prevailing mean benchmark forecast, where statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE. See the notes to Table 1 for the variable definitions. The sixth through ninth columns report the estimated weight on the predictive regression forecast based on SII in a combination forecast that takes the form of a convex combination of a predictive regression forecast based on SII and a predictive regression forecast based on one of the non-SII predictor variables in the first column, where statistical significance is based on the Harvey, Leybourne, and Newbold (1998) statistic for testing the null hypothesis that the weight on the SII-based forecast is equal to zero against the alternative hypothesis that the weight on the SII-based forecast is greater than zero; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Out-of-sample R^2 statistics (%)				Encompassing tests			
Predictor	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
DP	−2.06	−5.80	−10.97	−26.39	1.00***	1.00***	1.00***	1.00***
DY	−2.20	−5.66	−11.04	−25.82	1.00***	1.00***	1.00***	1.00***
EP	−1.14	−4.24	−8.85	−16.39	1.00***	1.00***	1.00***	1.00***
DE	−2.27	−6.29	−7.85	−3.56	1.00**	1.00***	1.00***	0.96***
RVOL	−0.56	−1.40	−1.77	−3.40	0.98***	1.00***	1.00***	1.00***
BM	−0.56	−1.75	−3.55	−9.68	1.00***	1.00***	1.00***	1.00***
NTIS	−3.23	−8.88	−19.06	−27.82	1.00***	1.00***	1.00***	1.00***
TBL	−0.38	−0.92	−1.66	−1.75	1.00**	1.00***	1.00***	1.00**
LTY	−0.31	−1.53	−3.66	−11.85	1.00***	1.00***	1.00***	1.00***
LTR	−0.51	−1.59	−0.94	−0.91	1.00***	1.00***	1.00***	0.94***
TMS	−0.76	−1.72	−1.43	3.35**	1.00***	1.00***	1.00***	0.83**
DFY	−3.07	−7.15	−8.92	−7.35	1.00***	1.00***	1.00***	1.00***
DFR	−1.75	−1.11	−0.39	−0.78	0.95**	1.00***	1.00***	1.00***
INFL	−0.64	−0.32	1.95*	3.24	1.00***	1.00***	1.00***	0.89***
SII	1.94***	6.54***	11.70***	13.24**	–	–	–	–

Table 6
Out-of-sample CER gains.

The table reports the annualized certainty equivalent return (CER) gain (in percent) for a mean-variance investor with relative risk aversion coefficient of three who allocates between equities and risk-free bills using a predictive regression excess return forecast based on the predictor variable in the first column relative to the prevailing mean benchmark forecast. See the notes to Table 1 for the variable definitions. The equity weight is constrained to lie between −0.5 and 1.5. Buy and hold corresponds to the investor passively holding the market portfolio. The forecast horizon and rebalancing frequency coincide and are given by h.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	1990:01−2014:12 out-of-sample period				1990:01−2006:12 out-of-sample period				2007:01−2014:12 out-of-sample period			
Predictor	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
DP	−3.19	−2.46	−3.50	−3.48	−4.47	−3.64	−5.54	−5.64	−0.48	0.00	0.67	0.99
DY	−2.96	−2.34	−3.34	−3.36	−4.35	−3.69	−5.53	−5.53	−0.02	0.49	1.16	1.14
EP	−0.34	−0.38	−1.12	−1.37	−1.02	−0.57	−1.51	−1.51	1.10	0.02	−0.30	−1.03
DE	−1.13	−1.57	−2.27	−0.47	−1.58	−1.40	−0.95	−0.48	−0.16	−1.88	−4.65	−0.77
RVOL	−1.82	−1.77	−1.48	−0.30	−3.03	−2.88	−2.48	−0.94	0.70	0.45	0.36	0.85
BM	−0.78	−0.63	−0.98	−1.32	−1.14	−0.87	−1.53	−1.91	−0.01	−0.12	0.15	−0.22
NTIS	−2.57	−2.77	−2.75	−3.62	−1.58	−1.10	−1.41	−1.94	−4.67	−6.28	−5.60	−7.87
TBL	0.66	0.35	−0.06	−0.82	1.15	0.95	0.42	−1.16	−0.40	−0.95	−1.09	−0.34
LTY	−0.05	−0.53	−0.79	−1.79	−0.33	−0.76	−1.17	−2.04	0.57	−0.02	0.02	−1.12
LTR	−0.95	0.41	−0.31	1.17	−0.98	1.21	0.55	1.91	−0.92	−1.27	−2.08	−0.40
TMS	0.25	0.87	0.60	1.40	1.05	2.17	1.00	0.13	−1.48	−1.95	−0.44	3.69
DFY	−4.90	−4.56	−4.69	−1.86	−4.43	−4.49	−5.85	−2.87	−5.93	−4.80	−2.53	−0.24
DFR	1.08	0.67	0.89	0.50	0.96	0.08	−0.23	0.29	1.34	1.87	3.05	0.89
INFL	−0.55	−0.48	1.87	1.68	0.62	0.30	0.63	−0.35	−3.01	−2.15	4.33	5.34
SII	4.17	4.65	5.44	3.43	0.88	0.73	0.57	−0.38	11.18	13.08	15.91	11.23
Buy and hold	1.70	2.59	2.25	2.04	2.07	2.96	1.74	2.26	0.91	1.70	3.06	1.03

Table 7
Sharpe ratios.

The table reports the annualized Sharpe ratio for a mean-variance investor who allocates between equities and risk-free bills using a predictive regression excess return forecast based on the predictor variable in the first column or the prevailing mean benchmark forecast. See the notes to Table 1 for the variable definitions. The equity weight is constrained to lie between −0.5 and 1.5. Buy and hold corresponds to the investor passively holding the market portfolio. The forecast horizon and rebalancing frequency coincide and are given by h.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	1990:01–2014:12 out-of-sample period				1990:01–2006:12 out-of-sample period				2007:01–2014:12 out-of-sample period			
Predictor	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$	$h=1$	$h=3$	$h=6$	$h=12$
Prevailing mean	0.39	0.31	0.37	0.35	0.38	0.33	0.45	0.37	0.40	0.28	0.19	0.28
DP	0.11	0.10	0.01	0.01	0.01	0.04	−0.08	−0.12	0.37	0.27	0.20	0.32
DY	0.12	0.11	0.02	0.02	0.02	0.04	−0.08	−0.11	0.43	0.32	0.24	0.33
EP	0.36	0.27	0.26	0.22	0.30	0.27	0.33	0.24	0.54	0.28	0.11	0.16
DE	0.31	0.24	0.21	0.34	0.29	0.27	0.38	0.36	0.39	0.14	−0.19	0.28
RVOL	0.28	0.24	0.26	0.32	0.20	0.18	0.26	0.31	0.45	0.36	0.26	0.33
BM	0.33	0.27	0.28	0.26	0.31	0.28	0.33	0.25	0.40	0.27	0.17	0.25
NTIS	0.20	0.14	0.19	0.19	0.26	0.24	0.34	0.24	0.11	−0.05	−0.02	0.11
TBL	0.45	0.37	0.37	0.33	0.47	0.41	0.48	0.35	0.39	0.27	0.18	0.28
LTY	0.38	0.27	0.30	0.17	0.37	0.28	0.36	0.18	0.45	0.27	0.14	0.11
LTR	0.33	0.35	0.35	0.42	0.32	0.40	0.49	0.47	0.35	0.22	0.10	0.29
TMS	0.41	0.38	0.41	0.43	0.45	0.45	0.52	0.39	0.34	0.25	0.25	0.50
DFY	−0.02	−0.02	0.02	0.21	−0.08	−0.07	−0.06	0.15	0.04	0.05	0.12	0.32
DFR	0.46	0.36	0.43	0.38	0.45	0.33	0.43	0.39	0.49	0.43	0.41	0.33
INFL	0.36	0.31	0.49	0.46	0.43	0.36	0.49	0.40	0.19	0.18	0.49	0.59
SII	0.66	0.60	0.72	0.53	0.44	0.37	0.49	0.38	1.05	1.06	1.22	0.93
Buy and hold	0.50	0.48	0.52	0.45	0.53	0.50	0.59	0.48	0.46	0.43	0.42	0.39

Table 8

Predictive regression estimation results for market return components, 1973:01–2014:12.

The table reports the ordinary least squares estimate of β_y for the predictive regression model,

$$y_{t+1} = \alpha_y + \beta_y \mathrm{SII}_t + \varepsilon_{t+1} \text{ for } t = 1, \ldots, T-1,$$

where y_t is one of three estimated components of the S&P 500 log return for month t and SII_t is the short interest index. The three estimated components of the S&P 500 log return are the expected return ($\hat{E}r_{t+1}$), cash flow news ($\hat{\eta}_{t+1}^{\mathrm{CF}}$), and discount rate news ($\hat{\eta}_{t+1}^{\mathrm{DR}}$), corresponding to $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{\mathrm{CF}}$, and $\hat{\beta}_{\mathrm{DR}}$, respectively. The components are estimated using the Campbell (1991) and Campbell and Ammer (1993) vector autoregression (VAR) approach based on a VAR comprised of the variables in the first and fifth columns, where "r" indicates the S&P 500 log return. See the notes to Table 1 for the variable definitions. "PC" indicates that the VAR includes the first three principal components extracted from the non-SII predictors in the first and fifth columns. The intercept term is set to zero for the cash flow news and discount rate news predictive regressions. Brackets below the $\hat{\beta}_y$ estimates report heteroskedasticity- and autocorrelation-robust t-statistics; *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VAR variables	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{\mathrm{CF}}$	$\hat{\beta}_{\mathrm{DR}}$	VAR variables	$\hat{\beta}_{\hat{E}}$	$\hat{\beta}_{\mathrm{CF}}$	$\hat{\beta}_{\mathrm{DR}}$
r, DP	−0.07	−0.35	0.09	r, DP, LTY	−0.08	−0.32	0.11
	[−3.13]***	[−2.27]**	[2.03]**		[−3.43]***	[−2.20]**	[1.60]
r, DP, DY	−0.06	−0.35	0.10	r, DP, LTR	−0.07	−0.35	0.09
	[−2.53]**	[−2.27]**	[2.23]**		[−2.71]***	[−2.28]**	[1.92]*
r, DP, EP	−0.08	−0.40	0.04	r, DP, TMS	−0.08	−0.34	0.09
	[−3.52]***	[−2.36]**	[0.98]		[−3.53]***	[−2.21]**	[1.64]
r, DP, DE	−0.08	−0.40	0.04	r, DP, DFY	−0.07	−0.36	0.09
	[−3.52]***	[−2.36]**	[0.98]		[−3.15]***	[−2.27]**	[1.98]**
r, DP, RVOL	−0.11	−0.27	0.13	r, DP, DFR	−0.09	−0.34	0.08
	[−3.64]***	[−1.95]*	[1.91]*		[−2.74]***	[−2.20]**	[1.92]*
r, DP, BM	0.01	−0.33	0.19	r, DP, INFL	−0.07	−0.35	0.09
	[0.50]	[−2.35]**	[2.89]***		[−3.24]***	[−2.27]**	[1.98]**
r, DP, NTIS	−0.05	−0.36	0.10	r, DP, PC	−0.05	−0.31	0.15
	[−2.49]**	[−2.32]**	[2.15]**		[−1.97]**	[−2.20]**	[2.23]**
r, DP, TBL	−0.09	−0.31	0.11				
	[−3.69]***	[−2.08]**	[1.44]				

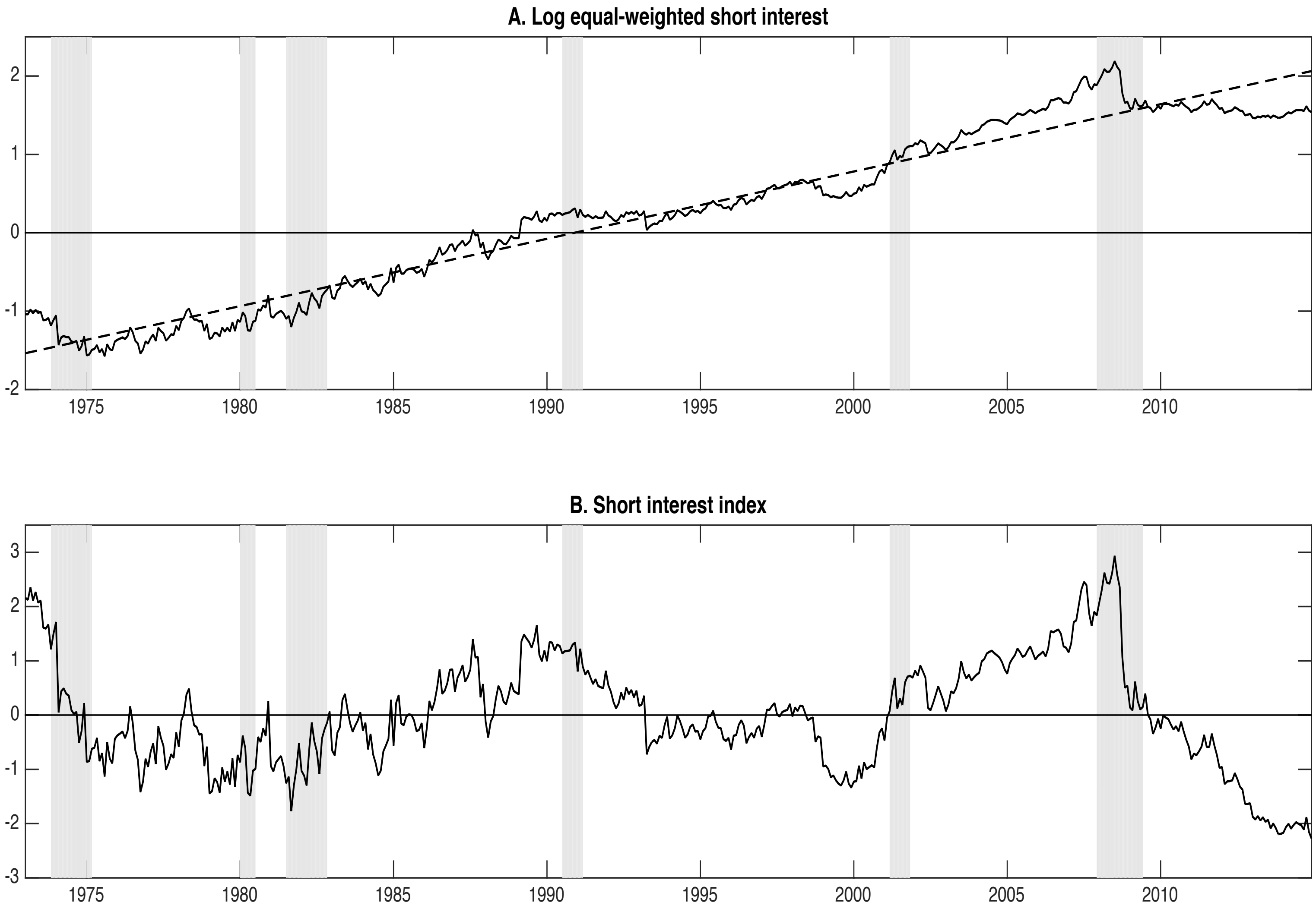

Fig. 1. Aggregate short interest, 1973:01–2014:12. The solid line in Panel A delineates the log of the equal-weighted mean across all firms of the number of shares held short in a given firm (from Compustat) normalized by each firm's shares outstanding; the dashed line is the linear trend for the series. Panel B delineates the deviation in the solid line from the dashed line in Panel A, where the deviation has been standardized to have a standard deviation of one. Vertical bars depict NBER-dated recessions.

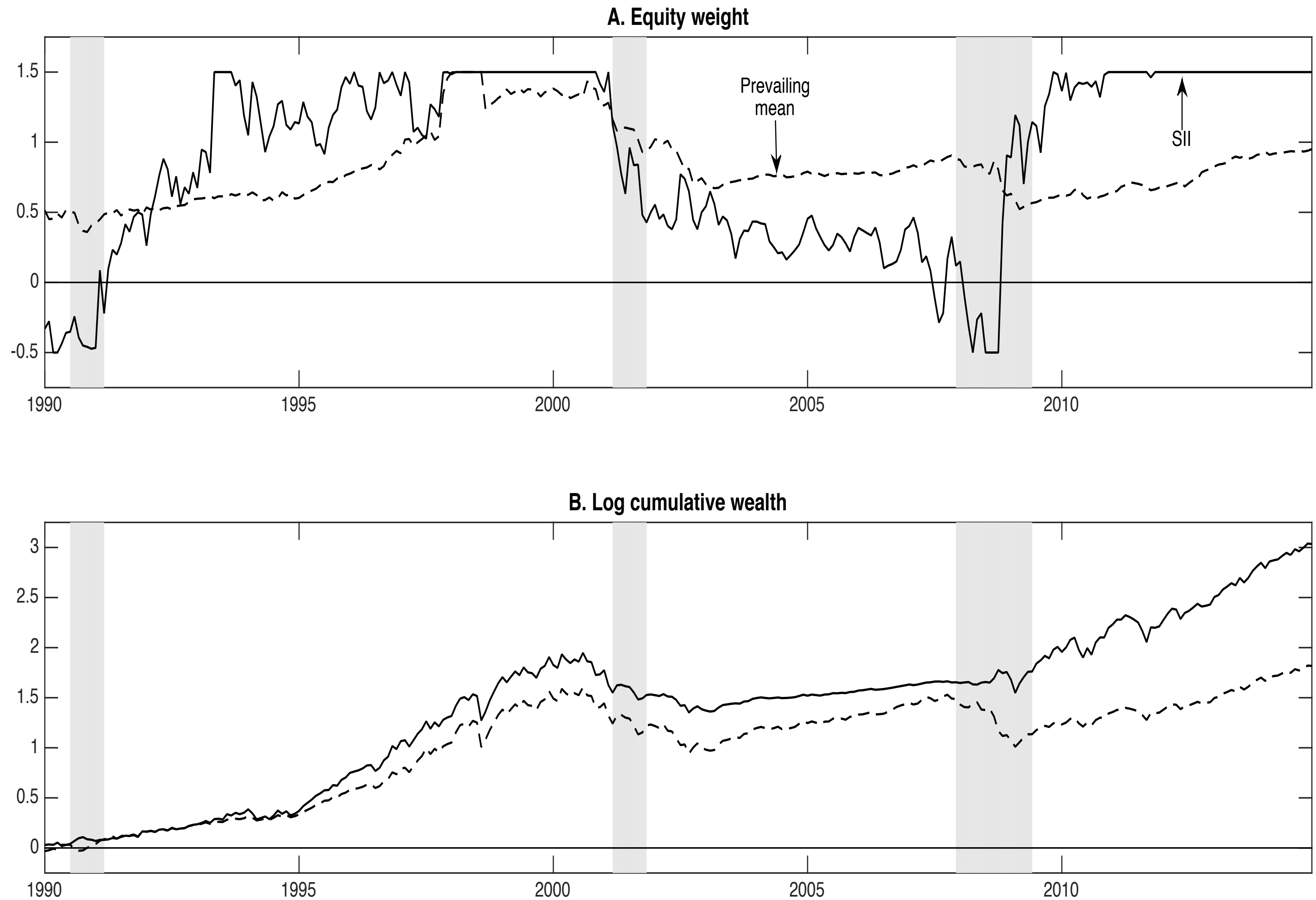

Fig. 2. Equity weights and log cumulative wealth, 1990:01–2014:12. Panel A delineates the equity weight for a mean-variance investor with relative risk aversion coefficient of three who allocates monthly between equities and risk-free bills using a predictive regression excess return forecast based on SII (solid line) or the prevailing mean benchmark forecast (dashed line). The equity weight is constrained to lie between -0.5 and 1.5. Panel B delineates the log cumulative wealth for the investor assuming that the investor begins with \$1 and reinvests all proceeds. Vertical bars depict NBER-dated recessions.