

Short Interest and Aggregate Stock Returns

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First Draft: August 1, 2014

This Draft: March 24, 2015

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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 sample and out of sample, with annual R^2 statistics of 13% and 11%, 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 anticipate future aggregate cash flows and associated market returns.

JEL classifications: C58, G12, G14

Key words: Short selling; Predictive regression; Asset allocation; Cash flow channel; Informed traders

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. Moreover, we show 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 the period 1973 to 2013. Each month, using data recently made available from 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 Figure 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 large increase in the number of hedge funds in existence, which has led to a sharp increase in the amount of capital devoted to short arbitrage. This upward trend obscures the true information content in aggregate short interest. Accordingly, we 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 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. Indeed, in-sample tests show that a one-standard-

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

deviation increase in SII corresponds to a six to seven percentage point decrease in future annualized excess returns. SII produces predictive regression R^2 statistics of 1.34% at the monthly horizon and 12.67% 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 similarly or better than all of the predictors at the monthly horizon. Furthermore, the predictive power of SII is robust to concerns about persistence based on the recently developed test of [Kostakis, Magdalinos, and Stamatogiannis \(2015\)](#).

[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%, 6.33%, 10.95%, and 10.94% at horizons of one, three, six, and twelve months, respectively, which are statistically significant and larger than those for all of the popular predictor variables considered by [Goyal and Welch \(2008\)](#). Using encompassing tests, we also show that forecasts based on SII have superior information content relative to forecasts based on the 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 324 and 533 basis points in annualized portfolio management fees at various rebalancing frequencies to have access to excess return forecasts based on SII relative to the constant expected excess return forecast. These utility gains far outweigh those provided by the [Goyal and Welch \(2008\)](#) predictor variables. Around the 2007–2008 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.

Why does SII predict future market returns? We present evidence that SII's predictive ability

²We 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.

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 the 14 popular predictors from [Goyal and Welch \(2008\)](#) to measure the discount rate and cash flow news components of stock return innovations. We then show that higher SII strongly predicts lower subsequent cash flow news. Furthermore, when we use the VAR approach 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 results almost entirely 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 the predictive power of short interest stems from information frictions. Specifically, short sellers appear to 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, Ertuck, 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

³These 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.

⁴In particular, [Seneca \(1967\)](#) uses the level of the S&P500 as the dependent variable in his main specification and normalizes aggregate short interest by volume (while it is in now common practice to normalize by shares outstanding). See [Hanna \(1968\)](#) for a critique of the findings in [Seneca \(1967\)](#).

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. Using a modern time-series approach and data recently made available by Compustat, we are the first to show that aggregate short interest is a powerful market return predictor.

We note that the predictive ability of aggregate short interest that we uncover is related to, but distinct from, the existing literature on firm-level short selling. The literature on firm-level short selling uncovers a significant relationship 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](#)). By its nature, such a cross-sectional relationship measures the effects of relative short interest positions and ignores the information in aggregate short selling, while we show that the total quantity of short selling in the stock market contains valuable information about future aggregate returns.

The rest of the paper is organized as follows. Section 1 describes our data, including the construction of SII. Section 2 reports in-sample and out-of-sample predictive regression results for SII and 14 popular predictor variables from [Goyal and Welch \(2008\)](#), while Section 3 reports results for the asset allocation analysis. Section 4 provides results for the VAR decomposition to analyze the economic underpinnings of SII's predictive ability, and Section 5 discusses possible interpretations of the results. Section 6 concludes.

1. 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.

1.1. 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 2013.⁶ 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 41-year period from January 1973 through December 2013.

Our short interest data cover a variety of asset classes, including common equities, ADRs, ETFs, and REITs. Each month, we calculate aggregate short interest as the equal-weighted mean of all asset-level short interest data (EWSI, hereafter).⁷

To relate our findings to the voluminous literature on market return predictability, we compare

⁵As 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.

⁶The 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.

⁷While many studies often exclude data on ADRs, ETFs, and REITs, it is likely that alternative asset classes, especially ETFs, contain valuable information about aggregate prices. 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.

the predictive ability of aggregate short interest to that of 14 monthly predictor variables from [Goyal and Welch \(2008\)](#), which constitute a set of popular predictors from the literature.⁸ 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 \(2007\)](#).⁹
6. Book-to-market ratio (BM): book-to-market value ratio for the DJIA.
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.

⁸Updated data for the variables in [Goyal and Welch \(2008\)](#) are available from Amit Goyal's webpage at <http://www.hec.unil.ch/agoyal/>.

⁹[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.

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.¹⁰

Finally, 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.¹¹

1.2. Sample properties

Panel A of Table 1 contains summary statistics for EWSI and the [Goyal and Welch \(2008\)](#) predictor variables over our 1973:01 to 2013:12 sample. EWSI has a mean of 2.08% (expressed as a percent of shares outstanding), a median of 1.29%, 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 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 5.01% over the last decade. Similarly, Panel A of Figure 1 plots the log of EWSI and clearly shows the secular increase in aggregate short interest over our 1973:01 to 2013:12 sample.

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.¹² There has also been a

¹⁰We account for the delay in CPI releases when testing the predictive ability of inflation.

¹¹These data are also from Amit Goyal's webpage.

¹²Because the equity lending market is an over-the-counter market, there is 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 \(2013\)](#) document a significant increase in the supply of shares available to be borrowed from 2005 to 2010.

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.

There is also statistical evidence for a trend in aggregate short interest. Consider the linear trend model:

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

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 Figure 1, Panel A, we use the [Harvey, Leybourne, and Taylor \(2007\)](#) procedure to test the significance of b in (1). The conventional t -statistic for testing the significance of b can lead to inaccurate inferences when u_t is highly persistent in (1). [Harvey, Leybourne, and Taylor \(2007\)](#) develop 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 (1).¹³

In light of the robust evidence for a trend in the log of EWSI, we remove the secular increase in aggregate short interest and isolate the economically relevant variation in short selling that reflects the changing beliefs of short sellers. Specifically, we estimate (1) using ordinary least squares (OLS) for our 1973:01 to 2013:12 sample and take the fitted residual, \hat{u}_t , as our detrended measure of aggregate short interest.¹⁴ By construction, \hat{u}_t has a mean of zero, and we standardize the series

¹³The [Harvey, Leybourne, and Taylor \(2007\)](#) $z_\lambda^{m\delta}$ statistics are 5.92, 5.69, and 5.34 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.

¹⁴We consider alternative detrending methods in Section 2. 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 $ADF^{GLS} (MZ_\alpha^{GLS})$ statistic is -2.95 (-24.42), which is significant at the 5% (1%) level.

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.

Panel B of Figure 1 depicts the SII series. SII exhibits significant fluctuations in Figure 1, Panel B, often around business-cycle turning points. Perhaps 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, 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.

1.3. 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 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 -0.26 . In other words, our SII measure appears to contain substantially different information from many of the stock return predictors used in the existing literature.

2. Predictive Regression Analysis

2.1. In-sample tests

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

$$r_{t:t+h} = \alpha + \beta x_t + \varepsilon_{t:t+h} \text{ for } t = 1, \dots, T - h, \quad (2)$$

where $r_{t:t+h} = (1/h)(r_{t+1} + \dots + r_{t+h})$, 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 (2). For a more powerful test

of predictability, [Inoue and Kilian \(2004\)](#) 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 (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 (2).

We estimate (2) 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 a standard deviation of one. We also take the negative of NTIS, TBL, LTY, INFL, and SII before estimating (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 2013:12 sample, after accounting for lags and overlapping observations, we have 491, 489, 486, and 480 usable observations for estimating (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 (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 (0.54). SII also exhibits significant predictive ability in the second column, and its $\hat{\beta}$ estimate (0.53) is very near the estimate for DFR and 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 53 basis point decrease in next month's equity market excess return (corresponding to a 6.36 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. DFR delivers the highest monthly R^2 statistic (1.42%), followed closely by SII (1.34%). 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 from the literature. The quarterly $\hat{\beta}$ estimate for SII is 0.59 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 7.08 percentage point decrease in future annualized excess returns. Among the remaining predictors, only RVOL and TMS have significant $\hat{\beta}$ estimates. The quarterly R^2 statistic for SII is a sizable 4.60% in the fifth column, which is well over twice as large as the next highest quarterly R^2 statistic (1.63% 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 four (three) are significant at the semi-annual (annual) horizon. The semi-annual (annual) R^2 statistic for SII is 8.24% (12.67%) 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 two rows of Table 3 report the OLS estimate of β_{SII} and corresponding t -statistic for

¹⁵The monthly autocorrelation coefficient for SII is 0.95, so that—like many of the 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 the Kostakis, Magdalinos, and Stamatogiannis (2015) IVX-Wald statistic to test $H_0: \beta = 0$ against $H_A: \beta \neq 0$ in (2) for SII. (Due to the nature of a Wald test, the test is two sided.) The IVX-Wald statistics equal 3.42, 4.46, 4.39, and 3.38 at the monthly, quarterly, semi-annual, and annual horizons, respectively, all of which are significant at conventional levels (based on the $\chi^2(1)$ distribution under the null).

the following predictive regression:

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

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 penultimate row of [Table 3](#) also reports the partial R^2 statistic corresponding to SII for (3).

Comparing the “SII (–)” and “SII (–)|PC” rows of [Table 3](#), we see that including the principal components in the predictive regression has very little effect on the predictive ability of SII. Moreover, 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 1.3](#), SII appears to contain information that is quite different from that contained in a variety of popular predictors, and this differential information is useful for predicting returns.

As explained in [Section 1.2](#), 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 (1) to allow for higher-order polynomial terms:

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

Equation (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 (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). Table 4 reports estimation results for the predictive regression (2) based on SII for the different trend specifications.¹⁶ The results show that the predictive power of SII is robust to linear, quadratic, and cubic detrending, as the $\hat{\beta}$ estimates are always statistically and economically significant in Table 4.

2.2. Out-of-sample tests

To examine the robustness of the in-sample results in Table 3, 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. Corresponding to each predictor, we compute a predictive regression forecast as

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

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β , respectively, in (2) based on data from the beginning of the sample through month t .¹⁷ 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, (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-à-vis the prevailing mean forecast—what Campbell and Thompson (2008) label the out-of-sample R^2 statistic (R_{OS}^2)—over the 1990:01 to 2013:12 forecast evaluation period.¹⁸ To ascertain whether the predictive regression forecast delivers a statistically significant improvement in MSFE, we use the Clark and West (2007) statistic

¹⁶To facilitate comparisons, we also report the prediction regression estimation results for SII based on linear detrending from Table 3.

¹⁷Note 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 (5), so that there is no “look-ahead” bias in the predictive regression forecast based on SII.

¹⁸Starting the out-of-sample period in 1990:01 provides a reasonably long initial in-sample period for reliably estimating the parameters used to generate the initial predictive regression forecasts.

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 $H_0: R_{OS}^2 \leq 0$ against $H_A: R_{OS}^2 > 0$).¹⁹

As indicated by the negative R_{OS}^2 statistics in the second column of Table 5, all 14 of the popular predictors from the literature 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_{OS}^2 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_{OS}^2 statistic for SII is sizable (6.33%) and significant.

SII continues to outperform the benchmark at the semi-annual and annual horizons, with R_{OS}^2 statistics of 10.95% and 10.94%, 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_{OS}^2 statistic of 1.88% 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_{OS}^2 statistic for INFL is 1.91%, which is insignificant, while the annual R_{OS}^2 statistic for TMS is reasonably large (2.42%) and significant but again well below that of SII.²⁰

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. Consider forming an optimal combination forecast as a convex combination of a predictive regression forecast based on one of the popular predictors and the

¹⁹The 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 the Diebold and Mariano (1995) and West (1996) 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 $h > 1$.

²⁰Analogously 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 detrending, the R_{OS}^2 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_{OS}^2 statistics for SII are qualitatively similar at the monthly, quarterly, and semi-annual horizons. The complete results are available from the authors upon request.

predictive regression forecast based on SII:

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

where $\hat{r}_{t:t+h}^i$ is the predictive regression forecast based on one of the popular predictors, $\hat{r}_{t:t+h}^{\text{SII}}$ is the predictive regression forecast based on SII, and $0 \leq \lambda \leq 1$. If $\lambda = 0$, then the optimal combination forecast given by (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 stock returns beyond the information that is 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 that is already contained in the popular predictor.

The sixth through ninth columns of Table 5 report the estimate of λ in (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 (6) is simply $\hat{r}_{t:t+h}^{\text{SII}}$, 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 $\hat{r}_{t:t+h}^i$ equals zero in (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.²¹ In sum, we have strong evidence that $\lambda = 1$ regardless of the popular predictor included in (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.

²¹Detailed results are available from the authors upon request.

3. 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 to equities during the subsequent month:

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

where γ is the investor’s coefficient of relative risk aversion, \hat{r}_{t+1} is a predictive regression excess return forecast,²² 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 (7) realizes an average utility or certainty equivalent return (CER) of

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

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 (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

²²Note that we forecast the simple excess return—and not the log excess return—for the asset allocation analysis.

regression forecast in place of the prevailing mean forecast. In this way, we measure the direct economic value of return predictability.²³

To analyze the economic value of return predictability at longer horizons, we assume that the 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 (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 2013:12 forecast evaluation period. We assume a relative risk aversion coefficient of three.²⁴ The performance of SII clearly stands out. At the monthly horizon, SII provides a hefty CER gain of 424 basis points. Among the 14 popular predictors, only TBL and DFR generate positive CER gain (6 and 164 basis points, respectively), but the gains are less than half that of SII. SII continues to generate very sizable CER gains of 467, 533, and 324 basis points at the quarterly, semi-annual, and annual horizons, respectively, all of which are higher than any of the gains for the 14 popular predictors. Only three (four) of the 14 popular predictors also produce positive CER gains at the quarterly and semi-annual (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 last four columns of Table 6 report CER gains for the 2007:01 to 2013:12 forecast evaluation period surrounding the Global Financial Crisis. For this out-of-sample period, SII

²³We always use the ten-year moving window variance forecast in (7), so that the portfolio weights only differ because of the excess return forecasts.

²⁴This 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.

generates stunning CER gains of 1,230, 1,417, 1,665, and 1,088 basis points at the monthly, quarterly, semi-annual, and annual horizons, respectively. More of the 14 predictors from the literature provide positive and sizable CER gains in the sixth through ninth columns compared to the second through fifth columns. However, the gains accruing to SII are approximately three to seven times higher than those accruing to the best of the 14 popular predictors. SII again generates much higher CER gains than a buy-and-hold strategy.²⁵

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 2013:12 evaluation period. The ratios for the portfolio based on the prevailing mean forecast range from 0.28 to 0.34 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 as gauged by the Sharpe ratio is especially impressive since the start of the Global Financial Crisis. The prevailing mean generates Sharpe ratios between 0.07 and 0.25 for the 2007:01 to 2013:12 evaluation period in the sixth through ninth columns of Table 7. Similarly, the predictors from the literature often produce Sharpe ratios that are relatively small (and a number are negative). The largest Sharpe ratios among the popular predictors are 0.45 and 0.52 for EP and DFR, respectively, at the monthly horizon. The buy-and-hold portfolio produces Sharpe ratios between 0.30 and 0.35 at each horizon. In sharp contrast, SII generates substantial Sharpe ratios ranging from 0.79 to 1.13 for the period surrounding the recent crisis.²⁶

²⁵It is well known that predictor variables often perform best during extreme economic conditions (e.g., [Rapach, Strauss, and Zhou, 2010](#); [Henkel, Martin, and Nadari, 2011](#)). Nevertheless, we note that the predictive ability of SII is robust across various subsamples and is not solely concentrated in the Global Financial Crisis. For the 1990:01 to 2006:12 forecast evaluation period predating the Global Financial Crisis, SII produces positive CER gains at the monthly, quarterly, and semi-annual horizons (82, 68, and 55 basis points, respectively) but not at the annual horizon (−44 basis points).

²⁶Again, we note that the predictive ability of SII is robust across subsamples. For the 1990:01 to 2006:12 evaluation period predating the Global Financial Crisis, SII generates Sharpe ratios of 0.44, 0.36, 0.49, and 0.38 at the monthly,

Figure 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 2013:12 forecast evaluation period. Because the prevailing mean 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 most notable differences between the equity weights of the two portfolios occur in the run-up to the Global Financial Crisis through the “recovery” from the Great Recession. 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 2013.

Panel B of Figure 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 2013, so that cumulative wealth grows substantially from the end of 2007 to the end of 2013. 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 2013 barely returns 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 2, the information contained in SII appears considerably more valuable than that found in a myriad of popular predictors from the literature.

quarterly, semi-annual, and annual horizons, respectively.

4. 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 well-known 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

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

where

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

$$k = -\log(\rho) - (1 - \rho) \log[(1/\rho) - 1], \quad (11)$$

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 (9) as

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

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

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

Letting E_t denote the expectation operator conditional on information through month t , (9) and (13) imply the following decomposition for the log stock return innovation:²⁷

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

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

$$\eta_{t+1}^r = \eta_{t+1}^{\text{CF}} - \eta_{t+1}^{\text{DR}}, \quad (15)$$

where

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

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

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

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 VAR(1) model:

$$y_{t+1} = A y_t + u_{t+1}, \quad (19)$$

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.²⁸ Letting e_1 denote an $(n+2)$ -vector with one as its first element and zeros for the remaining elements, the stock return

²⁷In deriving (14), we assume that p_t is in the month- t information set, so that $E_t p_t = p_t$.

²⁸We omit a constant term from (19) for notational convenience.

innovation and discount rate news component can be expressed as

$$\eta_{t+1}^r = e_1' u_{t+1} \quad (20)$$

and

$$\eta_{t+1}^{\text{DR}} = e_1' \rho A (I - \rho A)^{-1} u_{t+1}, \quad (21)$$

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

$$\eta_{t+1}^{\text{CF}} = \eta_{t+1}^r + \eta_{t+1}^{\text{DR}}. \quad (22)$$

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

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

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

$$r_{t+1} = E_t r_{t+1} + \eta_{t+1}^{\text{CF}} - \eta_{t+1}^{\text{DR}}. \quad (24)$$

With sample observations for y_t for $t = 1, \dots, T$, we can use OLS to estimate A and u_{t+1} ($t = 1, \dots, T - 1$) for the VAR model (19); denote the OLS estimates by \hat{A} and \hat{u}_{t+1} , respectively. We can also estimate ρ using (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 (20), (21), (22), and (23) yields $\hat{\eta}_{t+1}^r$, $\hat{\eta}_{t+1}^{\text{DR}}$, $\hat{\eta}_{t+1}^{\text{CF}}$, and $\hat{E}_t r_{t+1}$, respectively, for $t = 1, \dots, T - 1$.

Our idea is to 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:

$$r_{t+1} = \alpha + \beta \text{SII}_t + \varepsilon_{t+1} \quad \text{for } t = 1, \dots, T - 1. \quad (25)$$

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

$$\hat{E}_t r_{t+1} = \alpha_{\hat{E}} + \beta_{\hat{E}} \text{SII}_t + \varepsilon_{t+1}^{\hat{E}}, \quad (26)$$

$$\hat{\eta}_{t+1}^{\text{CF}} = \beta_{\text{CF}} \text{SII}_t + \varepsilon_{t+1}^{\text{CF}}, \quad (27)$$

$$\hat{\eta}_{t+1}^{\text{DR}} = \beta_{\text{DR}} \text{SII}_t + \varepsilon_{t+1}^{\text{DR}}, \quad (28)$$

for $t = 1, \dots, T - 1$.²⁹ Equation (24) implies the following relationship between the slope coefficient in (25) and those in (26) through (28):

$$\beta = \beta_{\hat{E}} + \beta_{\text{CF}} - \beta_{\text{DR}}. \quad (29)$$

By estimating the predictive regressions (25) through (28) and comparing the slope coefficients, we can gauge 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 (24).

To estimate the three components on the right-hand-side of (24), we use a VAR(1) comprised of the log stock return, log dividend-price ratio, and the first three principal components extracted from the set of 14 popular predictors from [Goyal and Welch \(2008\)](#).³⁰ As discussed in Section 2.1, principal components allow us to incorporate the information from the entire set of popular predictors in a tractable manner. If we treat the entire set of 14 predictor variables as a proxy for the market information set, then the VAR with the first three principal components provides a parsimonious framework for estimating $E_t r_{t+1}$, η_{t+1}^{CF} , and η_{t+1}^{DR} based on market expectations.

For our 1973:01 to 2013:12 sample period, regressing the S&P 500 log return on SII yields

$$r_{t+1} = \underset{[4.04]}{0.83} - \underset{[-2.60]}{0.54} \text{SII}_t + \hat{\varepsilon}_{t+1}, \quad R^2 = 1.41\%, \quad (30)$$

²⁹We exclude an intercept term from (27) and (28) to increase estimation efficiency because the the cash flow and discount rate news components (as well as SII) have zero means by construction.

³⁰We include the log dividend-price ratio in the VAR model, as [Engsted, Pedersen, and Tanggaard \(2012\)](#) show that it is important to include this variable in the VAR to properly estimate the discount rate and cash flow news components.

where heteroskedasticity-robust t -statistics are reported in parentheses.³¹ Again using the 1973:01 to 2013:12 sample period, regressing each of the estimated components on the right-hand-side of (24) on SII produces the following results:

$$\hat{E}_t r_{t+1} = \frac{0.82}{[23.10]} - \frac{0.05}{[-1.50]} \text{SII}_t + \hat{\varepsilon}_{t+1}^{\hat{E}}, \quad R^2 = 0.70\%, \quad (31)$$

$$\hat{\eta}_{t+1}^{\text{CF}} = \frac{-0.45}{[-2.92]} \text{SII}_t + \hat{\varepsilon}_{t+1}^{\text{CF}}, \quad R^2 = 1.51\%, \quad (32)$$

$$\hat{\eta}_{t+1}^{\text{DR}} = \frac{0.04}{[0.61]} \text{SII}_t + \hat{\varepsilon}_{t+1}^{\text{DR}}, \quad R^2 = 0.05\%, \quad (33)$$

Equation (32) shows that SII is a statistically and economically significant predictor of next month's cash flow news. Equation (31) indicates that SII is a significant predictor of next month's expected discount rate (at the 10% level for a one-sided lower-tail test), but the magnitude of the $\hat{\beta}_{\hat{E}}$ estimate is small. According to (33), SII is an insignificant predictor of next month's discount rate news. Interpreting (30) in light of (31) through (33), we see that the predictive power of SII is predominantly due to its ability to anticipate cash flow news, with higher SII predicting lower future returns by predicting lower future cash flow news. These results reiterate that notion that SII contains substantially different information from that found in popular return predictors; furthermore, the differential information in SII is particularly useful for predicting future aggregate cash flows.³²

5. Interpretation of Results

Sections 2 and 3 show that SII is perhaps the strongest known predictor of market returns. When we treat the information in 14 popular predictor variables as the market information set, Section 4 shows that the predictive power of SII stems almost exclusively from the cash flow channel. In

³¹Because the log return and log excess return are very highly correlated, these results are very similar to those in Table 3 for the S&P 500 log excess return (recalling that we take the negative of SII in Table 3).

³²We also estimated $E_t r_{t+1}$, η_{t+1}^{CF} , and η_{t+1}^{DR} using VARs comprised of the log return, log dividend-price ratio, and each of the Goyal and Welch (2008) predictor variables in turn (apart from the log dividend-price ratio, which is always included in the VAR). The results consistently indicate that the ability of SII to predict future stock returns is primarily due to its ability to predict future cash flow news. The complete results are available from the authors upon request.

what follows, we discuss several possible interpretations of these results.

5.1. 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; and Akbas, Boehmer, Ertuck, 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 the spirit of Grossman and Stiglitz (1980), one explanation is that short sellers receive compensation for acquiring and interpreting information. 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.³⁴ Of course, short sellers could also have acquired the information in our SII measure indirectly and utilized this information to anticipate future cash flows and returns; this analysis would also likely entail substantial processing costs. In sum, one explanation for the predictive ability of SII is that short sellers earn compensation for their 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

³³We note that the extant literature on firm-level short selling does not necessarily imply that short sellers are skilled at processing information at the aggregate level. The literature on firm-level short selling documents a significant relationship between cross-sectional variation in short interest and future returns; however, it is unclear if this is due to short interest's ability to predict idiosyncratic or systematic return variation.

³⁴As discussed in Section 1.1, historical short interest data extending back to 1973 were only made available on Compustat in 2014. Prior to 2014, the short interest data used to construct our SII measure were publicly available via the financial press, so that arbitrageurs could have, in theory, traded on our SII measure. Again, this would have required significant processing costs.

arbitrage risk. [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. These factors represent substantial limits to arbitrage. As such, the return to information about future aggregate cash flows in our SII measure potentially represents compensation for the risks and complexities of shorting.

5.2. Time-varying risk premium

An alternative explanation is that the predictive ability of SII relates to the time-varying equilibrium risk premium; that is, SII tracks time variation in the price and/or quantity of aggregate risk. Under this interpretation, the VAR in Section 4 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 estimates of the expected and unexpected components of the discount rate. This interpretation implies that short sellers do not possess an information advantage concerning future aggregate cash flows, as including SII in the VAR model will make SII uncorrelated with future cash flow news (by construction). However, we then need to explain why fluctuations in SII relate to time variation in the aggregate risk premium. Because SII is largely orthogonal to popular predictor variables thought to be related to the time-varying equity risk premium, it is not straightforward to link SII to time variation in the equity risk premium. Of course, because we do not directly observe the equilibrium equity risk premium, determining the ultimate source of SII's predictive ability is necessarily subject to the joint hypothesis problem.

6. 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 2013:12 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 regularly 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 2013:12 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, and the information contained in the SII-based forecast that is useful for out-of-sample return forecasting dominates the information found in forecasts based on the 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 suggest 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 and firm-specific news articles, 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. In contrast to existing market return predictors that primarily measure the state of the economy and market conditions, our short interest index reflects 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.

Finally, we discuss strategies for accommodating a potential end to the strong upward trend in our SII measure, so that we can continue to isolate the relevant information in aggregate short interest for predicting the equity risk premium. 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. As we show, the predictive power of SII is robust to quadratic and cubic detrending over our sample. To the extent that the secular trend in the log of EWSI flattens in the future, quadratic and/or cubic 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 1.2, 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, there is not significant evidence of a break in the linear trend.³⁵ At this point in time, we thus do not have significant evidence of a break in the trend. Going forward, we regularly test for a trend break: if there is insignificant evidence of a break, then we continue to compute SII using linear detrending; if there is significant evidence of a break, then we compute SII as the deviation from a linear trend with a break. Such a strategy should be effective for continuing to identify the predictive signal in aggregate short interest.

³⁵The [Harvey, Leybourne, and Taylor \(2009\)](#) t_λ statistics are 2.27, 2.32, and 2.42 at the 10%, 5%, and 1% levels, respectively, none of which are significant. Because a unique scaling factor is calibrated for the significant level, the t_λ statistic is different for each significance level.

References

- Akbas, F., E. Boehmer, B. Erturk, and S. Sorescu. 2013. Short Interest, Returns, and Fundamentals. Working Paper.
- Asquith, P., P. A. Pathak, and J. R. Ritter. 2005. Short Interest, Institutional Ownership, and Stock Returns. *Journal of Financial Economics* 78:243–276.
- Bliss, R. F., and N. Panigirtzoglou. 2004. Option-Implied Risk Aversion Estimates. *Journal of Finance* 59:407–466.
- Boehmer, E., C. Jones, and X. Zhang. 2008. Which Shorts are Informed? *Journal of Finance* 63:491–527.
- Campbell, J. Y. 1991. A Variance Decomposition for Stock Returns. *Economic Journal* 101:157–179.
- Campbell, J. Y., and J. Ammer. 1993. What Moves the Stock and Bond Markets? A Variance Decomposition for Long-Term Asset Returns. *Journal of Finance* 48:3–37.
- Campbell, J. Y., and R. J. Shiller. 1988. The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors. *Review of Financial Studies* 1:195–228.
- Campbell, J. Y., and S. B. Thompson. 2008. Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies* 21:1509–1531.
- Cavanagh, C., G. Elliott, and J. H. Stock. 1995. Inference in Models with Nearly Integrated Regressors. *Econometric Theory* 11:1131–1147.
- Clark, T. E., and M. W. McCracken. 2001. Tests of Equal Forecast Accuracy and Encompassing for Nested Models. *Journal of Econometrics* 105:85–110.
- Clark, T. E., and K. D. West. 2007. Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of Econometrics* 138:291–311.
- Desai, H., K. Ramesh, S. R. Thiagarajan, and B. V. Balachandran. 2002. An Investigation of the Informational Role of Short Interest in the Nasdaq Market. *Journal of Finance* 57:2263–2287.
- Diamond, D., and R. Verrecchia. 1987. Constraints on Short-Selling and Asset Price Adjustment

- to Private Information. *Journal of Financial Economics* 18:277–311.
- Diebold, F. X., and R. S. Mariano. 1995. Comparing Predictive Accuracy. *Journal of Business and Economic Statistics* 13:253–263.
- Diether, K. B., K.-H. Lee, and I. M. Werner. 2009. Short-Sale Strategies and Return Predictability. *Review of Financial Studies* 22:575–607.
- Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2012. How are Shorts Informed? Short Sellers, News, and Information Processing. *Journal of Financial Economics* 105:260–278.
- Engelberg, J. E., A. V. Reed, and M. C. Ringgenberg. 2015. Short Selling Risk. Working Paper.
- Engsted, T., T. Q. Pedersen, and C. Tanggaard. 2012. Pitfalls in VAR Based Return Decompositions: A Clarification. *Journal of Banking and Finance* 36:1255–1265.
- Ferreira, M. I., and P. Santa-Clara. 2011. Forecasting Stock Market Returns: The Sum of the Parts is More Than the Whole. *Journal of Financial Economics* 100:514–537.
- Goetzmann, W. N., and P. Jorion. 1993. Testing the Predictive Power of Dividend Yields. *Journal of Finance* 48:663–679.
- Goyal, A., and I. Welch. 2008. A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *Review of Financial Studies* 21:1455–1508.
- Grossman, S. J., and J. E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. *American Economic Review* 70:393–408.
- Hanna, M. 1968. Short Interest: Bearish Or Bullish?—Comment. *Journal of Finance* 23:520–523.
- Harvey, D. I., S. J. Leybourne, and P. Newbold. 1998. Tests for Forecast Encompassing. *Journal of Business and Economic Statistics* 16:254–259.
- Harvey, D. I., S. J. Leybourne, and A. M. R. Taylor. 2007. A Simple, Robust and Powerful Test of the Trend Hypothesis. *Journal of Econometrics* 141:1302–1330.
- Harvey, D. I., S. J. Leybourne, and A. M. R. Taylor. 2009. Simple, Robust and Powerful Tests of the Breaking Trend Hypothesis. *Econometric Theory* 25:995–1029.
- Henkel, S. J., J. S. Martin, and F. Nardari. 2011. Time-Varying Short-Horizon Predictability.

- Journal of Financial Economics* 99:560–580.
- Hodrick, R. J. 1992. Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. *Review of Financial Studies* 5:357–386.
- Inoue, A., and L. Kilian. 2004. In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use? *Econometric Reviews* 23:371–402.
- Karpoff, J. M., and X. Lou. 2010. Short Sellers and Financial Misconduct. *Journal of Finance* 65:1879–1913.
- Kostakis, A., T. Magdalinos, and M. P. Stamatogiannis. 2015. Robust Econometric Inference for Stock Return Predictability. *Review of Financial Studies*, forthcoming.
- Lamont, O. A., and J. C. Stein. 2004. Aggregate Short Interest and Market Valuations. *American Economic Review* 94:29–32.
- Ludvigson, S. C., and S. Ng. 2007. The Empirical Risk-Return Relation: A Factor Analysis Approach. *Journal of Financial Economics* 83:171–222.
- Managed Funds Association. 2012. Hedge Funds: Trends and Insights from the Industry and Investors. Washington, D.C.
- McCracken, M. W. 2007. Asymptotics for Out of Sample Tests of Granger Causality. *Journal of Econometrics* 140:719–752.
- Mele, A. 2007. Asymmetric Stock Market Volatility and the Cyclical Behavior of Expected Returns. *Journal of Financial Economics* 86:446–478.
- Nelson, C. R., and M. J. Kim. 1993. Predictable Stock Returns: The Role of Small Sample Bias. *Journal of Finance* 48:641–661.
- Ng, S., and P. Perron. 2001. Lag Length Selection and the Construction of Unit Root Tests with Good Size and Power. *Econometrica* 69:1519–1554.
- Pástor, L., and R. F. Stambaugh. 2009. Predictive Systems: Living with Imperfect Predictors. *Journal of Finance* 64:1583–1628.
- Pettenuzzo, D., A. Timmermann, and R. Valkanov. 2014. Forecasting Stock Returns Under

- Economic Constraints. *Journal of Financial Economics* 114:517–553.
- Prado, M. P., P. A. C. Saffi, and J. Sturgess. 2013. Ownership Structure, Limits to Arbitrage and Stock Returns: Evidence from Equity Lending Markets. Working Paper.
- Rapach, D. E., J. K. Strauss, and G. Zhou. 2010. Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. *Review of Financial Studies* 23:821–862.
- Rapach, D. E., and G. Zhou. 2013. Forecasting Stock Returns, in G. Elliott and A. Timmermann (eds.), *Handbook of Economic Forecasting*, Volume 2A. Amsterdam, The Netherlands: Elsevier.
- Senchack Jr., A. J., and L. T. Starks. 1993. Short-Sale Restrictions and Market Reaction to Short-Interest Announcements. *Journal of Financial and Quantitative Analysis* 28:177–194.
- Seneca, J. J. 1967. Short Interest: Bearish Or Bullish? *Journal of Finance* 22:67–70.
- Stambaugh, R. F. 1999. Predictive Regressions. *Journal of Financial Economics* 54:375–421.
- Torous, W., R. Valkanov, and S. Yan. 2004. On Predicting Stock Returns with Nearly Integrated Explanatory Variables. *Journal of Business* 77:937–966.
- West, K. D. 1996. Asymptotic Inference about Predictive Ability. *Econometrica* 64:1067–1084.
- Zhou, G. 2010. How Much Stock Return Predictability Can We Expect from an Asset Pricing Model? *Economics Letters* 108:184–186.

Table 1
Summary statistics, 1973:01–2013:12

(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Summary statistics					
Variable	Mean	Median	1st percentile	99th percentile	Std. dev.
DP	−3.61	−3.56	−4.47	−2.84	0.45
DY	−3.60	−3.56	−4.47	−2.83	0.45
EP	−2.81	−2.82	−4.62	−1.97	0.50
DE	−0.8	−0.86	−1.24	1.04	0.35
RVOL (ann.)	0.15	0.14	0.06	0.31	0.05
BM	0.50	0.38	0.13	1.14	0.29
NTIS	0.01	0.01	−0.05	0.04	0.02
TBL (% , ann.)	5.17	5.09	0.02	14.99	3.39
LTY (% , ann.)	7.27	7.22	2.25	13.96	2.68
LTR (%)	0.71	0.78	−6.86	9.37	3.15
TMS (% , ann.)	2.09	2.26	−2.24	4.37	1.52
DFY (% , ann.)	1.11	0.96	0.56	2.87	0.47
DFR (%)	0.01	0.06	−4.85	3.92	1.48
INFL (%)	0.35	0.31	−0.52	1.28	0.38
EWSI (%)	2.08	1.29	0.22	7.88	1.97
SII	0.00	10.11	−2.29	2.52	1.00
Panel B: Mean of EWSI across time					
Variable	1973–1982	1983–1992	1993–2002	2003–2013	
EWSI (%)	0.31	0.90	1.82	5.01	

The database contains 492 monthly observations for January 1973 to December 2013. The table displays summary statistics for 14 predictor variables from [Goyal and Welch \(2008\)](#) as well as 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 DJIA, 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. 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 1 for more details on the sample construction.

Table 2
Predictor variable correlations, 1973:01–2013:12

(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	0.24	0.24	-0.49	1.00											
RVOL	0.00	0.01	-0.25	0.36	1.00										
BM	0.90	0.90	0.82	-0.01	0.03	1.00									
NTIS	0.05	0.05	0.10	-0.08	-0.10	0.14	1.00								
TBL	0.67	0.66	0.66	-0.09	-0.09	0.69	0.09	1.00							
LTY	0.76	0.76	0.62	0.09	-0.02	0.71	0.14	0.90	1.00						
LTR	0.03	0.04	0.02	0.01	0.02	0.01	-0.07	0.01	-0.01	1.00					
TMS	-0.14	-0.14	-0.38	0.36	0.16	-0.28	0.05	-0.64	-0.24	-0.04	1.00				
DFY	0.47	0.48	0.12	0.44	0.44	0.45	-0.32	0.22	0.34	0.11	0.10	1.00			
DFR	0.01	0.03	-0.09	0.14	0.13	0.00	0.03	-0.05	0.00	-0.44	0.12	0.10	1.00		
INFL	0.40	0.40	0.46	-0.14	-0.03	0.50	0.14	0.46	0.37	-0.08	-0.38	-0.01	-0.07	1.00	
SII	-0.10	-0.11	-0.19	0.14	-0.17	-0.20	-0.26	-0.04	-0.08	-0.01	-0.05	-0.11	-0.09	0.01	1.00

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.

Table 3
In-sample predictive regression estimation results, 1973:01–2013:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predictor	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
	$\hat{\beta}$	R^2 (%)						
DP	0.17 [0.79]	0.13	0.18 [1.02]	0.46	0.21 [1.16]	1.11	0.22 [1.23]	2.49
DY	0.19 [0.91]	0.17	0.19 [1.07]	0.51	0.21 [1.19]	1.18	0.23 [1.26]	2.60
EP	0.10 [0.37]	0.05	0.07 [0.28]	0.06	0.06 [0.26]	0.10	0.08 [0.45]	0.37
DE	0.07 [0.27]	0.03	0.14 [0.63]	0.27	0.18 [0.99]	0.82	0.16 [1.41]	1.33
RVOL	0.37 [1.97]**	0.67	0.34 [2.18]**	1.63	0.28 [2.04]**	2.11	0.20 [1.42]	2.03
BM	0.00 [-0.02]	0.00	0.02 [0.11]	0.01	0.06 [0.30]	0.09	0.07 [0.37]	0.24
NTIS (-)	0.08 [0.29]	0.03	0.01 [0.03]	0.00	-0.01 [-0.03]	0.00	0.00 [0.01]	0.00
TBL (-)	0.25 [1.17]	0.30	0.20 [1.04]	0.53	0.16 [0.81]	0.64	0.13 [0.75]	0.83
LTY (-)	0.13 [0.59]	0.08	0.08 [0.41]	0.08	0.04 [0.22]	0.05	-0.04 [-0.21]	0.08
LTR	0.32 [1.58]**	0.49	0.14 [0.90]	0.26	0.24 [2.49]**	1.45	0.17 [3.38]***	1.44
TMS	0.33 [1.62]*	0.54	0.30 [1.64]*	1.23	0.27 [1.51]*	1.90	0.34 [2.17]**	6.05
DFY	0.17 [0.61]	0.14	0.18 [0.74]	0.47	0.26 [1.35]	1.78	0.20 [1.27]	2.07
DFR	0.54 [1.68]*	1.42	0.23 [1.29]	0.76	0.16 [1.36]	0.70	0.05 [0.82]	0.14
INFL (-)	-0.02 [-0.06]	0.00	0.16 [0.81]	0.36	0.27 [1.70]*	1.86	0.24 [1.94]*	2.84
SII (-)	0.53 [2.55]***	1.34	0.59 [2.91]***	4.60	0.58 [2.70]***	8.24	0.53 [2.54]**	12.67
SII (-) PC	0.51 [2.50]***	1.24	0.58 [2.85]***	4.43	0.58 [2.57]**	8.12	0.53 [2.43]**	12.45

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

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

where $r_{t:t+h} = (1/h)(r_{t+1} + \dots + r_{t+h})$, r_t is the S&P 500 log excess return for month t , and x_t is the predictor variable in the first column. 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” entry corresponds to a multiple predictive regression model that includes an intercept and four predictors: 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, heteroskedasticity- and autocorrelation-robust t -statistic, and partial R^2 statistic corresponding to SII.

Table 4
Predictive regression estimation results for alternative detrending methods, 1973:01–2013:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	$h = 1$		$h = 3$		$h = 6$		$h = 12$	
Detrending	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)	$\hat{\beta}$	R^2 (%)
Linear	0.53 [2.55]***	1.34	0.59 [2.91]***	4.60	0.58 [2.70]***	8.24	0.53 [2.54]**	12.67
Quadratic	0.57 [2.71]***	1.54	0.62 [3.07]***	5.22	0.61 [2.83]***	9.31	0.56 [2.67]**	14.34
Cubic	0.42 [1.75]**	0.84	0.48 [2.13]**	3.17	0.47 [2.01]**	5.76	0.40 [1.74]*	8.15

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

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

where $r_{t:t+h} = (1/h)(r_{t+1} + \dots + r_{t+h})$, r_t is the S&P 500 log excess return for month t , and SII_t is the short interest index. 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). 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. 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.

Table 5
Out-of-sample test results, 1990:01–2013:12

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predictor	Out-of-sample R^2 statistics (%)				Encompassing tests			
	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 12$
DP	−2.06	−5.71	−10.81	−26.47	1.00***	1.00***	1.00***	1.00***
DY	−2.19	−5.56	−10.88	−25.90	1.00***	1.00***	1.00***	1.00***
EP	−1.15	−4.26	−8.97	−16.87	1.00***	1.00***	1.00***	1.00***
DE	−2.29	−6.25	−7.73	−3.15	1.00**	1.00***	1.00***	0.97***
RVOL	−0.48	−1.24	−1.45	−2.79	1.00***	1.00***	1.00***	1.00***
BM	−0.57	−1.76	−3.55	−9.81	1.00***	1.00***	1.00***	1.00***
NTIS	−3.22	−8.89	−19.12	−28.01	1.00***	1.00***	1.00***	1.00***
TBL	−0.46	−1.19	−2.17	−2.58	1.00**	1.00***	1.00***	1.00**
LTY	−0.36	−1.67	−3.86	−11.61	1.00***	1.00***	1.00***	1.00***
LTR	−0.63	−1.63	−0.93	−0.48	1.00***	1.00***	1.00***	0.95***
TMS	−0.81	−1.92	−1.92	2.42*	1.00***	1.00***	1.00***	0.82**
DFY	−3.05	−7.02	−8.58	−7.14	1.00***	1.00***	1.00***	1.00***
DFR	−1.45	−1.06	−0.46	−0.91	0.94**	1.00***	1.00***	1.00**
INFL	−0.79	−0.61	1.88**	1.91	1.00***	1.00***	1.00***	0.91**
SII	1.94***	6.33***	10.95***	10.94**	—	—	—	—

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-à-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 predictive regression forecasts based on SII and 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.

Table 6
Out-of-sample CER gains

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predictor	1990:01–2013:12 out-of-sample period				2007:01–2013:12 out-of-sample period			
	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 12$
DP	−3.09	−2.29	−3.36	−3.38	−0.18	0.42	1.20	1.53
DY	−2.79	−2.10	−3.16	−3.29	0.44	1.01	1.72	1.67
EP	−0.06	−0.03	−0.79	−1.23	1.99	0.78	0.54	−0.87
DE	−0.29	−0.79	−2.09	−0.25	0.98	−0.39	−5.05	−0.54
RVOL	−1.49	−1.46	−1.43	−0.43	1.87	1.24	0.55	0.29
BM	−0.84	−0.67	−0.99	−1.35	0.04	−0.04	0.34	−0.12
NTIS	−2.41	−2.93	−3.14	−4.07	−5.89	−8.17	−7.73	−10.63
TBL	0.06	−0.37	−0.57	−1.09	−1.02	−1.57	−1.62	−0.88
LTY	−0.26	−0.63	−0.82	−1.59	−0.06	−0.44	−0.24	−1.04
LTR	−1.11	0.26	−0.16	1.23	−1.57	−1.59	−1.84	0.15
TMS	−0.10	0.34	0.08	0.85	−1.61	−2.04	−0.75	2.95
DFY	−4.76	−4.35	−4.13	−1.21	−6.57	−5.05	−1.78	0.35
DFR	1.64	0.66	0.79	0.50	3.59	1.90	2.87	0.98
INFL	−0.58	−0.90	1.46	1.00	−2.67	−3.39	4.09	3.80
SII	4.24	4.67	5.33	3.24	12.30	14.17	16.65	10.88
Buy and hold	1.67	2.51	2.12	1.93	0.82	1.41	2.64	0.22

The table reports annualized certainty equivalent return (CER) gains (in percent) for a mean-variance investor with relative risk 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 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 .

Table 7
Sharpe ratios

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Predictor	1990:01–2013:12 out-of-sample period				2007:01–2013:12 out-of-sample period			
	$h = 1$	$h = 3$	$h = 6$	$h = 12$	$h = 1$	$h = 3$	$h = 6$	$h = 12$
Prevailing mean	0.34	0.28	0.32	0.31	0.25	0.14	0.07	0.16
DP	0.06	0.07	−0.03	−0.02	0.22	0.14	0.08	0.22
DY	0.09	0.08	−0.01	−0.02	0.28	0.20	0.12	0.23
EP	0.33	0.24	0.23	0.17	0.45	0.17	0.01	0.03
DE	0.33	0.24	0.19	0.31	0.34	0.08	−0.36	0.18
RVOL	0.26	0.22	0.22	0.27	0.41	0.30	0.16	0.19
BM	0.28	0.23	0.23	0.21	0.25	0.12	0.05	0.14
NTIS	0.17	0.10	0.13	0.14	−0.06	−0.23	−0.17	−0.03
TBL	0.37	0.29	0.30	0.29	0.23	0.09	0.02	0.15
LTY	0.33	0.23	0.25	0.14	0.24	0.06	−0.03	−0.03
LTR	0.28	0.30	0.31	0.38	0.21	0.09	0.01	0.21
TMS	0.34	0.31	0.34	0.36	0.21	0.12	0.12	0.35
DFY	−0.07	−0.05	0.01	0.21	−0.11	−0.08	0.05	0.25
DFR	0.46	0.32	0.38	0.34	0.52	0.31	0.28	0.22
INFL	0.31	0.25	0.42	0.41	0.05	0.00	0.34	0.43
SII	0.62	0.56	0.67	0.48	1.00	1.01	1.13	0.79
Buy and hold	0.46	0.43	0.46	0.41	0.35	0.33	0.32	0.30

The table reports annualized Sharpe ratios 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 forecast. See the notes to Table 1 for the variable definitions. The equity weight is contained 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 . 0.00 indicates less than 0.005 in absolute value.

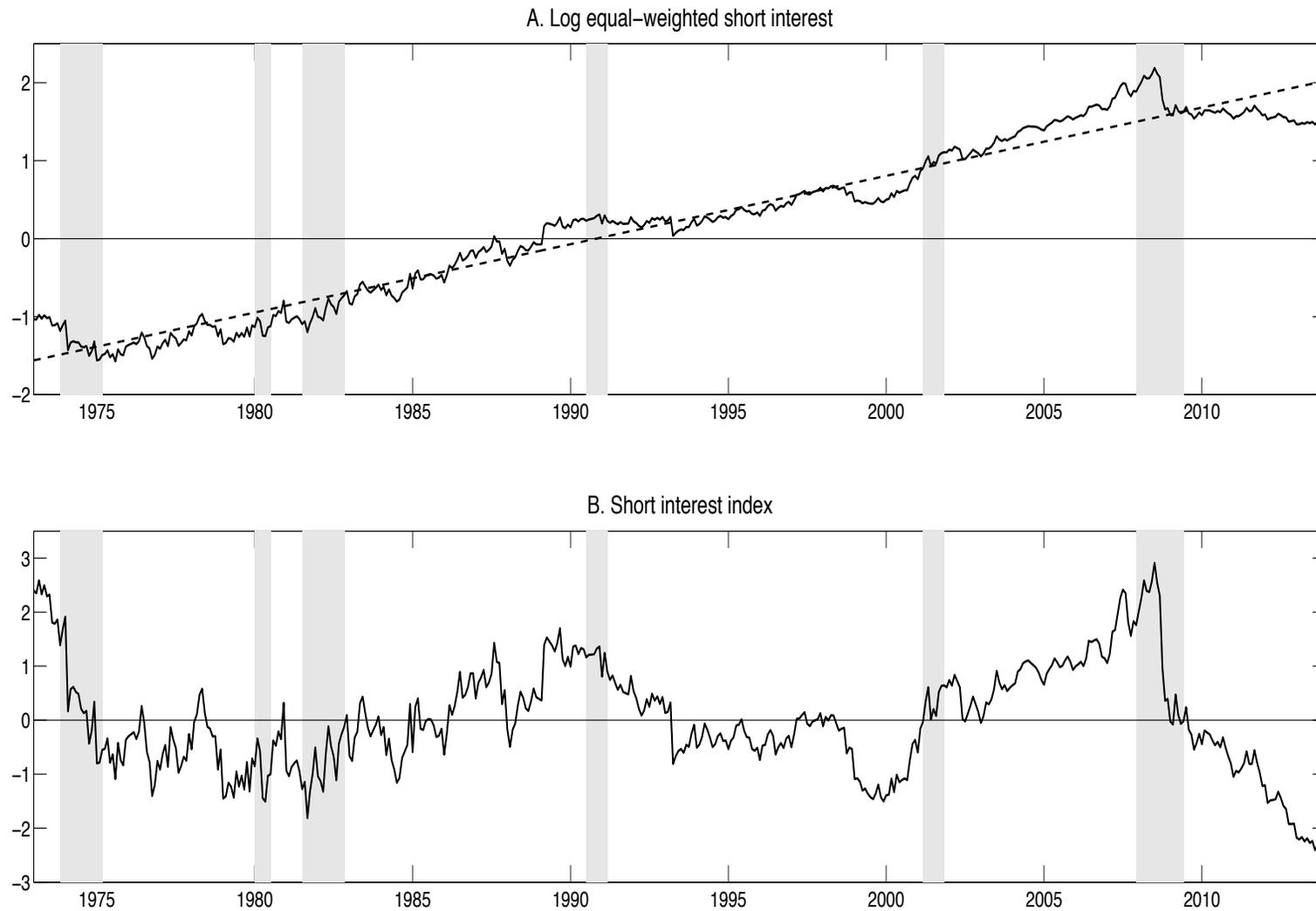


Figure 1
Aggregate short interest, 1973:01–2013:12

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.

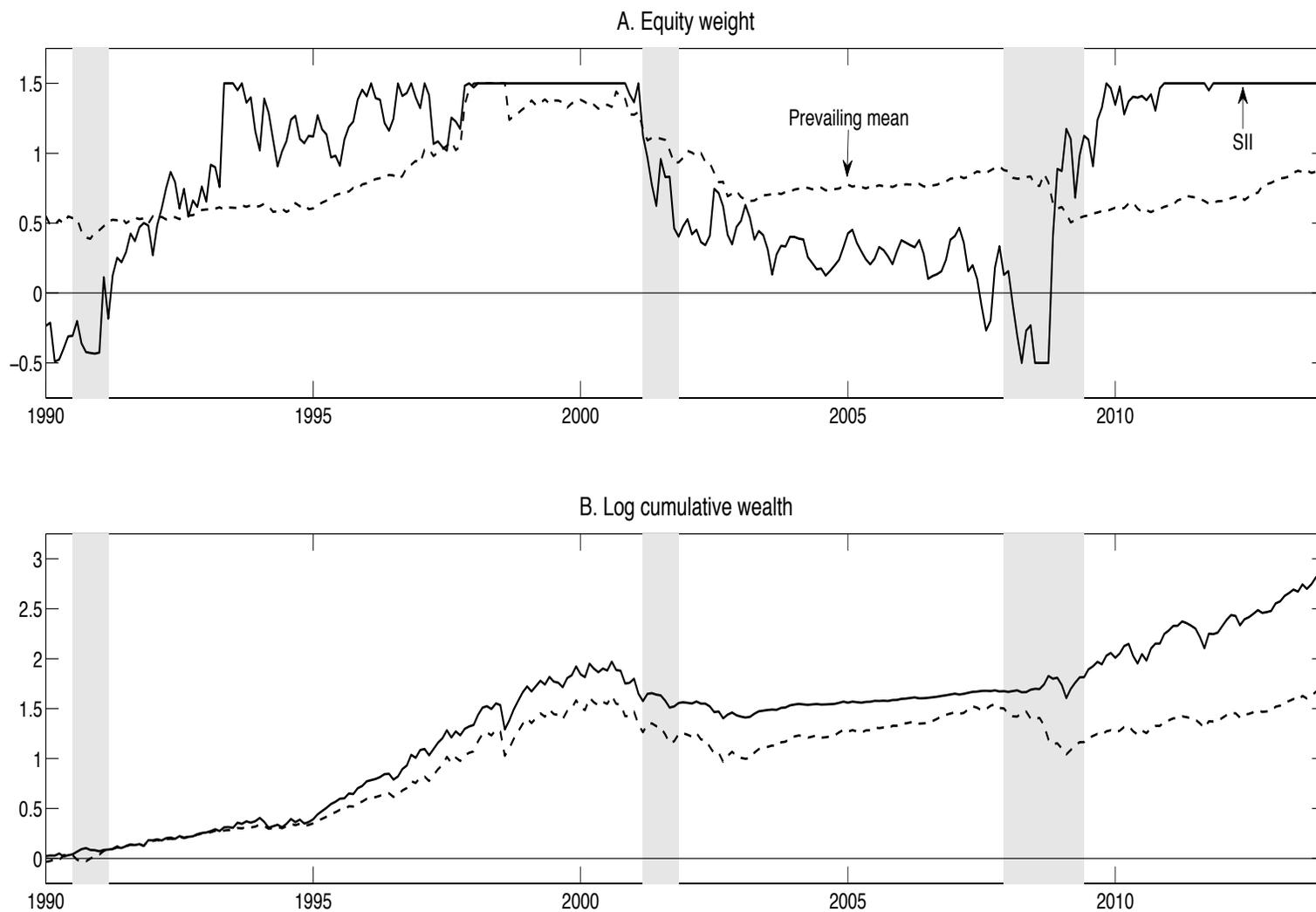


Figure 2
Equity weights and log cumulative wealth, 1990:01–2013:12

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 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.