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## GRA 19703 Master Thesis

### Thesis Master of Science 100% - W

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### Deltaker


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| **Navn:** | Jørgen Ruud Lunner og Stian Myran |


### Informasjon fra deltaker

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| **Tittel *:** | Revisiting "Short Interest and Aggregate Stock Returns": A Replication Study Incorporating Additional Predictor Variables and Addressing the Impact of the Financial Crisis |
| **Navn på veileder *:** | Alessandro Graniero |

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# Revisiting "Short Interest and Aggregate Stock Returns": A Replication Study Incorporating Additional Predictor Variables and Addressing the Impact of the Financial Crisis

## 1. Introduction

The question regarding predictability of stock returns has been a subject of inquiry in the world of finance for decades. Even though stock returns do not follow a clear, predictable pattern, research have demonstrated that a number of indicators can provide some insight into future stock returns. Goyal and Welch (2008) were among the first to do a comprehensive analysis of a wide number of factors that ostensibly may predict the equity premium. Although their conclusion at the time was that none of the variables analyzed merited strong endorsements (Goyal and Welch, 2008), the publishing of articles in financial journals attempting to anticipate the equity premium has not ceased since.

Predictor variables are organized into numerous categories, including Macroeconomic, sentiment, variance-related, and stock cross-section. It may be possible to predict stock returns to some extent due to the characteristics of equity markets and investor behavior. (Priestley, 2019). Fundamentally, stock prices are driven by earnings expectations, which are in turn affected by broader market conditions and the macroeconomic environment. If these factors change, future profit expectations will also shift, resulting in price fluctuations. This would essentially be prediction through a cash flow channel. Another possibility that has been extensively researched is a discount rate channel, this is movements driven by changes in expectations, related to future discount rates. Additionally, investor behavior may influence stock values to fluctuate in rather predictable ways. However, leveraging these predictions is not always simple or even practicable. This is due to tax, transaction, and model-related factors. It is also important to note that, according to the efficient market hypothesis, all accessible information at any one time is already reflected in prices, which practically precludes any ability to foresee and profit from stock price swings.

The original work "Short interest and aggregate stock returns" by Rapach, Ringgenberg, and Zhou (RRZ) proposes that short interest can predict future stock returns, with evidence confirming the function of short interest in anticipating changes in future aggregate cash flows and market returns. (Priestley, 2019). Recent research, particularly the article "Short interest, macroeconomic variables, and aggregate stock returns" by Richard Priestley, has raised doubts about the validity of these conclusions. Particularly, Priestley's argument is that the result of the original research is dependent on the inclusion of 2008, the year of the financial crisis. Excluding this time period renders short interest statistically insignificant and incapable of predicting future market moves, throwing serious doubt on RRZ's overall conclusion.

This master's thesis tries to duplicate and expand upon the original paper's findings. This will be accomplished by addressing the primary claims of the original research, namely that "short interest is arguably the strongest known predictor of the equity risk premium identified to date", "short interest outperforms a number of other popular return predictors" and lastly, that “the ability of short interest to predict future market returns stems predominantly from a cashflow channel”. (Rapach et al., 2016). We will take Priestley's concerns into account and include additional predictor variables identified in the literature in our study. The ultimate objective is to examine the impact of short interest in predicting stock returns and analyze whether the original paper's findings can withstand closer examination.

To accomplish this objective, we will incorporate four new predictor variables into our analysis, namely output gap ("ogap") by Cooper and Priestley (2009), the cross-section-based tail risk ("tail") by Kelly and Jiang (2014), the average correlation of stock returns ("avgcor") by Pollet and Wilson (2010), and the 14 technical indicators ("tchi") by Neely, Rapach, Tu and Zhou (2014). These four were selected based on the exhaustive analysis conducted by Goyal, Welch, and Zafirov in their study titled "A comprehensive 2021 look at the empirical performance of equity premium prediction II." These four variables were selected as the most promising monthly predictors and were thus an obvious addition to our research. By adding these variables, we expect to generate a more complete picture of the factors impacting aggregate stock returns and then reevaluate the importance of short interest in predicting stock market performance. (Rapach et al., 2016).

### 1.1 Motivation

This research is motivated by the 2020 "reddit army" activist campaign against wall street hedge funds. The goal of these events was to challenge the huge Wall Street hedge funds' short selling operations. The ultimate objective was to induce short squeezes, in which major institutional investors were compelled to purchase back shares of the underlying asset at ever-increasing prices to cover their short positions and reduce their losses. These occurrences piqued our attention in the topic of short selling. Which begs the question: who are these short sellers, and do they have superior information to individual investors? If this is the case, short sellers may have obtained knowledge that is not yet reflected in current prices; hence, the changing short interest may include crucial information on future stock price movements. How does it compare to other variables that seek to explain the time-varying character of future stock market returns and forecast the equity premium?

### 1.2 Thesis structure

The structure of the thesis will be as follows: In Section 2, a literature review of the most influential publications will be presented, examining the original work, Priestley's concerns, and the additional predictor variables. The third section will describe the methodology, including any changes from the original study and the addition of new predictor variables. In Section 4, The results of the replication and extension research will be presented and compared to the original paper. In addition, the ramifications of the results will be discussed in relation to the original article, Priestley's paper, and the broader literature on stock return prediction. Section 5 finishes the thesis by summing up the key results, conclusions, and contributions to the field of research.

## 2. Literature review

The primary purpose of this thesis is to reproduce the empirical findings of the original RRZ study and to reexamine the papers' key claims. The first assertion is that " short interest is arguably the strongest known predictor of the equity risk premium identified to date." (Rapach et al., 2016). To examine this assertion, we shall employ an approach comparable to that of Priestley's study. Like RRZ, Priestley finds a high correlation between short interest and future stock returns over the study period of 1973 to 2015. The link also appears to persist when running out of sample testing, 1990-2015. The predictability of the short-interest variable, however, vanishes entirely when the year 2008 is omitted from both in and out-of-sample testing, i.e., for the period before and after 2008. Priestley concludes, therefore, that the entire predictability of short interest is due to the inclusion of the year 2008. This gap and the subsequent result that leads to Priestley's conclusion, which the RRZ publication completely ignores, will be examined, and this thesis will contribute to its resolution.

The second assertion is that " short interest outperforms a host of other popular return predictors." (Rapach et al., 2016). To refute this assertion, we would like to include four additional variables in the analysis. The original work by RRZ employs fourteen variables collected by Goyal and Welch (2008). However, Goyal and Welch discovered that their predictors performed poorly, particularly when predicting stock returns after the oil price crisis of the mid-1970s. (Goyal and Welch, 2008). In order to refute this claim and conduct a more recent comparison, we introduce new variables that have all been deemed among the most promising predictor variables after extensive testing and reexamination in the paper by Goyal, Welch, and Zafirov entitled "A comprehensive 2021 look at the empirical performance of equity premium prediction II." They investigate 29 variables from 26 separate articles that were published after Goyal and Welch (2008). Using OLS in sample univariate forecasting regression, they first replicated and validated the findings for the majority of predictors. The sample was then expanded to 2021 for all predictors. The OOS performance was tested before finally, the performance of each variable in four straightforward investing strategies was evaluated. (GWZ, 2021) Their results were generally regarded as disappointing. The majority of the investigated variables lost any predictive ability. However, a handful of them were deemed promising, and we included four that had monthly observations that matched with the short interest variable in our study.

## 3. Methodology

### 3.1 Data

We got access to the data used in the original paper. That's why in this section, we describe how the authors compiled an aggregated short interest series and the predictive variables they compared with this series as well as the additional variables we have included in our study. We also received the original MATLAB code used in the creation of the paper from the authors, we have then translated the code into Python and replicated their main empirical results as well as expanding on their findings. Then, we used new predictor variables from the paper "A Comprehensive 2021 look at the empirical performance of equity premium prediction II" which the authors (Goyal, Welch and Zafirov) kindly provided as MATLAB code.

### 3.2 Short Interest Construction

In this section, we will briefly cover how exactly the short interest variable was constructed by the original authors, RRZ. The objective was to compile a consolidated series of short interest data from individual company-level information. This data was then evaluated based on its predictive power and compared with fourteen predictor variables highlighted in prior studies. Additionally, our research will introduce and examine the predictive abilities of four new variables that we have incorporated.

The data on raw short interest used in the creation of the short interest variable was gathered from Compustat and includes data ranging across a wide set of asset classes, like; common equities, ADRs (American depositary receipts), ETFs (Exchange traded funds), and REITs (Real estate investment trusts). The inclusion of ETFs is mentioned as particularly important because it is seen as one of the easiest and cheapest ways for an investor to attain short exposure to a desired sector or market. The end goal is to predict the excess return on a value-weighted market portfolio, more specifically the S&P 500 index's log return less the log return on a one-month Treasury bill. (Rapach et al., 2016).

The cumulative short interest series was constructed employing company-specific short interest data procured from Compustat, i.e., the quantity of shares shorted for a particular company. (Rapach et al., 2016). The data was also somewhat adjusted before the short interest series was constructed; most importantly, the raw data was normalized and assets with low market capitalization was excluded. Monthly, American stock exchanges disclose information regarding the quantity of short interest for each stock. At each point in time through the study, this data was accessible to investors, which is important for the usability of the predictor in a real-world setting. Using the original dataset, the short interest data initiates in January 1973, and our investigation spans until December 2014 (Rapach et al., 2016). With the updated dataset, the short interest data initiates at the same time but spans until December 2021. Every month, aggregate short interest is estimated as the equal-weighted average of all asset-level short interest data (referred to as EWSI) (Rapach et al., 2016).

Regarding the new dataset in which SII is recalculated and extended to December 2021, it is collected from the website of Guofu Zhou. Three modifications account for the minor difference between the new and original datasets. First off, the raw data on short interest from Compustat has changed marginally according to coauthor

Matthew Ringgenberg, this is due to revisions made in reports after they have been published, which cause the aggregate short interest number to change. Secondly, CRSP has altered the historical values of outstanding shares for a number of companies in its database in recent years. Lastly, the authors themselves added a new filter that excludes erroneous data around stock splits and buybacks. This filter compares short interest and shares outstanding to each one's own adjusted values; if there is a large discrepancy, these observations are dropped.

To contextualize the results within the market return predictability research field, the predictive power of aggregate short interest is contrasted with that of 14 monthly predictor variables from Goyal and Welch (2008). (Rapach et al., 2016). We also introduce a newer set of predictor variables into the comparison, as mentioned earlier. Following is a brief introduction to each of the 19 total predictor variables:

- Log dividend-price ratio (DP): This is calculated as the difference between the logarithm of a 12-month moving total of dividends paid on the S&P 500 index and the logarithm of stock prices on the same index. (Rapach et al., 2016)
- Log dividend yield (DY): This is calculated as the difference between the logarithm of a 12-month moving total of dividends and the logarithm of the lagged stock prices. (Rapach et al., 2016)
- Log earnings-price ratio (EP): It's the difference between the logarithm of a 12-month moving total of earnings on the S&P 500 index and the logarithm of stock prices. (Rapach et al., 2016)
- Log dividend-payout ratio (DE): It's computed as the logarithm of a 12-month moving total of dividends subtracted from the logarithm of a 12-month moving total of earnings. (Rapach et al., 2016)
- Excess stock return volatility (RVOL): It's measured using a 12-month moving standard deviation estimator, following the approach in Mele (2007). (Rapach et al., 2016)
- Book-to-market ratio (BM): This is the ratio of Dow Jones Industrial Average book value to market value. (Rapach et al., 2016)

- Net equity expansion (NTIS): This is the ratio of a 12-month moving sums of net equity issues by NYSE-listed stocks divided by their total year-end market capitalization. (Rapach et al., 2016)
- Treasury bill rate (TBL): This is the interest rate on a three-month Treasury bill. (Rapach et al., 2016)
- Long-term yield (LTY): This denotes the yield on long-term government bonds. (Rapach et al., 2016)
- Long-term return (LTR): This refers to the return on long-term government bonds. (Rapach et al., 2016)
- Term spread (TMS): It is the spread between the long-term yield and the Treasury bill rate. (Rapach et al., 2016)
- Default yield spread (DFY): "It is the difference between BAA- and AAA-rated corporate bond yields". (Rapach et al., 2016)
- Default return spread (DFR): It is calculated as the long-term corporate bond return subtracted from the long-term government bond return. (Rapach et al., 2016)
- Inflation (INFL): "This is calculated from the Consumer Price Index (CPI)". (Rapach et al., 2016). The values are lagged one month because information about inflation is released in the following month. (Rapach et al., 2016)
- Output Gap: The output gap is the difference between actual output and potential output of an economy. It serves as a measure of the cyclical position of an economy, with a positive output gap indicating that an economy is operating above its potential (overheating), while a negative output gap implies that it is operating below its potential (recessionary). The output gap is relevant for stock returns because it reflects changes in economic conditions that can influence corporate profits and investor sentiment. (Cooper and Priestley, 2009)
- Cross-section based Tail-Risk: Tail-risk is a measure of the risk of extreme negative events or losses in financial markets. The cross-section based tail-risk captures the distribution of potential extreme losses across individual stocks, providing insights into the overall risk profile of the stock market. This measure can help predict stock returns by identifying periods of increased risk and uncertainty, which may be associated with lower future returns due to higher risk aversion among investors. (Kelly and Jiang, 2014)

- Average Correlation of Stock Returns: This predictor variable measures the average pairwise correlation among individual stock returns in a given period. A higher average correlation implies that stocks are moving more in tandem, reflecting common factors or market-wide shocks driving returns. The average correlation of stock returns can provide insights into market dynamics and the degree of diversification potential available to investors, which may influence future stock returns. (Pollet and Wilson, 2010)
- Technical Indicators ("tchi"): The 14 technical indicators are derived from historical price and trading volume data, capturing various aspects of market trends, momentum, and investor sentiment. These technical indicators can help predict stock returns by identifying patterns and trends in market behavior that may persist or reverse in the future. The inclusion of these technical indicators allows for a comprehensive assessment of the role of market-based factors in predicting stock returns, complementing the other macroeconomic and risk-related predictors. (Neely et al., 2014)

### 3.3 Predictive regression

We use a predictive regression model, a common approach to analyze the predictability of total stock returns: $r_{t:t+h} = \alpha + \beta x_t \; + \varepsilon_{t_t+h}$ for $t = 1, \ldots, T - h$

Where $r_{t:t+h} = \frac{1}{h} \times (r_{t+1} + \cdots + r_{t+h})$ signifies the mean log excess return of the S&P 500 for the succeeding h months, and $x_t$ serves as a predictive factor. Our analysis seeks to validate the significance of β. To reinforce the precision of our tests, we incorporated the advice of Inoue and Kilian (2005) to apply a one-sided hypothesis. They recommend the use of one-sided tests in statistical analyses as they often align better with theoretical predictions of the sign of a coefficient, in this case, β. (Rapach et al., 2016). This is because, in economic theory, we typically have a specific expectation about the direction of a relationship, not just whether a relationship exists.

For example, in the case of predicting stock returns, theory might suggest that a certain predictor variable (X) should have a positive relationship. That is, when X increases, Y should also increase, implying $\beta > 0$. A one-sided test allows us to test exactly this kind of hypothesis, making it more powerful for detecting the predicted effect when it exists. On the other hand, if the predictor is believed to have a negative relationship, then the contrary would be true.

In contrast, a two-sided test would only test whether $\beta$ is different from zero, not whether it's greater or less than 0. Therefore, using a one-sided test when you have clear theoretical predictions about the sign of the relationship can increase the power of your test, helping to avoid type II errors.

However, we have in total 19 predictors that have both positive and negative relationships. The study solves this problem by multiplying every negative correlation variable with (-1). Then, it is possible to have a one-sided test that test if $\beta > 0$.

Nonetheless, as the original paper notes, making statistical inferences from this equation is challenging due to several known issues such as the Stambaugh (1999) bias and the overlap of observations when $h > 1$. (Rapach et al., 2016). Stambaugh (1999) bias refers to a statistical bias that can occur when using lagged predictor variables to forecast returns. This bias tends to upwardly distort the coefficient estimates, making the predictor variable appear more significant than it is. (Stambaugh, 1999). Another problem arises from the overlap of observations when h (the prediction horizon) is greater than one. (Nelson and Kim, 1993). This is because using overlapping data points can create autocorrelation, violating the fifth assumptions of ordinary least squares (OLS) regression that assume no heteroscedasticity and autocorrelation. This can lead to inefficient and biased coefficient estimates.

To combat these issues, the study uses a robust method for calculating the t-statistics which is resistant to heteroskedasticity and autocorrelation. Additionally, the study uses a method known as 'wild bootstrap' to calculate p-values for their hypothesis tests. (Rapach et al., 2016). Bootstrapping is a resampling technique that can be used to estimate the sampling distribution of a statistic when the true distribution is unknown or difficult to derive. This method is particularly useful in this context as it is robust to the aforementioned issues such as Stambaugh bias and overlapping observations. The 'wild' bootstrap is a specific form of bootstrapping that is suitable when the error terms are heteroskedastic. The study uses these methods to test the null hypothesis H0: $\beta = 0$ against the alternative hypothesis HA: $\beta > 0$.

Lastly the study performed a principal component regression. By using an orthogonal transformation, principal component analysis (PCA) creates a new set of variables called principal components from the original variables. These main components successfully eliminate multicollinearity since they are uncorrelated and linear combinations of the original variables. These elements also account for the variation in the data; the first principal component accounts for the greatest variation, the second for the next-largest, and so on. The principal components are then used as the new independent variables in a linear regression analysis. Principal components can be used in any number, but normally, you would use fewer than the original variables, concentrating on the ones that explain the most variance. (Rapach et al., 2016).

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

Here $\hat{f}_{1,t}$, $\hat{f}_{2,t}$ and $\hat{f}_{3,t}$ are the initial principal components taken from the Goyal and Welch (2008) predictors plus GWZ (2021). As Ludvigson and Ng (2007) demonstrated, principal components serve as an efficient method to include data from numerous economic variables in stock return predictive regression models. (Rapach et al., 2016). Instead of incorporating each variable separately, PCA allows us to use these principal components as comprehensive representatives of all variables. This simplifies the predictive regression model, allowing us to control for all these predictor variables while keeping the model relatively simple. This, in turn, helps in effectively assessing the predictive power of the SII, as the influence of the other predictors is already incorporated in the model through these principal components (Rapach et al., 2016).

### 3.4 Out-of-sample tests

To check the robustness of the in-sample results, we must include out-of-sample tests. This is due to the possibility that predictors can perform well in the in-sample period, but badly when tested out-of-sample. (Rapach et al., 2016). This is typical for predictors that were significant in the past but is not anymore due to a more efficient market. Our hypothesis is that the 14 GW predictors are no longer significant, and we decided to include four new predictors to reduce this effect. The general idea is that it is unfair to compare SII´s performance to other predictors that no longer perform.

In the study, a forecast is generated for each predictor using a predictive regression model. This is done by applying the formula:
$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t$ , in this equation $\hat{\alpha}_t$ and $\hat{\beta}_t$ are OLS estimates of $\alpha$ and β, and they are based upon data to month t. As a reference, the average forecast is used. This average forecast is the mean of all excess returns observed until the month t. Essentially, this benchmark presumes a constant excess return, hinting that β is zero and suggesting that returns are unpredictable. This concept aligns with the log model of stock prices, which is based on the random walk theory. (Rapach et al., 2016)

The focus is on gauging the degree of reduction in the mean squared forecast error (MSFE) when the predictive regression forecast is compared against the prevailing mean benchmark. This metric is coined as the out-of-sample R2 statistic (R2OS) by Campbell and Thompson (2008). (Rapach et al., 2016). The R2OS can be seen as an extension of the standard in-sample R2 measurement. And it’s intended to measure the quantity of variation in the dependent variable that can be explained by a model when applied to new observations. The R2OS measure is calculated by splitting the sample into a training set and a testing set. The training set is then used to estimate the model, obtaining the estimated coefficients, while the testing set evaluates the model’s predictive ability.

In order to determine whether the predictive regression forecast significantly improves the Mean Squared Forecast Error (MSFE), the statistical measure proposed by Clark and West (2007) is utilized. This method tests two contrasting hypotheses. The first is the null hypothesis, which states that the average MSFE using the prevailing method is equal to or less than the MSFE from the predictive regression. In essence, this implies that our new model doesn't improve the forecasting accuracy. The second is the alternative hypothesis, stating that the average MSFE using the prevailing method is in fact greater than the MSFE from our predictive regression. This would suggest that our model does indeed provide a more accurate forecast. These two hypotheses can also be expressed in terms of the Out-of-Sample R Squared statistic (R2OS), with the null hypothesis suggesting that R2OS is less than or equal to 0 and the alternative hypothesis suggesting that R2OS is greater than 0. (Rapach et al., 2016)

### 3.5 Forecast encompassing tests

Forecast encompassing tests are employed to directly compare the informative content of different predictive regression forecasts. For the main comparison, the SII based forecast is compared with individual predictive regression forecasts based on the GW predictors and our additional predictors.

The initial step involves constructing a convex combination forecast. This is essentially a balanced mixture of a predictive regression forecast grounded on one of the predictors and the predictive regression forecast rooted in the SII. By creating a convex blend of these two forecasts, the optimal combination forecast attempts to leverage the predictive strength of both models, optimizing the forecast's overall performance.

This combination forecast serves a dual purpose. First, it evaluates if incorporating other forecasts could enhance the predictive ability of the SII model. If the optimal combination places significant weight on the SII model and minimal to none on the other models, it indicates that the SII model encompasses all the valuable predictive information. On the other hand, if the combination forecast allocates considerable weight to other models, it suggests these models offer additional predictive information that the SII model doesn't capture. This approach, therefore, enables an accurate comparison of different predictive models while mitigating the risk of overlooking valuable information.

In the equation $\hat{r}^{*}_{t:t+h} = (1-\lambda)\hat{r}^{i}_{T:t+h} + \lambda\hat{r}^{\mathrm{SII}}_{T:t+h}$

Where $\hat{r}^{i}_{T:t+h}$ $\hat{r}^{\mathrm{SII}}_{T:t+h}$ symbolizes the predictive regression forecast hinged on SII, with λ falling within the range of 0 to 1. If λ equals 0, it means the optimal combination forecast excludes the forecast based on the SII. Therefore, the predictive power of the popular predictor is considered to encompass that of the SII. In this scenario, the SII doesn't provide any additional useful information for forecasting excess returns beyond what's already available from the compared predictor. We can then see that the second term is zero and the first term has a coefficient equal to 1. Therefore, the first term that includes the compared predictor has all the explanatory power. (Rapach et al., 2016)

On the other hand, if λ is greater than 0, the optimal combination forecast does include the forecast based on the SII. This implies that the compared predictor's forecast does not encompass the SII-based forecast. In other words, SII offers additional useful information for predicting excess returns that is not already provided by the popular predictor. Both of the terms in the equation explain some of the variation in excess return since none of the coefficients is equal to zero, unless of course λ=1. Then SII encompasses all the useful information the compared predictors contain. (Rapach et al., 2016).

### 3.6 Why equal-weighted short interest?

The reasons behind the equal-weighted short interest measure in the original study is based on a few reasonable assumptions. The decision was taken based on evidence gathered from research and observations from the sample, which lead RRZ to conclude that short interest had less of a significance in large-cap stocks as compared to mid-size stocks. Stocks of varying market capitalizations respond differently to short selling. Therefore, value weighted short interest would over represent large companies. Additionally, the equal-weighted approach captures short sellers' information from a broader variety of firms compared to the value-weighted short interest method. The variation of short interest in mid-size stocks turned out to be greater. It therefore makes more sense to equally weight the short interest measure, in order to capture more of the most active segment in relation to short interest, which turned out to be mid-size stocks. (Rapach et al., 2016).

### 3.7 Asset allocation

In the asset allocation section, a mean variance framework has been utilized. The weights of the portfolio allocated to equities are calculated using the following formula. $W_t = \frac{1}{\gamma} * \frac{\hat{r}+1}{\widehat{\sigma^2}t+1}$

Where $\gamma$ is the investors risk aversion coefficient and $\hat{r}_{t+1}$ is the predictive regression excess return forecast generated. $\widehat{\sigma_{t+1}}^2$ is a forecast of the variance in the excess returns. The forecast with regards to volatility are created by using a ten-year moving window of past returns. The weights are also restricted to be between -0,5 and 1,5. The certainty equivalent return or (CER) for an investor who allocates given the weights calculated above are calculated using the following formula. $CER = \overline{R_p} - 0{,}5 * \gamma * \sigma_p^2$. Where $\bar{R}_p$ and $\sigma_p^2$ are the portfolio estimates for the mean and variance over the forecast evaluation period. (Rapach et al., 2016).

### 3.8 Stock return decomposition

In the stock return decomposition section, there is employed a vector autoregression (VAR) model, which builds upon the work of Campbell (1991) and Campbell and Ammer (1993), in order to dissect stock returns into various components. The end goal is to develop a more comprehensive understanding of the factors driving stock returns as well as the predictive power of SII. (Rapach et al., 2016)

The first step involves defining the log stock return. This is calculated in the following way: $r_{t+1} = \log\left[\frac{(\mathrm{P}_{t+1}+D_{t+1})}{P_t}\right]$. $P_t$ represent the stock price, while $D_t$ is the dividend in month t. The model therefore takes account of both the changes in the stocks price, as well as the dividends paid, and can therefore be considered a comprehensive measure of the stocks return. The calculations of the stock return are simplified by the original authors using the (Campbell and Shiller, 1998) log linear approximation of $r_{t+1}$, which are given by the following equation: $r_{t+1} \approx k + \rho p_{t+1} + (1-\rho)d_{t+1} - p_t$. In this equation $\rho = \frac{1}{1+\exp(d-p)}$ and $k = -\log(\rho) - (1-\rho)\log\left[\left(\frac{1}{\rho}\right) - 1\right]$. Then Campbell and Shiller stock price decomposition is used, in order to express $p_t$ as: $p_t = \sum_{j=0}^{\infty} \rho^j\,(1-\rho)d_{t+1+j} - \sum_{j=0}^{\infty} \rho^j\, r_{t+1+j} + \frac{k}{1-\rho}$. Moving on, the log stock return innovation is then decomposed into two components, cash flow news and discount rate news. $\eta_{t+1}^{r} = \eta_{t+1}^{CF} - \eta_{t+1}^{DR}$. The stock return innovation, cash flow news and discount rate news are defined as follows: $\eta_{t+1}^{r} = r_{t+1} - E_t r_{t+1}$, $\eta_{t+1}^{CF} = (E_{t+1} - E_t)\sum_{j=0}^{\infty} \rho^j\,\Delta d_{t+1+j}$ and, $\eta_{t+1}^{DR} = (E_{t+1} - E_t)\sum_{j=1}^{\infty} \rho^j\, r_{t+1+j}$. Where $E_t$ denote the expectation conditional on information through month t.
A VAR model is employed in order to extract the two components, cash flow and the discount rate news from the stock return innovations. This statistical model captures linear interdependencies among different time series and is in this case used to separate stock return into two parts. One that's due to changes in expectations related to future cashflows and the second due to changes in the discount rates. Now, by rearranging the stock return innovation, using $r_{t+1} = E_t r_{t+1} + \eta_{t+1}^{r}$, the log stock return can be written as: $r_{t+1} = E_t r_{t+1} + \eta_{t+1}^{CF} - \eta_{t+1}^{DR}$. (Rapach et al., 2016).

Then a predictive regression model is considered for each of the individual components on the right hand side of the previous equation. $\widehat{E_t}\, r_{t+1=}\ \alpha_{\hat{E}} +\ \beta_{\hat{E}} SII_t + \varepsilon^{\hat{E}}_{t+1}$ , $\hat{\eta}^{CF}_{t+1} =\ \beta_{CF} SII_t + \varepsilon^{CF}_{t+1}$ and $\hat{\eta}^{DR}_{t+1} =\ \beta_{DR} SII_t + \varepsilon^{DR}_{t+1}$.

The predictive regression model for the log stock return based on SII is written as: $r_{t+1}\ =\ \alpha + \beta SII_t + \varepsilon_{t+1}$. Lastly, the relation between the estimated betas in the first three and the last equation is established, $\hat{\beta}\ =\ \hat{\beta}_{\hat{E}} + \hat{\beta}_{CF} - \hat{\beta}_{DR}$. By comparing the estimated betas in the four previous equations, it's possible to determine how SIIs ability to predict stock returns relates to its capability of anticipating the components on the right-hand side. (Rapach et al., 2016).

## 4. Results and discussion

The goal of this master's thesis was to replicate and confirm the key empirical findings of the paper "Short Interest and Aggregate Stock Returns," which has been accomplished. In addition, we intended to study the predictive power and robustness of SII in the context of the authors' original claims, with the end goal of providing solid evidence either in support of or against the aforementioned claims. In addition, we desired a more in-depth examination of the current status on the topic regarding predictability of stock return and the equity premium, utilizing the most exhaustive and credible research articles on this topic to date as references. This topic is covered in this section of the paper.

### 4.1 Predictive regression analysis

In this section, we will reproduce the key in-sample findings from RRZ (2016). We will also examine RRZ's assertion that " short interest outperforms a host of other popular return predictors." In addition to the fourteen factors from Goyal and Welch (2008) and the short interest variable developed by RRZ, we will offer additional results incorporating four new alternative variables.

In Table 3 of the exhibits, the in-sample predictive regression estimates for the complete sample period 1973:01-2014:12 is presented. The table contains the estimated beta coefficients and R2 for the predictive regression model. In addition, the heteroskedasticity and autocorrelation robust t-statistics are also shown. It is important to note that several predictor variables (NTIS, TBL, LTY, INFL, SII, SIIPC, OGAP, and TAIL) have been transformed to negative values; the rationale for this is discussed in the methodology section. Each predictive regression is computed on a monthly, quarterly, semiannual, and annual horizon. As evidenced by the result, four of the predictors proposed by Goyal and Welch (2008) demonstrate predictive ability at a monthly horizon. At the 5% level for RVOL, LTR, and TMS, and DFR are significant at the 10 percent level. DFR's estimated beta value is the highest among these four (0.50).

Short interest (SII) appears in the second-to-last row of the table; it has a significance level of 1 percent and an estimated beta coefficient of 0.50. The economic intuition behind this figure is that a one standard deviation increase in the SII predictor is connected with a 50 basis point decline in the excess return of the S&P 500 index for the following month. This would decrease the annualized excess return by around 6 percent. (Rapach et al., 2016). R2 of DFR is 1.24%, the same as SII, and they are the highest original predictor values at a monthly horizon. These results are identical to RRZ's findings; hence we are able to replicate the original paper's results.

TCHI is significant at the 5% level, while OGAP and TAIL are both significant at the 1% level. OGAP possesses the highest beta value among all included predictors (0,61). An increase of one standard deviation in OGAP is associated with a decrease of 0.61 basis points in the equities market's excess return for the next month. This is the same economic intuition as previously, but it is significantly more impactful in this instance. Annualized, this value corresponds to around 7.3% each year. At a monthly horizon, the R2 of OGAP is 1.86%, the highest of all studied variables.

The R2 estimates on a monthly horizon may appear relatively small and insignificant, which is not surprising given that monthly returns have a major random component.

However, if we examine Campbell and Thompson (2008), as the paper did, they claim that anything above a monthly R2 statistic of 0.5 percent should be regarded a noteworthy addition to return predictability. The majority of significant predictors are significantly above this threshold, with our newly added predictors at the very top. (Rapach et al., 2016)

Compared to the original predictor set, SII surpasses the competition in terms of predictability for quarterly, semi-annual, and annual horizons (h=3,6,12). On a quarterly time horizon, the beta estimate for SII is 0.56 with an R2 of 4.37 percent, which is again quite significant. It now outperforms each and every predictor variable, new and old, with the exception of OGAP. With a beta of 0.59 and an estimated R2 of 5%, OGAP is the top performer once again. Similarly, at the semi-annual horizon, OGAP and SII outperform the rest in terms of beta and R2 performance. With a beta of 0.57 and an R2 of 8.53 percent, OGAP once again emerged victorious. TAIL has the best annual performance with beta of 0.55 and R2 of 15.8%. OGAP also outperforms SII in this instance, despite the close competition.

The very last row of the table includes the predictive regression estimates, when including the first three principal components extracted from the other variables utilized, including the original variables from Goyal and Welch (2008) and the four new additions. The beta of SII is now 0.47 and the R2 is 1.07 percent; while the results are still significant down to the 1 percent level, they have decreased compared to the original paper's findings of 0.51 beta and R2 of 1.27 percent at a monthly horizon. Including the four additional predictor variables in the principal components affects the prediction ability of SII. On this basis, it is safe to conclude that SII still contain some information that is distinct from the collection of original and extra predictors, but the contribution of differential information is reduced.

Now let's illuminate Richard Priestley's primary argument against SII as a superior predictive variable. Figure 2, which depicts the log equal-weighted short interest as a solid line, demonstrates a constant rising trend beginning in the 1980s. The trend flattens out for a few years throughout the 2000s before resuming a higher trajectory into 2008. In 2008, we detect a significant peak, which is followed by a strong decline and leveling out for the remainder of the sample. The dotted line in figure 2 displays the linear trend for the time series. Until 2008, this dotted line is pretty consistent with the overall movement of the short interest measure across time. Thereafter, the remainder of the sample period is characterized by a noticeable change in direction. (Priestley, 2019)

The original authors RRZ argue that a linear linearly detrended version of the gap between the dashed and solid lines in figure A will " Capture the variation in short interest that is due to changes in beliefs of short sellers, and not just secular changes in equity lending conditions and/or the amount of capital devoted to short arbitrage" (Priestley, 2019).

This gap is depicted in Figure 1 and is designated SII (Short interest index). On closer examination, one observes a trend similar to the one stated previously, namely a major decline around the year 2000, followed by an upward trend over the next eight years, culminating in a peak around 2008. The economic interpretation of this eight-year era of accumulation is a period during which asset prices are excessively high and short sellers anticipate a market decline. This is a fairly lengthy time to hold a short position in anticipation of a 2008 correction, as Priestley emphasized in his study. (Priestley, 2019). Such a position would undoubtedly incur enormous unrealized losses during the anticipated period, as well as substantial transaction fees. One could therefore question the profitability and durability of a trading strategy based on such an indicator. This ties in with the concern raised by Goyal and Welch (2008) in their paper, that “the models would not have helped an investor with access only to information available at the time to time the market.” (Goyal and Welch, 2008)

The evidence presented in the preceding paragraphs necessitates more examination, particularly in relation to RRZ's prior assertion that "short interest is arguably the strongest known predictor of the equities risk premium identified to date." (Rapach et al., 2016). The in-sample data were divided into distinct eras as seen in table 3 panel B, one of which contains the sharp decline around the year of the financial crisis and the other of which excludes 2008. The purpose of this notion is to determine if the predictive power of SII remains steady throughout the sample, or if the only reason for its fairly impressive performance is the financial crisis's distinctive pattern and significant decline. (Priestley, 2019) According to the evidence presented in the section above, table 3 demonstrates that the SII has strong predictive power and significance across all horizons for the 1973:01-2014:12 sample period.

This may lead us to conclude that SII is a strong predictor of stock return in the sample and that it offers impressive explanatory power, not only when compared to older, somewhat out-of-date predictors, but also when compared to newer comparable predictors, which have demonstrated recent promise and research potential. However, if we examine the findings in panel B of table 3, we get a completely distinct and contradictory piece of evidence about the significance of SII. In a shorter sample period, from 1973:01 to 2007:12, which excludes the impact of the financial crisis, the coefficient estimate of SII on a monthly horizon falls to 0.21 with an R2 of 0.15, and the results are no longer statistically significant. At longer horizons, the outcomes remain unchanged, the coefficients decline, and R2 as well as significance levels are low. Based on this, the conclusion is that SII does not demonstrate the ability to predict stock returns in a sample spanning 1973 to 2008. (Priestley, 2019). To further show the significance of year 2008, we've added two more time periods. The period between 2008:01-2014:12 and 2009:01-2014:12. In the first period, including 2008, the SII has a significant forecasting ability. The estimated coefficient at a monthly horizon is statistically significant at the 1% level, with an estimated beta value of 1.03 and an R2 of 8.24%. The calculated coefficient for the second period, excluding 2008, falls to -0.16 with an R2 of 0.11 percent, and the results are no longer statistically significant. This finding significantly confirms Priestley's theory and subsequent conclusion that SII's excellent predicting power is only valid for a 12-

month period out of a total sample length of 504. Approximately 98 percent of the sample lacks support for the authors' original assertion regarding the superiority of SII.

Let's now evaluate the second claim of  RRZ, which asserts that "short interest outperforms a host of other popular return predictors" both in and out of sample. SII is compared in an inappropriate context, which is the first issue with this assertion. As previously stated, the Goyal and Welch 2008 variables have a highly dubious track record in predicting market returns since the mid-1970s Oil Crisis. This was acknowledged by Goyal and Welch (2008) in their own paper. They determined that the models performed badly overall and that evidence from the past 30 years clearly contradicts all of them. "By assuming that the equity premium is like it has always been, an investor would have predicted just as well". (GW, 2008). This is a solid argument against RRZ's overall comparison. It is not necessarily the outperformance of SII relative to the GW variables, but rather that the GW variables cannot forecast stock returns in general.

For this reason, we decided to incorporate a more recent set of predictor variables, which would hopefully make the comparison more accurate. The initial GW variables were all macroeconomic predictor variables, meaning their purpose was to gauge business and economic conditions and, by extension, to account for variation in expected returns attributable to these factors. SII, on the other hand, is defined by RRZ as “covering informed investors' shorting of the market based on knowledge not yet absorbed into prices” (Rapach et al., 2016), a sentiment-related predictor. In order to give a bit of diversity to the comparison, our newly included predictors cover a slightly broader range of categories.

This provides a smooth segue into the correlation estimates between SII and the new GWZ variables. The predictor variable correlations for the sample period 1973:01 to 2014:12 is presented in Table 2. The highest correlation coefficient is 0.17 between

OGAP and SII. TAIL, TCHI, and AVGCOR have a correlation of -0.02, -0.14, and 0.1, respectively.

We have already discussed SII's excellent in-sample prediction capabilities, its superiority over the original predictors, and the reasons for this success. If we now examine table 3, panel A, we find that SII has been consistently outperformed by some of the new entrants throughout all four-time horizons. At each horizon, OGAP surpasses SII in terms of coefficient estimate impact, R2 estimate, and statistical significance. TAIL also outperforms on a monthly and yearly timescale. Last two of the most recent additions are marginally off when compared to SII's performance but perform either comparably or significantly better than the best of the initial GW predictors. Considering the problematic robustness of the SII predictor and the fact that its in-sample performance can be improved upon, there is reason to call RRZ's claim into severe questioning. Table 3 displays the in-sample predictive regression on monthly S&P 500 excess returns of each variable, and the "Result" section provides a comprehensive discussion of the findings. This research demonstrates that the addition of new, up-to-date predictor variables makes the analysis and subsequent comparison considerably more competitive.

As previously mentioned in the methodology section, the SII variable was created via linear detrending. RRZ wished to examine the SII's sensitivity to the detrending technique utilized in its construction. Table 4 in the appendix displays the predictive regression results using four distinct detrending techniques on the log of EWSI deviation. With the SII predictor detrended using Linear, Quadratic, Cubic, and Stochastic methods, four distinct predictive regression estimation outcomes are produced. We manage to identically replicate the RRZ results; SII's predictive regression estimate appears to be fairly consistent and resistant. The beta estimates remain substantial for all detrending methods at all horizons, with the exception of the cubic detrending method at the annual horizon. (Rapach et al., 2016). One interesting observation is that the quadratic detrending method produce slightly higher beta estimates with more explanatory power, in terms of R2. This finding holds true across all four horizons. This finding ties nicely in with the earlier mentioned critique from Priestley (2019), regarding the linear detrending used in creation of the SII measure and the clear break of said linear trend when examining figure 2. Looking back through the graph, it is not obvious that there exists a linear trend in the short interest data from 1973:01-1989:12, nor after the year 2008. (Priestley, 2019)

### 4.3 Out-of-sample testing

To further support the previous findings, let us examine the out-of-sample testing that was conducted. Now, it is essential to keep in mind the dubious validity of out-of-sample testing, as discussed in (Inoue and Kilian, 2006). The researchers concluded that "results from in-sample tests of predictability will typically be more credible than results from out-of-sample tests," particularly for small sample sizes, because predictors tested out-of-sample often fail. Regardless, out-of-sample tests could still serve as an important signal of the robustness of in-sample results. (Priestley, 2019)

Table 5, Panel A, displays the results of an out-of-sample test conducted between 1990:01 and 2014:12. The table depicts the reduction in the mean square forecasting error at each horizon (h=1,3,6,12) for a predictive regression forecast of the S&P 500 log excess return based on each of the predictor variables, relative to the prevailing mean forecast of the benchmark ($\beta = 0$).

This is sometimes referred to as the out-of-sample R2, a term coined by Campbell and Thompson (2008). (Rapach et al., 2016). A negative out-of-sample R2 value in the table shows that a predictor underperformed the prevailing mean benchmark in terms of MSFE across multiple time horizons. Conversely, a positive value would indicate outperformance. The CW column displays statistical significance based on the Clark and West (2007) test statistic. Where the null hypothesis is that the MSFE of the prevailing mean is less or equal to that of the predictive regression. The alternative hypothesis is that the MSFE of the predictive regression is less than that of the prevailing mean. (Rapach et al.,2016).

SII outperformed all the original predictors proposed by Goyal and Walch (2008), hence the results are identical to those discovered by RRZ. In actuality, the prevailing mean benchmark beat all the original predictors in terms of MSFE at a monthly horizon. At a semi-annual horizon, INFL exceeds the prevailing mean benchmark with a significant out-of-sample R2 of 1.95 percent. At an annual horizon, INFL and TMS surpass the prevailing mean benchmark, but TMS is the only one with a significant out-of-sample R2 of 3.35 percent.

SII consistently outperforms both the benchmark and the initial predictor variables across all time horizons. SII are significant at a monthly horizon with an out-of-sample R2 of 1.94 percent. Moving forward to the quarterly horizon, the out-of-sample R2 remains significant at 6,54 percent. On a semi-annual and yearly horizon, the out-of-sample R2 is still significant, with values of 11.70 and 13.24 percent, respectively. The results are likewise statistically significant at the 1% level.

Now we redirect our focus to the newly added GWZ (2021) predictor variables. In terms of out-of-sample R2, SII still appears to have the greatest predictive ability, but the differences are smaller than they were with the initial predictor set. Both TAIL and TCHI are significant at the 10% level at the monthly horizon, with out-of-sample R2 values of 0.30 percent and 1.20 percent, respectively. On a quarterly timescale, TAIL stays significant but the out-of-sample R2 decreases, whereas OGAP becomes significant at the 5 percent level with an R2 of 1.17 percent. Semi-annually, OGAP and TAIL are significant, whilst yearly, they are both significant and considerably closer to SII in terms of out-of-sample R2, with TAIL being significant at a 1 percent level and out-of-sample R2 of 12 percent. TCHI is also significant at a yearly horizon. Among all examined predictors, SII performed the best in terms of predictive power for this time span, including 2008.

Panel B of Table 5 represents out-of-sample testing for the shorter period 1990:01-2007:12, which excludes the year of the 2008 financial crisis. Now, SII has zero out-of-sample forecasting ability, the out-of-sample R2 is negative for every time horizon, the predictor underperformed the prevailing mean benchmark in terms of MSFE and none of the estimates are significant. This confirms Priestley's results. On the other hand, several GWZ (2021) variables continue to perform admirably. TAIL and TCHI are significant at both the semiannual and annual horizons, with out-of-sample R2 estimates of 3.5% (19.3%) and 5.87 %, respectively (2,86%). The situation is identical to that of the in-sample testing results. SII has little predictive power out-of-sample when the sample period ends just before 2008. Again, confirming the in-sample results, SII's predictive performance appears to depend on the inclusion of 2008 data.

### 4.4 Forecast encompassing tests

Table 5, panel C and D, list the lambda estimates for each predictive variable, as well as the Harvey, Leybourne and Newbold (1998) test statistic. Where the null hypothesis (alternative hypothesis) is that the weight on the SII-based forecast is equal to zero (greater than zero). (Rapach et al., 2016). A lambda value of one indicates that the best combination forecast solely use SII information. A score less than one indicates that the predictive variable provides some information to the combination forecast.

To briefly summarize the original paper, in panel C covering the time period 1990:01-2014:12 all lambdas are huge, the majority equal to one, and those that are not are still quite close. Moreover, they are all significant. Given that the null hypothesis that the weight on the GW predictors is equal to zero cannot be rejected, we reach the same conclusion as RRZ, namely that SII has a superior information content when compared to the original variables, and the predictive regression forecast based on SII will indeed encompass the forecast that is derived from the original predictors.

Now, let us expand the analysis by adding four new predictors. If we look at the monthly horizon, the lambda values for three out of four are noticeably lower than the GW predictors. In the case of TCHI, which has a lambda of 0,72 we cannot reject the null hypothesis that the weight on the SII-based forecast is equal to 0. Some of the lambdas from the new predictors are extremely close to 0.5 at the longest horizon, like OGAP (0,59) and TAIL (0,52), indicating that they have about as much weight as SII in the predictive regression forecast, and so make a large contribution of additional information. This is a recurring theme throughout all four horizons, the new predictors seem to have superior informational content compared to the GW predictors and contribute with some new information useful for forecasting excess returns beyond what is found in the SII predictor. Despite the fact that SII still encompasses the forecasts provided by the new predictors at the majority of horizons, there is evidence to the contrary.

If we look at panel D, which display the same results for period 1990:01-2007:12, it is easy to notice SII`s lack of out-of-sample predictability in this period. The lambda values are smaller than before and for some of the new variables like TAIL and TCHI as well as INFL and DFR from the original GW sample the value tends towards zero at the longer horizons and the null hypothesis of zero weighting on the SII-based forecast cannot be rejected in a lot of the cases. In other words, the forecast based on the predictors, encompasses the predictive regression forecast which is based on SII, SII does not contribute with useful information for forecasting excess returns.

### 4.5 Asset allocation

Let's take a look at the economic significance of the variable's predicting ability from the perspective of asset allocation before concluding. Firstly, it is essential to emphasize that even though several of the variables provide portfolios with solid performance in terms of CER gain and Sharpe ratios relative to the buy-and-hold strategy, the stated performance cannot necessarily be replicated due to several real-world constraints. First, the construction of the predictors and the estimation performed during their creation process. Second, it would be quite challenging for an investor to know beforehand which variables to utilize in their allocation. The portfolios must be often rebalanced for performance to materialize, and it is not obvious that any of the methods would outperform the buy-and-hold strategy after accounting for rebalancing.

In this section of the thesis, we will examine SII, the GW predictors, and the predictive accuracy of the new GWZ predictors from an asset allocation viewpoint. In other words, how well can asset allocation be guided by the many predictor variables utilized in the predictive regression forecasts? As the original authors did, we will analyze a mean-variance investor that allocates between risk-free assets and stocks based on a predictive regression estimate of excess stock returns. (Rapach et al., 2016). Based on each prediction horizon, the rebalancing of the portfolio and, consequently, the weights of each security type will be determined and calculated. The performance of each predictor will be measured using certainty equivalent return (CER) gains and Sharpe ratios. The CER for the prevailing mean excess return forecast is also computed, and the CER gain in the table represents the difference in CER between the predictive regression forecast derived from the predictor variables and the prevailing mean benchmark. The CER gain is annualized as well. (Rapach et al., 2016)

Now, let's take a look at table 6, which depicts the annualized certainty equivalent return (CER) gain of each predictor variable in the column to the far left, relative to the prevalent mean benchmark. This is an out-of-sample test, which means we will examine the CER gains in various out-of-sample time periods. The original authors included three distinct time periods; this is the complete OOS period from 1990:01 to 2014:12, the years before the financial crisis 1990:01-2006:12 and 2007:01-2014:12, which includes the financial crisis. In addition, we include the post-crisis period from 2009:01 to 2014:12. We will mostly disregard the findings associated with the GW variables due to their poor performance, with the buy-and-hold strategy outperforming them in the majority of cases. Examining SII reveals a mixed picture.

From exceptional performance, surpassing every comparable in the time surrounding the financial crisis, with CER gains of 1,118, 1,308, 1,591, and 1,118 basis points throughout the four horizons. To a very poor performance in the years preceding the financial crisis, with CER gains of 88, 73, 57, and -0.38 basis points over the respective time horizons, significantly below the buy-and-hold approach.

When we move our attention to our newly introduced variables, we notice something intriguing. In terms of CER gain, both TAIL and TCHI outperformed the buy-and-hold strategy prior to the financial crisis. This was a feat neither the original variables nor SII were able to accomplish. TAIL achieves a gain of 215, 190, 240, and 424 basis points at every horizon. The performance of the TAIL predictor in this period is due to its construction. The original authors Keely and Jiang (2014) claim that "tail risk positively forecasts excess returns" (Keely and Jiang, 2014). And since investors are tail risk averse, increases in said risk will raise investors required return. This imposes a positive relationship between tail risk and future returns. According to the authors, tail risk was increasing rapidly through the tech crisis of the early 2000s and peaking around 2003. The same pattern was not observed around the financial crisis of 2008 and may therefore explain this predictors performance during the pre-crisis subperiod. (Keely and Jiang, 2014). TCHI, on the other hand, achieves 298, 151, and 240 basis points over the first three time horizons, with an annual horizon that is poor.

During the time encompassing the financial crisis, all new variables underperform SII. However, they are far closer than the initial results. Where the original data indicate that SII outperforms everyone else by a significant multiple, OGAP performs extremely well and is only marginally behind. Examining the findings for the whole out-of-sample period reveals that OGAP, TAIL, and TCHI all perform admirably. Infrequently outperforming SII, such as TCHI's CER gain at a monthly horizon of 432 basis points and TAIL's CER gain at an annual horizon of 367 basis points. In the period following the financial crisis, SII continued to outperform the other predictor variables, which struggled to outperform the buy-and-hold strategy. The best of the rest appears to be AVGCOR, which performs adequately over quarterly to annual time periods, but still struggles to regularly outperform the buy-and-hold strategy.

It should come as no surprise that the results are remarkably similar to those obtained from the larger sample. SII outperforms the buy-and-hold strategy during the out-of-sample period, delivering a substantial margin. The GWZ variables, however, pose a challenge at all horizons and even outperform at half of them. During the pre-crisis out-of-sample era, SII performs poorly and is outperformed by a number of GWZ (2021) variables. Interestingly, buy-and-hold outperforms virtually all variable-generated portfolios throughout this period. SII performs exceptionally well during the global financial crisis, followed by OGAP.

Interestingly, looking at the period "after" the financial crisis, from 2009:01 to 2014:12, SII achieves the highest CER gain of all predictors, which is intriguing considering that the in-sample data demonstrate no predictive capacity over the same time frame. Examining the Sharpe ratios for the same period reveals that the performance of SIIs is considerably diminished but continues to perform decently when compared to the competition. However, its typically surpassed by at least one other variable and closely followed by the buy-and-hold strategy at all time horizons. Notably, the sample period is really short, and in light of the criticism surrounding out-of-sample testing conducted on tiny samples, we are inclined to trust the in-sample results.

Table 7 displays the Sharpe ratios generated by the portfolios constructed in table 6. The value in the table has been annualized. The relationship between the various predictors is essentially the same as in the preceding table, except that the Sharpe ratios exclude the estimate of investor risk aversion used by the CER computation. In addition, the table includes the Sharpe ratios for the prevailing mean. Before the financial crisis, portfolios based on the prevailing mean generated Sharpe ratios between 0.33 and 0.45. SII generates portfolios with Sharpe ratios ranging from 0.37

to 0.49, which just exceeds the market average but underperforms buy-and-hold. Again, the newly added predictors perform significantly better than the original, with TAIL and TCHI consistently outperforming SII across all time horizons. During the financial crisis, SII again beats everyone at all time horizons, with the exception of OGAP, which has the highest Sharpe ratio at an annual horizon. For the whole out-of-sample period, SII delivers Sharpe ratios ranging from 0.53 to 0.72 and surpasses the prevailing mean, "buy and hold," and all other traditional predictors. However, it is surpassed on a monthly horizon by TCHI (0.70) and on an annual horizon by TAIL (0,56).

In the years following the financial crisis, SII yields decent Sharpe ratios, but nothing more. It never yields the highest Sharpe ratios and is also outperformed by the prevailing mean on a monthly and yearly time horizon. Notably, this is one of the few cases in the entire analysis when the old predictor variables proposed by GW perform better than the new factors added from GWZ (2021).

When examining the predictive variables from the perspective of asset allocation, considering SII's reliance on 2008, very few, if any, of the predictive variables are particularly impressive. Taking into account both the entire out-of-sample period and the period preceding the financial crisis, none of the predictors appear to produce results that are significantly superior to the buy-and-hold strategy. Considering that the portfolios built by the predictors contain both long and short positions, which incur substantial transaction costs along the way. Leverage is also expensive and should be considered; the model allows for up to 50% leverage, which would incur a borrowing fee.

The leverage could also be problematic for a portfolio constructed with SII, where most of the performance is connected to a short time period. Consequently, there would be times of low performance accompanied by a high degree of leverage. Figures 3 and 4 provide a graphic representation of this issue. Figure 3 depicts the equity weight difference between the SII portfolio and the prevailing mean. Firstly, we observe lengthy periods of leverage much above 1 in the years preceding the financial crisis, a time when it is known that SII perform poorly. Secondly, it is not difficult to comprehend why the SII portfolio have performed so well throughout the financial crisis. The short position in 2008, followed by a heavily leveraged position in a recovering market, would generate a substantial profit. Figure 4 also clearly illustrates the gains; the prevailing mean closely matches SII throughout the data until 2008, after which the shift in performance is highly obvious.

There is always a cost associated with the acquisition and processing of information. This is related to the market efficiency theory discussed at the beginning of the thesis. Whereas the current perspective is that markets are at best inefficiently efficient, meaning that opportunities may exist, but the excess return created is merely compensation for the information cost. Consequently, we reach the same result as (GW, 2008) and (GWZ, 2021) did. In the eyes of a real-world investor, we lack confidence in the ability of any of the examined variables to anticipate the future equity premium.

### 4.6 SII extended to 2021

Table 8 displays the in-sample results for the predictive regression forecast based on SII, where the SII measure is re calculated and extended until 2021:12. The reasons behind this re calculation and the changes made by the original authors is covered in the methodology section. The correlation between the new and the old SII data is really high, and the changes has no impact on the final result.

In table 8 we have included the same subsample periods as we did in table 3 panel B, in order to show that the original results and conclusions still remains applicable after the change in data. In addition we have included the samples 1973:12-2021:12, 2008:01-2021:12 and 2009:01-2021:12. The results are very similar to our results using the original data from 1973:01-2014:12. Over the entire sample period

1973:01-2021:12 SII is highly significant with an estimated beta value of 0,52, t-stat of 2,40 and R2 of 1,47% at a monthly horizon. The results are very much significant across all four horizons in this sample period. In the sample period 1973:01-2007:12 the results, just as before show zero significance and therefore no predictive ability for SII. In order to test SIIs suggested reliance on the year 2008, we can have a look at the two subperiods surrounding the financial crisis. Just as before when 2008 is included, as in the subsample 2008:01-2021:12, SII is significant with an estimated beta value of 0,65, t-stat of 1,69 and R2 of 3,18% at a monthly horizon. Removing the year 2008, as in the subsample 2009:01-2021:12 removes all predictability and SII is no longer significant.

Let's now compare the results for the subsample 2008:01-2014:12 in table 8, with the extended subsample 2008:01-2021:12. The results of the shorter subsample with estimated beta value of 1,75, t-stat of 2,03 and R2 of 8,6% at a monthly horizon indicates stronger predictability and significance compared to the one extended until 2021:12 with an estimated beta value of 0,65, t-stat of 1,69 and R2 of 3,18%. This is yet another indication of SIIs reliance on the year 2008. When the sample is extended, the explanatory power and significance falls. This holds true across all horizons.

In figure 5, SII extended until 2021:12 is visualized. After the break around 2008, the pattern is virtually identical to figure 1; SII has continued to decline. Extending the sample to 2021:12 has no positive effect on SII's predictive ability, as the results point in the same direction as the original sample tests, and SII is highly dependent on the year 2008 in order to be significant.

### 4.7 Stock return decomposition

Table 9 display the estimates of the OLS regressions, $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ with each of the components estimated based on VARs which comprise of S&P 500 log return, the log dividend-price ratio as well as one of the predictive variables included in the analysis. The log dividend price ratio is always included in the VAR, the reasons why RRZ do this, is based on the paper “Pitfalls in VAR based return decompositions: A clarification” by (Engsted, Pedersen and Tanggaard, 2012). They find that the asset price always needs to be included in the VAR for it to be valid, and in the case of equity return decomposition, the dividend-price ratio is the correct choice. (Engsted, et al., 2012).

As can be seen by table 9 panel A, we have correctly replicated the findings of RRZ. For the 1973:01-2014:12 period, the estimated $\hat{\beta}$ coefficient of the predictive regression model for the log stock return based on SII is -0,51 with a corresponding t-stat of -2,53. In each of the VARs the $\hat{\beta}_{\hat{E}}$, $\hat{\beta}_{CF}$ and $\hat{\beta}_{DR}$ all contribute to the total share of $\hat{\beta}$. Just as RRZ, we observe $\hat{\beta}_{CF}$ outperforming the two other components, in terms of statistical significance, estimate magnitude and corresponding contribution as an individual share of $\hat{\beta}$. RRZ therefore reasonably assumes SIIs ability to predict cash flow news to be the most important economical source of SIIs predictive ability on stock returns. (Rapach et al., 2016). A potential conclusion is therefore that SII indeed do forecast changes in future aggregate cashflows for the sample period 1973:01-2014:12.

Once more let’s consider a sample period ending just before the financial crisis, 1973:01-2007:12 as displayed in Table 9 panel B. (Priestley, 2019). What we now observe is consistent with all off our previous findings, the results are no longer statistically significant. $\hat{\beta}$ drops to -0,31 with a t-statistic of just -1,46. The individual VAR estimates of $\hat{\beta}_{CF}$ still has the largest magnitude and contribution, but the vast majority has no significance. These results, leads ever closer to the conclusion of Priestly, that the predictive ability of SII is closely tied to the financial crisis. (Priestley, 2019). This also permits us to query the third and final claim made by RRZ, that “the ability of short interest to predict future market returns stems predominantly from a cashflow channel” and that “short sellers are informed traders who are able to anticipate changes in future aggregate cashflows". (Rapach, et al., 2016).

## 5. Conclusion

In this paper, we have replicated the main empirical findings presented in the original paper by RRZ and conducted additional research into their claims regarding the superiority of short interests in terms of predictability and its quite impressive outperformance relative to other popular predictor variables in the literature. To evaluate the resilience, we employed a technique similar to the one employed by Richard Priestley in his article "Short interest, Macroeconomic variables, and aggregate stock returns." In addition, we have incorporated four brand-new, up-to-date predictor variables with an established track record from credible sources. These are extracted from Goyal, Welch, and Zaforov's research paper "A comprehensive look at the empirical performance of equity premium prediction II."

RRZ asserts that short sellers have knowledge of aggregate stock prices, which manifests itself in the shorting of costly equities as a result of inaccurate cashflow projections. (Priestley, 2019).  According to the authors, this occurs via a cash flow channel. These knowledgeable investors short sell overvalued securities and reap profits, thereby correcting mispriced stock prices. (Rapach et al., 2016). In-sample and out-of-sample performance of the SII relative to other common macroeconomic variables in predicting stock returns is the paper's primary justification for its claims. In terms of CER gain and Sharpe ratios, they also give evidence about the economic usefulness of SII's predictive abilities from the standpoint of asset allocation. We have offered evidence in this study that calls into doubt the original author's conclusions. The most compelling argument is that the inclusion of year 2008 is critical to SII's forecasting capability. In-sample testing reveals that samples from both before and after 2008 lack statistical significance for SII. In the form of graphs demonstrating clear interruptions in the trend around the year 2008, we have also supplied visual evidence to support this conclusion.

In addition, we dispute the assertion of SII's superiority by introducing new, credible variables into the comparison. Simply by adding these extra variables, two possible flaws are shown. The performance of the original GW variables is often terrible, making for a really subpar comparison. Second, that SII's performance can be surpassed in terms of in-sample performance.

This thesis' objective was not necessarily to disprove the original authors' conclusions, but rather to dispute their assertion by reviewing the data offered in publications with opposing views. By doing so and considering all the previously presented evidence, we feel confident enough to at least question the original conclusion and argue that the amazing performance of SII as a predictor may be the result of outliers in the data.

6. References


Short Interest and Aggregate Stock Returns by David Rapach, Matthew C. Ringgenberg, Guofu Zhou :: SSRN (Rapach et al., 2016).

Short Interest, Macroeconomic Variables and Aggregate Stock Returns by Richard Priestley :: SSRN (Priestley, 2019)

A Comprehensive 2021 Look at the Empirical Performance of Equity Premium Prediction II by Amit Goyal, Ivo Welch, Athanasse Zafirov :: SSRN (Goyal et al., 2021) (GWZ,2021)

A Comprehensive Look at the Empirical Performance of Equity Premium Prediction by Amit Goyal, Ivo Welch :: SSRN (Goyal and Welch, 2008) (GW,2008)

In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use? by Atsushi Inoue, Lutz Kilian :: SSRN (Inoue and Kilian, 2006)

Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? by John Y. Campbell, Samuel Brodsky Thompson :: SSRN (Campbell and Thompson, 2008)

The Empirical Risk-Return Relation: A Factor Analysis Approach by Serena Ng, Sydney C. Ludvigson :: SSRN (Ludvigson and Ng, 2007)

Forecasting the Equity Risk Premium: The Role of Technical Indicators by Christopher J. Neely, David Rapach, Jun Tu, Guofu Zhou :: SSRN (Neely et al., 2014)

Average Correlation and Stock Market Returns by Joshua Matthew Pollet, Mungo Ivor Wilson :: SSRN (Pollet and Wilson, 2010)

Tail Risk and Asset Prices by Bryan T. Kelly, Hao Jiang :: SSRN (Keely and Jiang, 2014)

Time-Varying Risk Premiums and the Output Gap by Ilan Cooper, Richard Priestley :: SSRN (Cooper and Priestley, 2009)

Predictive Regressions by Robert F. Stambaugh :: SSRN (Stambaugh, 1999)

Predictable Stock Returns: Reality or Statistical Illusion? by Charles R. Nelson, Myung Jig Kim :: SSRN (Nelson and Kim, 1993)

Exhibits:

Table 1: Summary statistics 1973:01-2014:12
Panel A:

| Variable | Mean | Median | 1st percentile | 99th percentile | Std dev |
|---|---|---|---|---|---|
| DP | -3,62 | -3,57 | -4,47 | -2,85 | 0,44 |
| DY | -3,61 | -3,57 | -4,47 | -2,84 | 0,44 |
| EP | -2,82 | -2,83 | -4,54 | -1,97 | 0,49 |
| DE | -0,80 | -0,86 | -1,24 | 1,00 | 0,34 |
| 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% | 14,95% | 3,44% |
| LTY (ann) | 7,17% | 7,07% | 2,26% | 13,87% | 2,73% |
| LTR | 0,74% | 0,82% | -6,47% | 8,94% | 3,12% |
| TMS (ann) | 2,11% | 2,35% | -1,96% | 4,37% | 1,51% |
| DFY (ann) | 1,10% | 0,96% | 0,56% | 2,81% | 0,47% |
| DFR | -0,01% | 0,05% | -4,77% | 3,86% | 1,47% |
| INFL | 0,34% | 0,29% | -0,49% | 1,28% | 0,34% |
| OGAP | 0,77% | -0,55% | -12,07% | 13,01% | 6,72% |
| TAIL | 0,44 | 0,45 | 0,37 | 0,50 | 0,03 |
| TCHI | -0,06 | 0,82 | -2,68 | 1,06 | 1,46 |
| AVGCOR | 0,29 | 0,27 | 0,09 | 0,65 | 0,11 |
| EWSI (%) | 2,15 | 1,31 | 0,22 | 7,82 | 1,98 |
| SII | 0,00 | -0,09 | -2,11 | 2,44 | 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 correlation, 1973:01-2014:12

| Variable | DP | DY | EP | DE | RVOL | BM | NTIS | TBL | LTY | LTR | TMS | DFY | DFR | INFL | OGAP | TAIL | TCHI | AVGCOR | 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 | | | | | |
| OGAP | -0,48 | -0,49 | -0,11 | -0,46 | -0,16 | -0,20 | 0,00 | -0,07 | -0,35 | -0,06 | -0,47 | -0,38 | -0,10 | 0,15 | 1,00 | | | | |
| TAIL | 0,12 | 0,12 | 0,00 | 0,15 | -0,22 | -0,11 | -0,14 | -0,13 | 0,02 | 0,12 | 0,33 | -0,09 | 0,00 | -0,22 | -0,48 | 1,00 | | | |
| TCHI | -0,17 | -0,14 | -0,04 | -0,16 | -0,11 | -0,24 | 0,04 | -0,09 | -0,10 | -0,05 | 0,04 | -0,26 | 0,04 | -0,15 | -0,24 | 0,11 | 1,00 | | |
| AVGCOR | -0,01 | -0,02 | -0,09 | 0,11 | 0,41 | -0,02 | -0,33 | -0,30 | -0,30 | 0,10 | 0,15 | 0,33 | -0,02 | -0,13 | -0,01 | -0,04 | -0,26 | 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 | 0,17 | -0,02 | -0,14 | 0,10 | 1,00 |

Table 3: In-sample predictive regression estimation results, 1973:01-2014:12
Panel A:

| | h=1 | | | | h=3 | | | | h=6 | | | | h=12 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Predictor | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| DP | 0,15 | 0,75 | 0,21 | 0,12 | 0,17 | 0,94 | 0,20 | 0,39 | 0,19 | 1,06 | 0,18 | 0,93 | 0,20 | 1,12 | 0,18 | 2,06 |
| DY | 0,18 | 0,86 | 0,18 | 0,15 | 0,18 | 0,99 | 0,19 | 0,44 | 0,19 | 1,10 | 0,18 | 1,00 | 0,21 | 1,15 | 0,18 | 2,18 |
| EP | 0,09 | 0,37 | 0,37 | 0,04 | 0,06 | 0,27 | 0,41 | 0,05 | 0,06 | 0,25 | 0,41 | 0,09 | 0,08 | 0,43 | 0,36 | 0,34 |
| DE | 0,06 | 0,23 | 0,42 | 0,02 | 0,12 | 0,57 | 0,35 | 0,22 | 0,16 | 0,88 | 0,28 | 0,68 | 0,14 | 1,21 | 0,20 | 1,03 |
| RVOL | 0,35 | 1,90 | 0,03 | 0,62 | 0,33 | 2,12 | 0,04 | 1,53 | 0,27 | 1,95 | 0,06 | 1,90 | 0,18 | 1,26 | 0,16 | 1,58 |
| BM | -0,01 | -0,05 | 0,48 | 0,00 | 0,01 | 0,06 | 0,46 | 0,00 | 0,04 | 0,23 | 0,40 | 0,05 | 0,05 | 0,29 | 0,38 | 0,14 |
| NTIS (-) | 0,07 | 0,27 | 0,42 | 0,02 | 0,00 | 0,00 | 0,52 | 0,00 | -0,01 | -0,02 | 0,52 | 0,00 | 0,02 | 0,07 | 0,49 | 0,02 |
| TBL (-) | 0,26 | 1,28 | 0,11 | 0,34 | 0,22 | 1,20 | 0,16 | 0,67 | 0,19 | 0,99 | 0,22 | 0,91 | 0,17 | 0,99 | 0,24 | 1,38 |
| LTY (-) | 0,15 | 0,71 | 0,26 | 0,10 | 0,10 | 0,57 | 0,34 | 0,15 | 0,08 | 0,40 | 0,42 | 0,15 | 0,00 | 0,03 | 0,53 | 0,00 |
| LTR | 0,33 | 1,67 | 0,05 | 0,55 | 0,14 | 0,92 | 0,19 | 0,27 | 0,23 | 2,48 | 0,01 | 1,41 | 0,15 | 2,90 | 0,00 | 1,14 |
| TMS | 0,33 | 1,66 | 0,05 | 0,56 | 0,31 | 1,72 | 0,07 | 1,33 | 0,28 | 1,62 | 0,09 | 2,14 | 0,36 | 2,27 | 0,04 | 6,52 |
| DFY | 0,15 | 0,55 | 0,31 | 0,11 | 0,16 | 0,66 | 0,33 | 0,37 | 0,24 | 1,24 | 0,19 | 1,51 | 0,19 | 1,18 | 0,19 | 1,75 |
| DFR | 0,50 | 1,58 | 0,07 | 1,24 | 0,23 | 1,26 | 0,13 | 0,72 | 0,16 | 1,38 | 0,10 | 0,71 | 0,06 | 0,89 | 0,24 | 0,17 |
| INFL (-) | 0,06 | 0,21 | 0,45 | 0,02 | 0,17 | 0,90 | 0,26 | 0,43 | 0,26 | 1,62 | 0,12 | 1,81 | 0,27 | 2,04 | 0,08 | 3,64 |
| OGAP(-) | 0,61 | 3,21 | 0,00 | 1,86 | 0,59 | 3,57 | 0,00 | 5,04 | 0,57 | 3,29 | 0,00 | 8,53 | 0,52 | 2,94 | 0,01 | 13,99 |
| TAIL(-) | 0,57 | 3,16 | 0,00 | 1,59 | 0,48 | 3,25 | 0,00 | 3,27 | 0,51 | 3,70 | 0,00 | 6,95 | 0,55 | 3,98 | 0,00 | 15,79 |
| TCHI | 0,49 | 2,02 | 0,03 | 1,20 | 0,40 | 1,78 | 0,08 | 2,28 | 0,38 | 1,71 | 0,10 | 3,78 | 0,23 | 1,30 | 0,17 | 2,70 |
| AVGCOR | 0,30 | 1,25 | 0,10 | 0,46 | 0,42 | 2,25 | 0,03 | 2,54 | 0,37 | 2,62 | 0,02 | 3,58 | 0,24 | 1,66 | 0,10 | 2,89 |
| SII (-) | 0,50 | 2,50 | 0,01 | 1,24 | 0,56 | 2,88 | 0,00 | 4,37 | 0,57 | 2,73 | 0,01 | 8,07 | 0,53 | 2,70 | 0,02 | 12,89 |
| SII (-)\|PC | 0,47 | 2,39 | 0,01 | 1,07 | 0,54 | 2,91 | 0,00 | 4,19 | 0,54 | 2,86 | 0,01 | 8,23 | 0,50 | 3,38 | 0,01 | 14,24 |

Panel B: In-sample predictive regression results, short interest.

| | | | | h=1 | | | | h=3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-1982:12 | 0,68 | 1,97 | 0,02 | 1,71 | 0,72 | 2,56 | 0,02 | 5,82 |
| S&P 500 VW | EWSI | Linear | 1983:01-1992:12 | 0,84 | 1,14 | 0,14 | 1,28 | 0,65 | 1,03 | 0,21 | 2,39 |
| S&P 500 VW | EWSI | Linear | 1993:01-2002:12 | 0,36 | 0,49 | 0,30 | 0,18 | 0,63 | 0,92 | 0,22 | 1,74 |
| S&P 500 VW | EWSI | Linear | 2003:01-2014:12 | 0,62 | 2,42 | 0,01 | 4,50 | 0,72 | 2,68 | 0,02 | 13,83 |
| S&P 500 VW | EWSI | Linear | 2008:01-2014:12 | 1,03 | 2,01 | 0,04 | 8,24 | 1,12 | 2,38 | 0,05 | 23,27 |
| S&P 500 VW | EWSI | Linear | 2009:01-2014:12 | -0,16 | -0,26 | 0,60 | 0,11 | -0,26 | -0,60 | 0,68 | 1,11 |
| S&P 500 VW | EWSI | Linear | 1973:12-2007:12 | 0,21 | 0,71 | 0,24 | 0,15 | 0,22 | 0,87 | 0,22 | 0,47 |

| | | | | h=6 | | | | h=12 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-1982:12 | 0,65 | 2,34 | 0,06 | 9,04 | 0,77 | 3,53 | 0,04 | 28,10 |
| S&P 500 VW | EWSI | Linear | 1983:01-1992:12 | 0,53 | 1,34 | 0,17 | 4,08 | 0,49 | 1,79 | 0,13 | 9,53 |
| S&P 500 VW | EWSI | Linear | 1993:01-2002:12 | 0,53 | 0,70 | 0,30 | 2,28 | -0,37 | -0,45 | 0,58 | 1,56 |
| S&P 500 VW | EWSI | Linear | 2003:01-2014:12 | 0,79 | 2,60 | 0,03 | 25,37 | 0,76 | 3,10 | 0,03 | 41,47 |
| S&P 500 VW | EWSI | Linear | 2008:01-2014:12 | 1,19 | 2,85 | 0,08 | 38,02 | 0,87 | 3,28 | 0,17 | 49,59 |
| S&P 500 VW | EWSI | Linear | 2009:01-2014:12 | -0,22 | -0,61 | 0,66 | 1,63 | 0,03 | 0,13 | 0,48 | 0,09 |
| S&P 500 VW | EWSI | Linear | 1973:12-2007:12 | 0,18 | 0,75 | 0,26 | 0,64 | 0,08 | 0,30 | 0,40 | 0,25 |

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

| | | | | h=1 | | | | h=3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-2014:12 | 0,50 | 2,50 | 0,01 | 1,24 | 0,56 | 2,88 | 0,01 | 4,37 |
| S&P 500 VW | EWSI | Quadratic | 1973:01-2014:12 | 0,56 | 2,74 | 0,00 | 1,57 | 0,62 | 3,12 | 0,01 | 5,38 |
| S&P 500 VW | EWSI | Cubic | 1973:01-2014:12 | 0,40 | 1,68 | 0,06 | 0,79 | 0,46 | 2,07 | 0,04 | 3,06 |
| S&P 500 VW | EWSI | Stochastic | 1973:01-2014:12 | 0,42 | 1,98 | 0,02 | 0,91 | 0,49 | 2,56 | 0,01 | 3,50 |
| | | | | h=6 | | | | h=12 | | | |
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-2014:12 | 0,57 | 2,73 | 0,02 | 8,07 | 0,53 | 2,70 | 0,02 | 12,89 |
| S&P 500 VW | EWSI | Quadratic | 1973:01-2014:12 | 0,62 | 2,92 | 0,01 | 9,79 | 0,56 | 2,87 | 0,02 | 15,51 |
| S&P 500 VW | EWSI | Cubic | 1973:01-2014:12 | 0,46 | 1,99 | 0,06 | 5,72 | 0,40 | 1,76 | 0,11 | 8,35 |
| S&P 500 VW | EWSI | Stochastic | 1973:01-2014:12 | 0,51 | 2,74 | 0,02 | 7,44 | 0,45 | 2,83 | 0,02 | 11,02 |

Table 5: Out-of-sample test results, 1990:01-2014:12
Panel A:

| | h=1 | | h=3 | | h=6 | | h=12 | |
|---|---|---|---|---|---|---|---|---|
| Predictor | R2OS (%) | CW | R2OS (%) | CW | R2OS (%) | CW | R2OS (%) | CW |
| DP | -2,06 | -1,29 | -5,80 | -1,59 | -10,97 | -1,81 | -26,39 | -2,62 |
| DY | -2,20 | -1,27 | -5,66 | -1,63 | -11,04 | -1,90 | -25,82 | -2,62 |
| EP | -1,14 | -0,52 | -4,24 | -0,94 | -8,85 | -1,21 | -16,39 | -2,36 |
| DE | -2,27 | -0,69 | -6,29 | -1,35 | -7,85 | -2,04 | -3,56 | -0,01 |
| RVOL | -0,56 | 0,48 | -1,40 | 0,35 | -1,77 | 0,19 | -3,40 | -0,57 |
| BM | -0,56 | -0,90 | -1,75 | -1,26 | -3,55 | -1,50 | -9,68 | -1,96 |
| NTIS | -3,23 | -1,96 | -8,88 | -2,46 | -19,06 | -2,35 | -27,82 | -1,90 |
| TBL | -0,38 | 0,40 | -0,92 | 0,09 | -1,66 | -0,21 | -1,75 | -0,19 |
| LTY | -0,31 | -0,48 | -1,53 | -1,58 | -3,66 | -2,17 | -11,85 | -3,37 |
| LTR | -0,51 | 0,23 | -1,59 | -0,43 | -0,94 | 0,92 | -0,91 | 0,49 |
| TMS | -0,76 | 0,28 | -1,72 | 0,21 | -1,43 | 0,41 | 3,35 | 1,66 |
| DFY | -3,07 | -1,83 | -7,15 | -2,18 | -8,92 | -1,42 | -7,35 | -1,16 |
| DFR | -1,75 | 0,27 | -1,11 | -0,05 | -0,39 | 0,44 | -0,78 | -0,27 |
| INFL | -0,64 | -0,49 | -0,32 | 0,20 | 1,95 | 1,61 | 3,24 | 1,25 |
| OGAP | -0,34 | 1,15 | 1,17 | 1,74 | 4,20 | 2,00 | 9,93 | 2,08 |
| TAIL | 0,30 | 1,45 | 0,09 | 1,40 | 2,03 | 1,99 | 12,00 | 2,76 |
| TCHI | 1,20 | 1,32 | 1,82 | 1,05 | 3,82 | 1,24 | 2,99 | 1,45 |
| AVGCOR | -1,16 | -0,07 | -1,48 | 0,75 | 1,62 | 1,22 | -1,25 | 0,24 |
| SII | 1,94 | 2,79 | 6,54 | 3,24 | 11,70 | 3,04 | 13,24 | 2,29 |
| Alternative detrending | | | | | | | | |
| Quadratic | 1,45 | 2,90 | 5,74 | 3,98 | 10,36 | 4,06 | 12,62 | 3,57 |
| Cubic | 0,39 | 1,16 | 2,78 | 1,81 | 6,03 | 1,89 | -0,76 | 0,99 |
| Stochastic | 0,96 | 1,97 | 4,28 | 2,73 | 8,16 | 2,90 | 9,89 | 2,38 |

Panel B: 1990:01-2007:12

| | h=1 | | h=3 | | h=6 | | h=12 | |
|---|---|---|---|---|---|---|---|---|
| Predictor | R2OS (%) | CW | R2OS (%) | CW | R2OS (%) | CW | R2OS (%) | CW |
| DP | -3,27 | -1,30 | -10,45 | -1,65 | -23,38 | -2,01 | -51,13 | -3,13 |
| DY | -3,59 | -1,37 | -10,34 | -1,75 | -23,67 | -2,15 | -50,12 | -3,17 |
| EP | -1,05 | -0,65 | -3,56 | -0,82 | -8,99 | -1,19 | -23,17 | -3,14 |
| DE | -1,81 | -0,80 | -3,64 | -0,65 | -6,12 | -0,80 | -7,91 | -0,78 |
| RVOL | -1,73 | -0,46 | -4,96 | -0,83 | -7,41 | -0,99 | -9,27 | -1,56 |
| BM | -0,86 | -0,83 | -2,80 | -1,05 | -6,66 | -1,30 | -17,45 | -1,85 |
| NTIS | -2,84 | -1,04 | -7,36 | -1,39 | -19,54 | -2,24 | -28,95 | -2,19 |
| TBL | -0,49 | 0,39 | -0,83 | 0,30 | -1,79 | 0,02 | -3,13 | -0,26 |
| LTY | -0,41 | -0,47 | -1,70 | -1,45 | -4,52 | -1,93 | -15,05 | -3,47 |
| LTR | -0,83 | -0,09 | -0,06 | 0,80 | -0,35 | 1,16 | -0,68 | 0,55 |
| TMS | -1,11 | 0,23 | -2,88 | 0,14 | -3,18 | 0,28 | -1,33 | 0,77 |
| DFY | -3,37 | -1,17 | -9,42 | -1,88 | -18,27 | -2,05 | -17,36 | -2,56 |
| DFR | -2,64 | -0,64 | -1,72 | -1,65 | -1,84 | -1,30 | 0,44 | 0,33 |
| INFL | -0,03 | 0,44 | 0,05 | 0,48 | -0,66 | 0,33 | -0,63 | 0,40 |
| OGAP | -3,02 | 0,09 | -5,96 | 0,36 | -7,05 | 0,56 | -3,22 | 0,74 |
| TAIL | -0,13 | 1,10 | -0,59 | 1,14 | 3,50 | 1,80 | 19,36 | 2,53 |
| TCHI | 0,59 | 0,89 | 1,90 | 1,14 | 5,87 | 1,81 | 2,86 | 1,30 |
| AVGCOR | 0,32 | 0,90 | 1,40 | 1,48 | 1,49 | 1,04 | -0,83 | 0,25 |
| SII | -0,15 | 0,55 | -0,43 | 0,65 | -0,23 | 0,78 | -8,12 | 0,10 |
| Alternative detrending | | | | | | | | |
| Quadratic | 0,13 | 1,34 | 1,83 | 2,29 | 3,94 | 2,45 | -1,25 | 1,96 |
| Cubic | -1,14 | 0,21 | -2,63 | 0,44 | -4,13 | 0,41 | -24,64 | -0,02 |
| Stochastic | -0,06 | 0,75 | 0,59 | 1,15 | 0,47 | 0,88 | -1,99 | 0,48 |

Panel C: Encompassing tests, 1990:01-2014:12

GW predictor encompasses SII?

| | h=1 | | h=3 | | h=6 | | h=12 | |
|---|---|---|---|---|---|---|---|---|
| Predictor | lambda | HLN | lambda | HLN | lambda | HLN | lambda | HLN |
| DP | 1,22 | 4,47 | 1,22 | 5,40 | 1,25 | 5,15 | 1,30 | 4,34 |
| DY | 1,22 | 4,51 | 1,22 | 5,40 | 1,26 | 5,21 | 1,30 | 4,36 |
| EP | 1,30 | 2,86 | 1,34 | 3,92 | 1,39 | 3,95 | 1,28 | 3,87 |
| DE | 1,19 | 2,66 | 1,25 | 3,76 | 1,26 | 4,15 | 0,96 | 3,09 |
| RVOL | 0,98 | 3,34 | 1,04 | 4,07 | 1,11 | 3,82 | 1,01 | 3,07 |
| BM | 1,28 | 3,34 | 1,28 | 4,22 | 1,32 | 4,15 | 1,29 | 3,64 |
| NTIS | 1,19 | 4,08 | 1,22 | 4,76 | 1,32 | 4,29 | 1,14 | 3,70 |
| TBL | 1,23 | 2,59 | 1,29 | 3,24 | 1,37 | 3,21 | 1,09 | 2,73 |
| LTY | 1,28 | 2,87 | 1,27 | 4,00 | 1,30 | 4,13 | 1,13 | 3,70 |
| LTR | 1,01 | 3,06 | 1,14 | 3,73 | 1,06 | 3,68 | 0,94 | 2,93 |
| TMS | 1,14 | 2,85 | 1,19 | 3,43 | 1,21 | 3,07 | 0,83 | 2,34 |
| DFY | 1,27 | 4,26 | 1,28 | 4,79 | 1,20 | 4,28 | 1,06 | 3,32 |
| DFR | 0,95 | 2,15 | 1,13 | 3,87 | 1,15 | 3,69 | 1,00 | 2,76 |
| INFL | 1,25 | 2,85 | 1,18 | 3,55 | 1,12 | 3,29 | 0,89 | 2,55 |
| OGAP | 0,83 | 2,65 | 0,81 | 3,49 | 0,79 | 3,52 | 0,59 | 2,36 |
| TAIL | 0,74 | 2,27 | 0,84 | 3,42 | 0,79 | 3,50 | 0,52 | 3,03 |
| TCHI | 0,72 | 1,42 | 0,96 | 2,82 | 0,96 | 3,05 | 0,88 | 2,74 |
| AVGCOR | 1,02 | 2,71 | 0,88 | 3,23 | 0,93 | 2,88 | 0,94 | 2,53 |

Panel D: Encompassing tests, 1990:01-2007:12

| | GW predictor encompasses SII? | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | h=1 | | h=3 | | h=6 | | h=12 | |
| Predictor | lambda | HLN | lambda | HLN | lambda | HLN | lambda | HLN |
| DP | 1,20 | 3,48 | 1,23 | 4,02 | 1,32 | 3,80 | 1,34 | 3,09 |
| DY | 1,25 | 3,55 | 1,24 | 4,03 | 1,36 | 3,89 | 1,35 | 3,11 |
| EP | 1,07 | 1,78 | 1,05 | 2,89 | 1,18 | 3,32 | 1,02 | 2,57 |
| DE | 0,93 | 1,85 | 0,83 | 1,91 | 0,92 | 2,08 | 0,49 | 1,19 |
| RVOL | 0,88 | 2,35 | 0,90 | 2,73 | 0,91 | 2,52 | 0,54 | 1,41 |
| BM | 1,04 | 1,68 | 1,06 | 2,15 | 1,30 | 2,72 | 1,03 | 2,04 |
| NTIS | 0,90 | 2,68 | 0,86 | 3,47 | 1,00 | 3,76 | 0,79 | 3,09 |
| TBL | 0,62 | 1,07 | 0,56 | 0,98 | 0,67 | 1,06 | 0,22 | 0,43 |
| LTY | 0,70 | 0,93 | 0,80 | 1,49 | 1,02 | 2,22 | 0,77 | 1,84 |
| LTR | 0,73 | 1,42 | 0,45 | 1,01 | 0,51 | 1,59 | 0,17 | 0,50 |
| TMS | 0,73 | 1,54 | 0,72 | 1,69 | 0,67 | 1,39 | 0,30 | 0,79 |
| DFY | 1,02 | 3,03 | 1,08 | 3,50 | 1,13 | 3,26 | 0,78 | 1,83 |
| DFR | 1,02 | 1,88 | 0,73 | 1,55 | 0,68 | 1,48 | 0,02 | 0,06 |
| INFL | 0,43 | 0,62 | 0,40 | 0,72 | 0,55 | 1,02 | 0,11 | 0,26 |
| OGAP | 0,84 | 2,16 | 0,75 | 2,51 | 0,69 | 2,43 | 0,40 | 1,36 |
| TAIL | 0,50 | 1,33 | 0,51 | 1,70 | 0,42 | 1,79 | 0,19 | 1,19 |
| TCHI | 0,17 | 0,25 | 0,13 | 0,25 | -0,07 | -0,17 | -0,06 | -0,14 |
| AVGCOR | 0,42 | 1,00 | 0,42 | 1,68 | 0,43 | 1,41 | 0,26 | 0,80 |

Table 6: Out-of-sample CER gains

| | 1990:01-2014:12 | | | | 2007:01-2014:12 | | | | 1990:01-2006:12 | | | | 2009:01-2014:12 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 | h=1 | h=3 | h=6 | h=12 |
| DP | -3,19 | -2,46 | -3,50 | -3,48 | -0,48 | 0,00 | 0,67 | 0,99 | -4,47 | -3,64 | -5,54 | -5,64 | -2,14 | -1,71 | -1,94 | -2,18 |
| DY | -2,96 | -2,34 | -3,34 | -3,36 | -0,02 | 0,49 | 1,16 | 1,14 | -4,35 | -3,69 | -5,53 | -5,53 | -2,20 | -1,68 | -2,07 | -2,12 |
| EP | -0,34 | -0,38 | -1,12 | -1,37 | 1,10 | 0,02 | -0,30 | -1,03 | -1,02 | -0,57 | -1,51 | -1,51 | -2,82 | -3,78 | -4,94 | -4,69 |
| DE | -1,13 | -1,57 | -2,27 | -0,47 | -0,16 | -1,88 | -4,65 | -0,77 | -1,58 | -1,40 | -0,95 | -0,48 | -0,70 | -2,04 | -5,74 | -0,95 |
| RVOL | -1,82 | -1,77 | -1,48 | -0,30 | 0,70 | 0,45 | 0,36 | 0,85 | -3,03 | -2,88 | -2,48 | -0,94 | 1,28 | 0,57 | -0,13 | 0,59 |
| BM | -0,78 | -0,63 | -0,98 | -1,32 | -0,01 | -0,12 | 0,15 | -0,22 | -1,14 | -0,87 | -1,53 | -1,91 | -0,50 | -0,70 | -0,89 | -1,10 |
| NTIS | -2,57 | -2,77 | -2,75 | -3,62 | -4,67 | -6,28 | -5,60 | -7,87 | -1,58 | -1,10 | -1,41 | -1,94 | 0,31 | -1,16 | -0,28 | 1,30 |
| TBL | 0,66 | 0,35 | -0,06 | -0,82 | -0,40 | -0,95 | -1,09 | -0,34 | 1,15 | 0,95 | 0,42 | -1,16 | 4,61 | 2,73 | 1,94 | 1,31 |
| LTY | -0,05 | -0,53 | -0,79 | -1,79 | 0,57 | -0,02 | 0,02 | -1,12 | -0,33 | -0,76 | -1,17 | -2,04 | 0,76 | -1,25 | -2,29 | -5,37 |
| LTR | -0,95 | 0,41 | -0,31 | 1,17 | -0,92 | -1,27 | -2,08 | -0,40 | -0,98 | 1,21 | 0,55 | 1,91 | -2,24 | -0,88 | -0,37 | -1,74 |
| TMS | 0,25 | 0,87 | 0,60 | 1,40 | -1,48 | -1,95 | -0,44 | 3,69 | 1,05 | 2,17 | 1,00 | 0,13 | 3,25 | 2,10 | 2,98 | 4,48 |
| DFY | -4,90 | -4,56 | -4,69 | -1,86 | -5,93 | -4,80 | -2,53 | -0,24 | -4,43 | -4,49 | -5,85 | -2,87 | -1,94 | -1,03 | 1,03 | 0,88 |
| DFR | 1,08 | 0,67 | 0,89 | 0,50 | 1,34 | 1,87 | 3,05 | 0,89 | 0,96 | 0,08 | -0,23 | 0,29 | -5,15 | -2,82 | 3,14 | 0,93 |
| INFL | -0,55 | -0,48 | 1,87 | 1,68 | -3,01 | -2,15 | 4,33 | 5,34 | 0,62 | 0,30 | 0,63 | -0,35 | -1,85 | -0,52 | 3,84 | 4,43 |
| OGAP | 1,14 | 2,38 | 2,15 | 3,10 | 7,46 | 7,75 | 8,54 | 8,75 | -1,81 | -0,12 | -0,91 | 0,42 | 4,68 | 4,14 | 2,85 | 3,84 |
| TAIL | 2,27 | 1,94 | 2,12 | 3,67 | 2,50 | 1,98 | 1,72 | 2,18 | 2,15 | 1,90 | 2,40 | 4,24 | 0,74 | -0,10 | -1,32 | 4,21 |
| TCHI | 4,32 | 2,21 | 3,34 | 0,10 | 7,14 | 3,66 | 5,29 | 0,28 | 2,98 | 1,51 | 2,40 | 0,02 | 0,76 | -2,69 | -0,40 | -0,78 |
| AVGCOR | -0,28 | 0,19 | 0,08 | -1,22 | -3,07 | -0,80 | 0,40 | -4,12 | 1,02 | 0,56 | -0,26 | -0,31 | 2,61 | 6,39 | 6,38 | 5,29 |
| SII | 4,17 | 4,65 | 5,44 | 3,43 | 11,18 | 13,08 | 15,91 | 11,23 | 0,88 | 0,73 | 0,57 | -0,38 | 6,97 | 7,78 | 10,27 | 8,98 |
| Buy and hold | 1,70 | 2,59 | 2,75 | 2,04 | 0,91 | 1,70 | 5,24 | 1,03 | 2,07 | 2,96 | 1,43 | 2,26 | 3,15 | 4,16 | 8,16 | 5,68 |

Table 7: Sharpe ratios

| | 1990:01-2014:12 | | | | 2007:01-2014:12 | | | | 1990:01-2006:12 | | | | 2009:01-2014:12 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 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 | h=1 | h=3 | h=6 | h=12 |
| Prevailing mean | 0,39 | 0,31 | 0,37 | 0,35 | 0,40 | 0,28 | 0,19 | 0,28 | 0,38 | 0,33 | 0,45 | 0,37 | 1,22 | 1,14 | 1,40 | 1,53 |
| DP | 0,11 | 0,10 | 0,01 | 0,01 | 0,37 | 0,27 | 0,20 | 0,32 | 0,01 | 0,04 | -0,08 | -0,12 | 1,13 | 1,07 | 1,35 | 1,16 |
| DY | 0,12 | 0,11 | 0,02 | 0,02 | 0,43 | 0,32 | 0,24 | 0,33 | 0,02 | 0,04 | -0,08 | -0,11 | 1,16 | 1,06 | 1,37 | 1,17 |
| EP | 0,36 | 0,27 | 0,26 | 0,22 | 0,54 | 0,28 | 0,11 | 0,16 | 0,30 | 0,27 | 0,33 | 0,24 | 0,93 | 0,71 | 0,60 | 0,76 |
| DE | 0,31 | 0,24 | 0,21 | 0,34 | 0,39 | 0,14 | -0,19 | 0,28 | 0,29 | 0,27 | 0,38 | 0,36 | 1,31 | 0,90 | 0,83 | 0,86 |
| RVOL | 0,28 | 0,24 | 0,26 | 0,32 | 0,45 | 0,36 | 0,26 | 0,33 | 0,20 | 0,18 | 0,26 | 0,31 | 0,98 | 0,83 | 0,84 | 1,48 |
| BM | 0,33 | 0,27 | 0,28 | 0,26 | 0,40 | 0,27 | 0,17 | 0,25 | 0,31 | 0,28 | 0,33 | 0,25 | 1,22 | 1,13 | 1,46 | 1,45 |
| NTIS | 0,20 | 0,14 | 0,19 | 0,19 | 0,11 | -0,05 | -0,02 | 0,11 | 0,26 | 0,24 | 0,34 | 0,24 | 1,29 | 1,06 | 1,46 | 1,25 |
| TBL | 0,45 | 0,37 | 0,37 | 0,33 | 0,39 | 0,27 | 0,18 | 0,28 | 0,47 | 0,41 | 0,48 | 0,35 | 1,24 | 1,14 | 1,44 | 1,44 |
| LTY | 0,38 | 0,27 | 0,30 | 0,17 | 0,45 | 0,27 | 0,14 | 0,11 | 0,37 | 0,28 | 0,36 | 0,18 | 1,33 | 1,17 | 1,34 | 1,23 |
| LTR | 0,33 | 0,35 | 0,35 | 0,42 | 0,35 | 0,22 | 0,10 | 0,29 | 0,32 | 0,40 | 0,49 | 0,47 | 0,76 | 0,84 | 1,17 | 0,79 |
| TMS | 0,41 | 0,38 | 0,41 | 0,43 | 0,34 | 0,25 | 0,25 | 0,50 | 0,45 | 0,45 | 0,52 | 0,39 | 1,08 | 0,96 | 1,18 | 1,74 |
| DFY | -0,02 | -0,02 | 0,02 | 0,21 | 0,04 | 0,05 | 0,12 | 0,32 | -0,08 | -0,07 | -0,06 | 0,15 | 0,89 | 0,87 | 1,19 | 1,01 |
| DFR | 0,46 | 0,36 | 0,43 | 0,38 | 0,49 | 0,43 | 0,41 | 0,33 | 0,45 | 0,33 | 0,43 | 0,39 | 0,58 | 0,67 | 1,26 | 1,67 |
| INFL | 0,36 | 0,31 | 0,49 | 0,46 | 0,19 | 0,18 | 0,49 | 0,59 | 0,43 | 0,36 | 0,49 | 0,40 | 0,95 | 0,88 | 1,50 | 1,16 |
| OGAP | 0,47 | 0,47 | 0,54 | 0,53 | 0,86 | 0,78 | 0,78 | 1,04 | 0,21 | 0,26 | 0,40 | 0,35 | 1,10 | 0,99 | 0,99 | 1,72 |
| TAIL | 0,54 | 0,44 | 0,52 | 0,56 | 0,59 | 0,44 | 0,30 | 0,45 | 0,52 | 0,44 | 0,60 | 0,60 | 1,08 | 0,86 | 0,93 | 1,14 |
| TCHI | 0,70 | 0,46 | 0,63 | 0,35 | 0,93 | 0,59 | 0,65 | 0,29 | 0,59 | 0,41 | 0,63 | 0,37 | 1,03 | 0,73 | 1,10 | 1,26 |
| AVGCOR | 0,38 | 0,37 | 0,38 | 0,32 | 0,30 | 0,37 | 0,33 | 0,27 | 0,45 | 0,37 | 0,42 | 0,34 | 0,98 | 1,09 | 1,23 | 1,32 |
| SII | 0,66 | 0,60 | 0,72 | 0,53 | 1,05 | 1,06 | 1,22 | 0,93 | 0,44 | 0,37 | 0,49 | 0,38 | 1,18 | 1,16 | 1,43 | 1,49 |
| Buy and hold | 0,50 | 0,48 | 0,52 | 0,45 | 0,46 | 0,43 | 0,42 | 0,39 | 0,53 | 0,50 | 0,59 | 0,48 | 1,15 | 1,08 | 1,31 | 1,63 |

Table 8: In-sample predictive regression results, short interest extended to 2021:12.

| | | | | h=1 | | | | h=3 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-1982:12 | 1,14 | 2,03 | 0,02 | 1,69 | 1,24 | 2,72 | 0,02 | 6,07 |
| S&P 500 VW | EWSI | Linear | 1983:01-1992:12 | 0,94 | 1,09 | 0,14 | 0,98 | 0,71 | 0,93 | 0,22 | 1,70 |
| S&P 500 VW | EWSI | Linear | 1993:01-2002:12 | 1,01 | 0,98 | 0,18 | 0,77 | 1,33 | 1,46 | 0,13 | 4,19 |
| S&P 500 VW | EWSI | Linear | 2003:01-2014:12 | 1,18 | 2,48 | 0,01 | 5,40 | 1,36 | 2,82 | 0,02 | 16,71 |
| S&P 500 VW | EWSI | Linear | 2008:01-2014:12 | 1,75 | 2,03 | 0,02 | 8,60 | 1,93 | 2,48 | 0,05 | 24,65 |
| S&P 500 VW | EWSI | Linear | 2009:01-2014:12 | -0,27 | -0,26 | 0,59 | 0,10 | -0,43 | -0,56 | 0,66 | 0,97 |
| S&P 500 VW | EWSI | Linear | 1973:12-2007:12 | 0,30 | 1,07 | 0,17 | 0,21 | 0,28 | 1,24 | 0,16 | 0,56 |
| S&P 500 VW | EWSI | Linear | 2008:01-2021:12 | 0,65 | 1,69 | 0,06 | 3,18 | 0,68 | 1,79 | 0,09 | 9,75 |
| S&P 500 VW | EWSI | Linear | 2009:01-2021:12 | 0,04 | 0,11 | 0,44 | 0,01 | -0,02 | -0,06 | 0,51 | 0,01 |
| S&P 500 VW | EWSI | Linear | 1973:01-2021:12 | 0,52 | 2,40 | 0,01 | 1,47 | 0,56 | 2,77 | 0,01 | 4,79 |

| | | | | h=6 | | | | h=12 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Excess return | Short interest | Detrending | Sample | beta-hat | t-stat | p-value | R2 (%) | beta-hat | t-stat | p-value | R2 (%) |
| S&P 500 VW | EWSI | Linear | 1973:01-1982:12 | 1,17 | 2,75 | 0,05 | 10,46 | 1,39 | 4,42 | 0,03 | 33,29 |
| S&P 500 VW | EWSI | Linear | 1983:01-1992:12 | 0,53 | 1,01 | 0,22 | 2,45 | 0,49 | 1,25 | 0,20 | 5,74 |
| S&P 500 VW | EWSI | Linear | 1993:01-2002:12 | 1,28 | 1,38 | 0,19 | 7,14 | 0,14 | 0,11 | 0,47 | 0,11 |
| S&P 500 VW | EWSI | Linear | 2003:01-2014:12 | 1,48 | 2,78 | 0,02 | 30,08 | 1,39 | 3,45 | 0,03 | 47,27 |
| S&P 500 VW | EWSI | Linear | 2008:01-2014:12 | 2,04 | 3,06 | 0,07 | 40,32 | 1,47 | 3,54 | 0,14 | 51,70 |
| S&P 500 VW | EWSI | Linear | 2009:01-2014:12 | -0,38 | -0,60 | 0,64 | 1,58 | 0,05 | 0,16 | 0,46 | 0,11 |
| S&P 500 VW | EWSI | Linear | 1973:12-2007:12 | 0,23 | 0,98 | 0,22 | 0,78 | 0,15 | 0,56 | 0,34 | 0,57 |
| S&P 500 VW | EWSI | Linear | 2008:01-2021:12 | 0,71 | 1,77 | 0,13 | 17,54 | 0,51 | 1,75 | 0,17 | 20,52 |
| S&P 500 VW | EWSI | Linear | 2009:01-2021:12 | 0,00 | -0,01 | 0,48 | 0,00 | 0,04 | 0,17 | 0,44 | 0,16 |
| S&P 500 VW | EWSI | Linear | 1973:01-2021:12 | 0,56 | 2,67 | 0,02 | 9,32 | 0,51 | 2,56 | 0,04 | 13,26 |

Table 9: Stock return decomposition 1973:01-2014:12
Panel A:

| | Expected return | | Cash flow news | | Discount rate news | | | Total return | |
|---|---|---|---|---|---|---|---|---|---|
| VAR variables | beta-hat | t-stat | beta-hat | t-stat | beta-hat | t-stat | Sum | beta-hat | t-stat |
| r, DP | -0,07 | -3,13 | -0,35 | -2,27 | 0,09 | 2,03 | -0,51 | | |
| r, DP, DY | -0,06 | -2,53 | -0,35 | -2,27 | 0,10 | 2,23 | -0,51 | | |
| r, DP, EP | -0,08 | -3,52 | -0,40 | -2,36 | 0,04 | 0,98 | -0,51 | | |
| r, DP, DE | -0,08 | -3,52 | -0,40 | -2,36 | 0,04 | 0,98 | -0,51 | | |
| r, DP, RVOL | -0,11 | -3,64 | -0,27 | -1,95 | 0,13 | 1,91 | -0,51 | | |
| r, DP, BM | 0,01 | 0,50 | -0,33 | -2,35 | 0,19 | 2,89 | -0,51 | | |
| r, DP, NTIS | -0,05 | -2,49 | -0,36 | -2,32 | 0,10 | 2,15 | -0,51 | | |
| r, DP, TBL | -0,09 | -3,69 | -0,31 | -2,08 | 0,11 | 1,44 | -0,51 | | |
| r, DP, LTY | -0,08 | -3,43 | -0,32 | -2,20 | 0,11 | 1,60 | -0,51 | | |
| r, DP, LTR | -0,07 | -2,71 | -0,35 | -2,28 | 0,09 | 1,92 | -0,51 | | |
| r, DP, TMS | -0,08 | -3,53 | -0,34 | -2,21 | 0,09 | 1,64 | -0,51 | | |
| r, DP, DFY | -0,07 | -3,15 | -0,36 | -2,27 | 0,09 | 1,98 | -0,51 | | |
| r, DP, DFR | -0,09 | -2,74 | -0,34 | -2,20 | 0,08 | 1,92 | -0,51 | | |
| r, DP, INFL | -0,07 | -3,24 | -0,35 | -2,27 | 0,09 | 1,98 | -0,51 | | |
| r,DP,OGAP | -0,12 | -3,46 | -0,26 | -1,78 | 0,13 | 1,73 | -0,51 | | |
| r,DP,TAIL | -0,06 | -1,67 | -0,38 | -2,27 | 0,07 | 1,25 | -0,51 | | |
| r,DP,TCHI | -0,13 | -4,01 | -0,37 | -2,11 | 0,01 | 0,09 | -0,51 | | |
| r,DP,AVGCOR | -0,04 | -1,93 | -0,33 | -2,33 | 0,14 | 2,06 | -0,51 | | |
| r, DP, PC | -0,14 | -2,98 | -0,27 | -1,93 | 0,11 | 1,20 | -0,51 | | |
| SII | | | | | | | | -0,51 | -2,53 |

Panel B: Stock return decomposition 1973:01-2007:12

| | Expected return | | Cash flow news | | Discount rate news | | | Total return | |
|---|---|---|---|---|---|---|---|---|---|
| VAR variables | beta-hat | t-stat | beta-hat | t-stat | beta-hat | t-stat | Sum | beta-hat | t-stat |
| r, DP | 0,00 | -0,05 | -0,21 | -1,32 | 0,10 | 1,97 | -0,31 | | |
| r, DP, DY | -0,02 | -0,63 | -0,21 | -1,32 | 0,11 | 2,28 | -0,31 | | |
| r, DP, EP | 0,01 | 0,46 | -0,24 | -1,57 | 0,05 | 0,86 | -0,31 | | |
| r, DP, DE | 0,01 | 0,46 | -0,24 | -1,57 | 0,05 | 0,86 | -0,31 | | |
| r, DP, RVOL | 0,05 | 1,87 | -0,15 | -1,01 | 0,10 | 1,52 | -0,31 | | |
| r, DP, BM | -0,08 | -1,97 | -0,20 | -1,34 | 0,18 | 2,42 | -0,31 | | |
| r, DP, NTIS | -0,11 | -2,68 | -0,31 | -1,76 | 0,10 | 1,00 | -0,31 | | |
| r, DP, TBL | -0,07 | -1,98 | -0,25 | -1,50 | 0,13 | 1,45 | -0,31 | | |
| r, DP, LTY | -0,09 | -2,82 | -0,23 | -1,47 | 0,17 | 2,29 | -0,31 | | |
| r, DP, LTR | 0,02 | 0,47 | -0,20 | -1,29 | 0,09 | 1,74 | -0,31 | | |
| r, DP, TMS | 0,00 | 0,12 | -0,23 | -1,39 | 0,08 | 1,24 | -0,31 | | |
| r, DP, DFY | 0,05 | 1,72 | -0,21 | -1,23 | 0,05 | 0,88 | -0,31 | | |
| r, DP, DFR | 0,00 | -0,11 | -0,20 | -1,28 | 0,11 | 2,02 | -0,31 | | |
| r, DP, INFL | -0,01 | -0,16 | -0,22 | -1,35 | 0,09 | 1,82 | -0,31 | | |
| r,DP,OGAP | 0,01 | 0,15 | -0,23 | -1,36 | 0,07 | 1,28 | -0,31 | | |
| r,DP,TAIL | -0,05 | -0,90 | -0,24 | -1,49 | 0,12 | 1,56 | -0,31 | | |
| r,DP,TCHI | 0,00 | -0,07 | -0,26 | -1,33 | 0,05 | 0,93 | -0,31 | | |
| r,DP,AVGCOR | -0,14 | -3,81 | -0,18 | -1,30 | 0,27 | 2,90 | -0,31 | | |
| r, DP, PC | -0,09 | -1,30 | -0,16 | -1,17 | 0,24 | 2,34 | -0,31 | | |
| SII | | | | | | | | -0,31 | -1,46 |

Figures:

Figure 1: SII 1973:01-2014:12

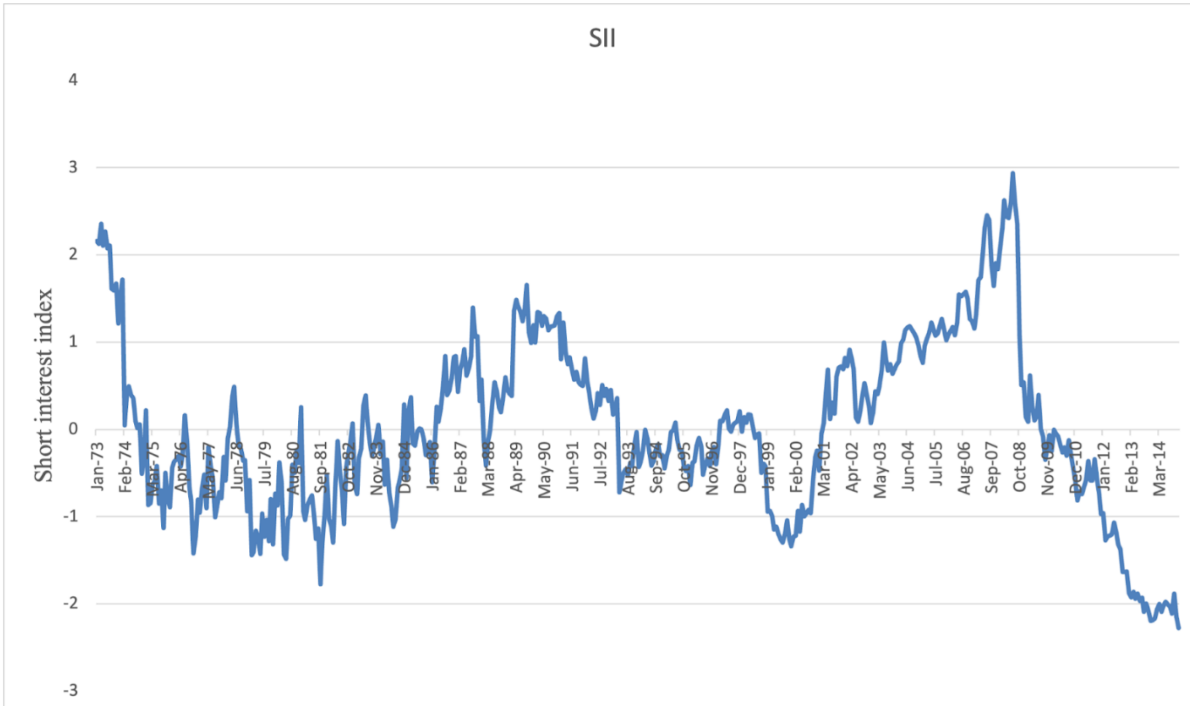


Figure 2: EWSI 1973:01-2014:12

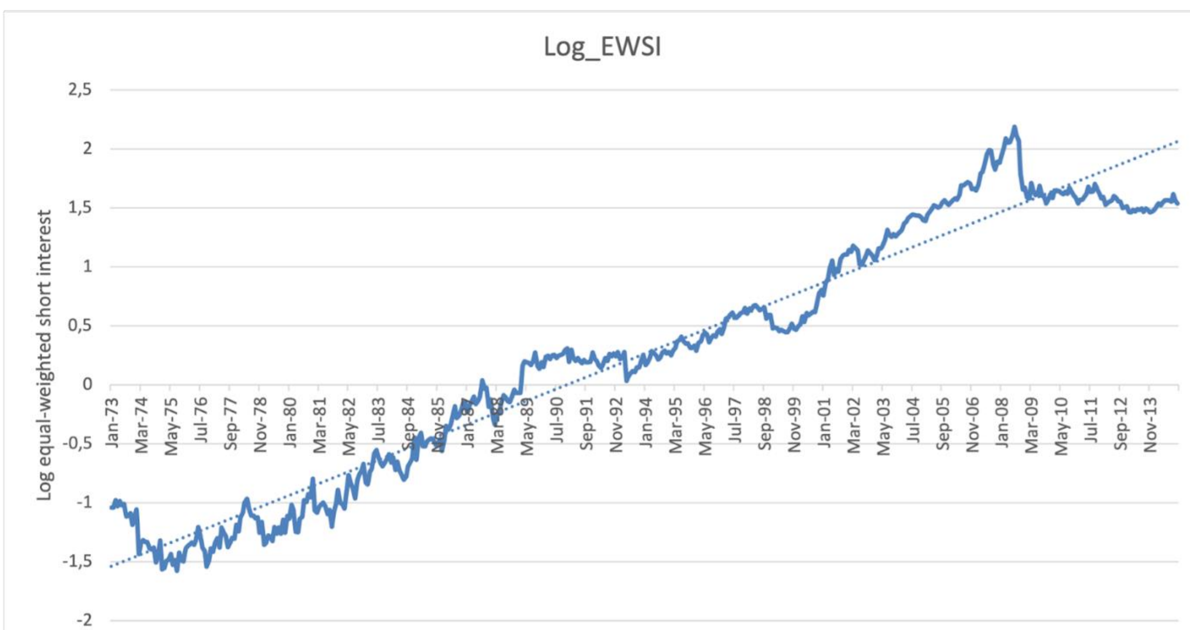

Figure 3: SII equity weight

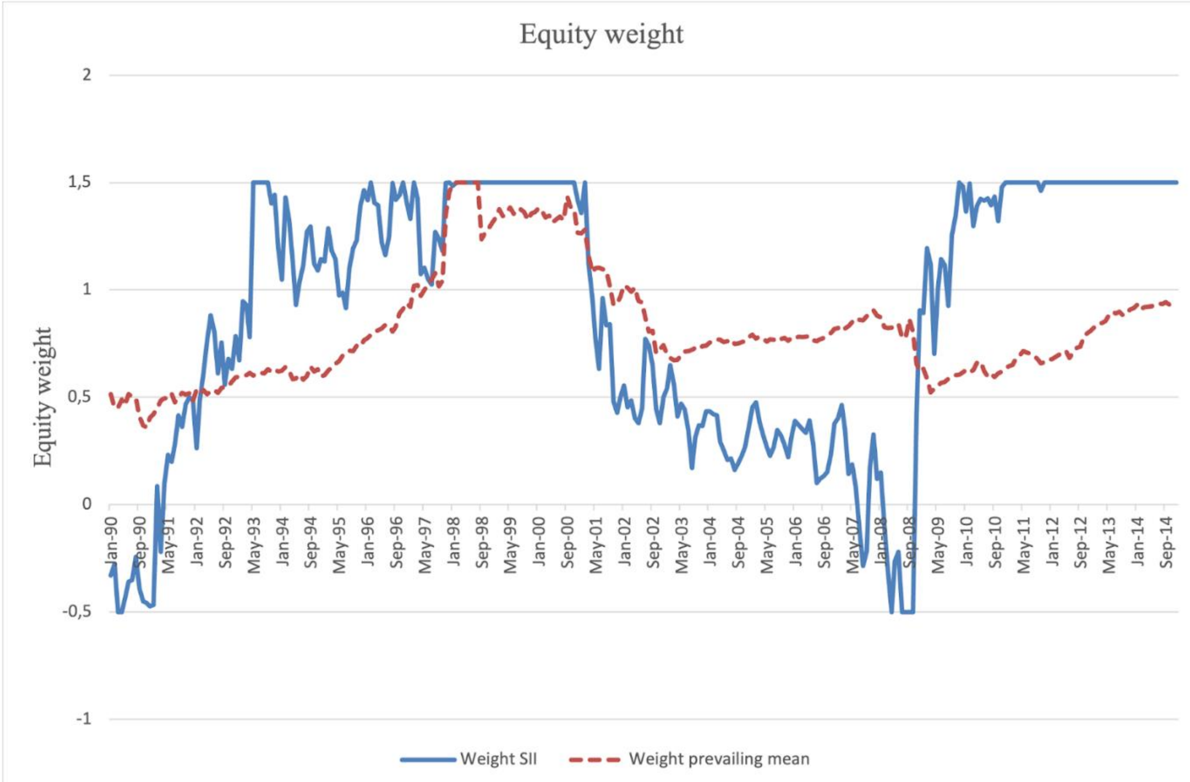


Figure 4: Cumulative return of SII vs prevailing mean

Figure 5: SII 1973:01-2021:12