Short Interest, Macroeconomic Variables and Aggregate Stock Returns

Richard Priestley

Abstract

Rapach, Ringgenberg and Zhou (2016) claim that for the sample period 1973 to 2014 "short interest is arguably the strongest known predictor of aggregate stock returns", that it "outperforms a host of popular predictors", and that it represents "informed traders who are able to anticipate changes in future aggregate cashflows". We show that the entire evidence regarding these claims disappears if we exclude data on short interest for the calendar year of 2008 when the financial crisis had its largest impact on stock markets. In contrast, we show that macroeconomic variables can predict aggregate returns and combining forecasts based on macroeconomic variables provides consistent and stable forecasts in periods that include and exclude the financial crisis.

JEL Classification: G1, G11, G12

Keywords: Predictability, short interest, macroeconomic variables, financial crisis.

1 Introduction

The debate regarding stock return predictability has focussed on two issues. First, are stock returns predictable? Second, if they are, why are they? The first issue has examined statistical challenges with predictability and in-sample versus out-of-sample performance. The second issue has tried to distinguish between explanations based on rational variation in expected returns, behavioral biases, and information channels. Goyal and Welch's (2008) assessment of the predictive power of a set of financial and economic based predictor variables that are meant to track business conditions led to a questioning of the idea that expected returns vary with business conditions. More recently, investor sentiment based variables have been shown to predict returns. These measures of sentiment, or investor beliefs, suggest that short sellers acquire information about aggregate market prices that are not reflected in current prices and earn returns when this information is revealed in prices in the future.

Rapach, Ringgenberg, and Zhou (2016) (henceforth RRZ) use short interest, a measure of total short sales for the aggregate stock market to proxy investors' beliefs. The idea is that current high levels of short selling indicate that this group of investors believe the market is over-valued and hence future returns will be lower. RRZ argue that prices are driven too high because future cashflow forecasts are too optimistic. Informed investors know this, short the aggregate market and make money when the correction for this over optimistic forecast of future aggregate cashflows reduces future prices.

RRZ claim to have found empirical evidence that first, "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date", second, that it "outperforms a host of popular return predictors" and third, that short interest predicts returns "through a cash flow channel" implying that short sellers are "able to anticipate changes in future aggregate cash flows and associated changes in future market returns". The dual finding of the apparent success of short interest in predicting aggregate stock returns and the failure of economic and financial based variables to predict returns, suggests that stock return predictability is not due to variation in expected returns and, or, risk, but rather it is due to informed investors correcting market prices. This finding has important implications since many recent developments of asset pricing models introduce good and bad times in the economy in order to match key asset pricing moments (see, for example, Campbell and Cochrane (1999), Constantinidies and Duffie (1996), Bansal and Yaron (2004), Reitz (1988), Gârleanu and Panageas (2015), and for a review Cochrane (2017)). The finding that traditional measures of business conditions such as the Goyal and Welch (2008) variables do not predict returns is a concern for theoretical models that build on variations in state variables over the business cycle.

This paper reexamines the findings in RRZ and provides new evidence regarding the ability of measures of business conditions to predict returns. In particular, we document that the results in RRZ, which look at a sample from 1973 to 2014, are largely attributable to a single calendar year of short interest, notably 2008 the year that the financial crisis had its largest negative impact on the stock market. As in RRZ, we find that over the entire sample period of 1973 to 2014 a regression of monthly stock returns at time t on the index of short interest at time $t-1$ produces a coefficient estimate of around -0.5 which is statistically significant at the 1% level. The adjusted $\overline{R}$, $\overline{R}^2$ is around 1%, confirming RRZ's strong economic and statistical relationship between stock returns and short interest. However, now consider Figure 1 which plots the raw short interest data created by RRZ. From the year 2000 short interest climbs from around two to historically high levels in 2008 of around nine, before subsequently falling dramatically by about a half for the rest of the sample period. The high levels of short interest at the beginning of 2008 are followed by future lower returns as the financial crisis took hold in 2008. For example, historically high values of short interest were subsequently followed by returns of -8% in June 2008, -9% in September 2008 and -17% in October 2008.

It is clear that there is a strong negative relation between the level of short interest and future stock returns in 2008. In fact, this relation is so strong in 2008 that closer examination reveals that the full sample period estimates appear statistically significant only because of the inclusion of 2008. We find no evidence of stock return predictability in the sample from 1973 to the end of 2007, a period of over 400 monthly observations. The estimated coefficient on short interest falls from its full sample estimate of -0.5 to around -0.2, has a t-statistic of less than one and an $\overline{R}^2$ one tenth of that for the full sample. If we run the regression from the beginning of 2008 to the end of 2014, the estimate is very large at -1.04, highly statistically significant and the $\overline{R}^2$ is over 7%. When considering the sample period from the start of 2009 to the end of 2014, the estimate falls to -0.06, is not statistically significant and the $\overline{R}^2$ is -0.14.

These results indicate that RRZ's first claim that "short interest .... is arguably *the* strongest predictor of the equity premium identified to date" holds only during the financial crisis in 2008. Outside of this period, either before or after, short interest cannot predict stock returns.

RRZ's second claim that short interest is "arguably" the best predictor of stock returns is not only sensitive to the sample period, but is also sensitive to the choice of the alternative set of predictor variables. It is well known that the Goyal and Welch (2008) set of macroeconomic and financial predictor variables that RRZ consider struggle to predict stocks returns in the post oil crisis of the early 1970s, that is the conclusion of the Goyal and Welch (2008) paper. However, there are alternative macroeconomic predictor variables that are often theoretically motivated that RRZ omit from their analysis which have been used to predict stock returns. We consider the following variables: Lettau and Ludvigson's (2001) *cay*, Santos and Veronesi's (2006) labour to consumption variable, *slc*, Bansal, Khatchatrian, and Yaron's (2005) consumption volatility, σ_c, the investment to capital ratio of Cochrane (1991), $\frac{i}{k}$, and the output gap of Cooper and Priestley (2009), *gap*.

Using quarterly data over the 1973Q1 to 2014Q4 sample period, we find that like short interest, *cay*, *gap*, and to a lesser extent, $\frac{i}{k}$ can predict stock returns. In the period prior to the financial crisis, 1973Q1 to 2007Q4, both *cay* and *gap* can predict stock returns. This shows that both *cay* and *gap* can predict returns over the whole sample and the sub-sample prior to the financial crisis, something that short interest cannot do. Consumption volatility has the opposite predictor patterns to short interest in that it is able to predict returns in the period prior to the financial crisis, but not in the full sample that includes the financial crisis. The investment to capital ratio has some predictive power over the entire sample period but, like short interest, none in the sample period prior to the financial crisis. Santos and Veronesi's (2006) labour to consumption variable has no predictive power for returns either in the full sample or the sample prior to the financial crisis.

Over the full sample period a regression of excess returns on short interest and one of either *cay*, *gap*, or $\frac{i}{k}$ reveals that the macroeconomic variable predict future returns in the presence of short interest. When we regress returns on short interest only, these three macroeconomic variables can explain the residuals from this regressions. It is clear that short interest and the macroeconomic variables do not contain the same information about future returns and that the macroeconomic variables have a role in predicting stock returns even in a sample that includes 2008.

RRZ also undertake out-of-sample tests which we also perform for short interest and the macroeconomic variables. These tests confirm our in-sample findings: short interest is a strong predictor of returns in the out-of-sample period of 1990 to 2014 which is used in RRZ. However, in the out-of-sample period of 1990 to the end of 2007, there is no evidence of out-of-sample predictive power. That is, if an investor had followed the signals from short interest over a seventeen year period starting in 1990, they would not have performed better than using the historic mean. Of course, given that in-sample tests tend to have more power that out-of-sample tests (Inoue and Kilian (2005)), the results that the out-of-sample test find no evidence of predictability of returns by short interest in the period up to the end of 2007 is not surprising.

The out-of-sample results show that both cay and gap can both predict stock returns out-of-sample both over the full sample and the sample period that stops prior to the financial crisis at the end of 2007. Consistent with the in-sample results, $\frac{i}{k}$ can predict returns out-of-sample over the entire sample, like short interest. This predictability of returns by $\frac{i}{k}$ is evident in the period before the 2008 only at the three and four quarter horizons. Consumption volatility has out-of-sample predictive power in the period prior to the financial crisis, but not after it. Generally, because of the difficulty in executing a test of real time trading strategy for variables like SI and macroeconomic variables, we think of the results of the out-of-sample regressions as support to the in-sample regressions, rather than an indication that a successful trading rule might be possible.

One way that might improve forecasts that are linked to the macroeconomy is to combine single forecasts. Rapach, Strauss and Zhou (2009) provide a thorough motivation for combining forecasts and show that this is potentially very useful for macroeconomic variables. We provide new evidence that combining the five macroeconomic variables considered here into one forecast produces out-of-sample performance that is generally the same in the period prior to the financial crisis and the entire sample period that includes the financial crisis. The out-of-sample $\overline{R}^2s$ range from 2.5% at the one quarter horizon to 8.5% at the four quarter horizon over the entire period and 2.1% at the one quarter horizon to 7.8% at the four quarter horizon for the period before the financial crisis.

RRZ argue that the predictability of stock returns that they find over the entire sample period can be attributed to short interest's ability to predict cash flow news. RRZ argue that short sellers are informed traders who generate excess returns from their ability to better process information about future cash flows than the market as a whole. RRZ estimate a vector autoregression (VAR) following Campbell (1991) and subsequently decompose stock returns into expected returns, discount rate news, and cash flow news components. RRZ find that short interest predicts returns through predicting cash flow news. RZZ argue that this finding supports extant research that claims short sellers are informed traders who process firm specific information and earn a reward for doing so (see, for example, Boehmer, Jones, and Zhang (2008), Karpoff and Lou (2010), Engelberg, Reed, and Ringgenberg (2012), and Akbas, Boehmer, Erturk, and Sorescu (2013)).

Using five different versions of a VAR to estimate cash flow news, we also replicate RRZ's finding for the full sample period showing that short interest predicts cash flow news. In the final quarter of 2008 and the first quarter of 2009, cash flow news fell by 0.19, a record, and 0.10. This corresponds to previous highs in short interest in the proceeding quarters. However, this effect is completely absent in the period prior to the financial crisis. So, it appears that short interest is only informative about cash flow news, as it is about stock returns, in the financial crisis of 2008. It is also plausible that since cash flow news is backed out from a forecast of future stock returns in the VAR, the cash flow news inherits the large unexpected negative returns in this period mechanically and the relationship between cash flow news and short interest is even spurious in 2008.

Taken together, the results in this paper show that there is little support, outside of the year 2008, for RRZ's information advantage explanation of stock return predictability where the market misprices stocks and a select set of informed investors who are short selling hold information about a cash flow channel that informs about future returns. Instead, we find evidence which shows a consistent level of predictability by macroeconomic variables and particularly a combined forecast that produces very similar performance both before the financial crisis and over the entire sample period. The evidence that we present suggests that return predictability reflects mainly rational variation in expected returns captured by business cycle related variables. This is good news for recent asset pricing models that focus on identifying good and bad times in the economy in order to match key asset pricing moment (Cochrane (2017)).

The results we present also illustrate a general point that it is important to fully take account of the impact of outliers, or spikes in data in predictive regressions and estimates of VARs. Our findings show that it takes only a very few observations to ensure statistical significance of estimated coefficients over a long sample period. However, we show that this does not necessarily mean that a causal effect is present over an entire sample period.

The rest of the paper is organized as follows. In section 2, we reproduce the main in-sample results in RRZ using their data and show that short interest's ability to predict stock returns is closely related to data on short interest from the year 2008. We then introduce a set of macroeconomic variables that contain information about future stock returns that is unrelated to short interest and show that they can predict stock returns in a sample both before the financial crisis and including the financial crisis. Section 3 presents out-of-sample predictability results. These are entirely consistent with our in-sample findings. Section 4 shows that combining macroeconomic variables into a single forecast produces stable, statistically significant and economically meaningful forecasts of future stock returns. These are arguably the strongest predictors of the equity premium. In section 5, we document that the role of short interest as described in RRZ as a measure of beliefs about future cash flows news that the market has failed to properly incorporate is also entirely dependent on the year 2008. Before this year, there is no evidence to support the idea that investors who are shorting the market have information about future cash flows. Section 6 provides a conclusion.

2 In-sample Predictability

In this section of the paper, we address RRZ's first two claims that first, "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date", and second, that it "outperforms a host of popular return predictors". To address the first question, we begin by replicating the main in-sample results in RRZ and then examine stock return predictability in samples that do and do not include the calendar year 2008 where the financial crisis hit the stock market the hardest. We then present new results using an alternative set of macroeconomic variables to address RRZ's second claim.

2.1 Short Interest and Stock Returns

Data from Goufu Zhou's webpage: http://apps.olin.wustl.edu/faculty/zhou/ are available for Standard and Poor's stock returns and various measures of short interest for the period January 1973 to December 2014. RRZ report regressions with log excess returns. We report results using excess returns and real returns instead of log returns that RRZ use. This has no impact on the results and excess returns and log excess returns produce almost identical results. RRZ use an equally weighted version of short interest which has a linear trend removed giving a mean zero residual which is then standardized to have a standard deviation of one.

Figure 1 plots the actual data on short interest, SI. There is an upward trend in SI that starts in the early 1980s but increases at a much higher rate after 2000. There is a distinct peak in the series in 2008 followed by a sharp fall and then a basically flat line out to the end of 2014. RRZ argue for detrending SI based on an assumption that the upward trend reflects a growing equity lending market that facilitates the ease of short selling rather than necessarily indicating that there has been an increase in short selling that is signalling short sellers beliefs that prices are currently too high. RRZ argue that a linear detrended version will "capture the variation in short interest that is due to changes in the beliefs of short sellers, and not simply secular changes in equity lending conditions and/or the amount of capital devoted to short arbitrage".

Figure 2 plots linearly detrended SI which has a more cyclical pattern. Recall that the meaning of the detrending is to capture the changes in beliefs of short sellers. From around 1989 to 2000 there is a general downward trend and from 2000 to 2008 a strong upward trend. This would represent long periods of either decreasing or increasing short positions. The upward trend from 2000 to 2008 is interesting since it indicates an eight year period of prices being potentially too high and short sellers expecting prices should fall. This is a long time to hold a short position before the eventual correction in prices in 2008 and would involve considerable costs. However, irrespective of this, whether one considers Figure 1 or Figure 2, it is clear that there is a sudden, unique, and very large drop in the value of SI in 2008 and we know that there are large falls in equity prices in 2008 associated with the financial crisis. This motivates our analysis of the role of SI in predicating returns in a sample before this big drop in SI in 2008, as well as in a sample, like RRZ, that includes this big drop. We are aiming to answer the question of whether SI is a predictor of stocks returns in general over the entire sample period or specifically in the financial crisis.

In their empirical analysis RRZ multiply SI by minus one in order to obtain coefficient estimates that are positive. RRZ also report the actual R^2. In the results that we report, we do not multiple the estimates by minus one and we report the adjusted R^2, $\overline{R}^2$, because we later estimate multivariate regressions for which the $\overline{R}^2$ is appropriate. Using monthly returns and a one month horizon, RRZ estimate the following regression for the period 1973:1 to 2014:12

$$r_t = \alpha + \beta_{SI} * SI_{t-1} + u_t \tag{1}$$

where r_t is the log excess return on the Standard and Poors value weighted market index, SI is short interest and u_t is the residual. RRZ report a coefficient estimate, β_{SI}, of 0.50 that is statistically significant at the 1% level and a R^2 of 1.24. RRZ also construct three, six, and twelve month returns using overlapping one month returns. Statistically significant coefficient estimates at the three, six and twelve month horizons using overlapping returns are reported as 0.56, 0.57, and 0.53 (note that RRZ divide the estimates by the number of months in the horizon) and R^2s of 4.37, 8.07, and 12.89. These are the main findings in RRZ and coupled with their other findings in their Table 3 that the thirteen Goyal and Welch (2008) predictor variables are poor predictors of returns, leads them to claim that "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date", and that it "outperforms a host of popular return predictors".

We now provide evidence that these two claims of RRZ are conditional on the inclusion of a single year, 2008, of SI in the data. Panel A of Table 1 reproduces the main in-sample results of RRZ's paper using excess returns and real returns. At the one month horizon the estimated coefficient on short interest is -0.49 for excess returns and -0.49 for real returns.[1] These estimates are statistically significant at the 1% level. The $\overline{R}^2s$ are around 1% which are, by construction, slightly smaller than the R^2 of RRZ but the unreported R^2 is very similar to that of RRZ. The results in Panel A of Table 1 for the three, six, and twelve month horizons

[1] If we use the log of excess returns, then we replicate RRZ's results exactly.

are consistent with those reported in Table 3 of RRZ. Our estimates reported in Panel A for excess returns, divided by the number of months in the horizon, are -0.54, -0.57, and -0.55 for the three, six and twelve month horizons and the $\overline{R}^2$s are 3.99, 7.55, and 12.89. Similar results are reported in Panel A for real returns and similar unreported results are available for log excess returns. In summary, Panel A of Table 1 confirms the findings of RRZ and extends them to cover real returns. On the basis of the full sample estimates, SI does appear to be a good predictor of stock returns with impressive explanatory power at the one month to one year horizon.

Motivated by the time series patterns in SI as illustrated in Figures 1 and 2 and, in particular, the large drop in SI in 2008, Panel B of Table 1 now repeats the analysis in Panel A but for the shorter sample period of 1973:1 to 2007:12 which omits the impact of the financial crisis on the stock market in 2008. The first striking result is that at the one month horizon the coefficient on SI falls to -0.21, has a t-statistic of 0.95, and the $\overline{R}^2$ is now negative. Looking at the longer horizons we find estimates (divided by the number of months in the horizon) of -0.24, -0.22, and -0.24 for the three, six and twelve month horizons, all of which have t-statistics around one and very low $\overline{R}^2$s of 0.42, 0.86, and 2.24. Consequently, there is no evidence that SI can predict stock returns in a sample period covering thirty five years from 1973 to the end of 2007. Similar results are reported for real returns.

The findings in Panel B offer a completely different interpretation of the role of SI. There are no cases, across real or excess returns, and across all four horizons of any predictability. The estimated coefficients are reduced by more than fifty per cent, there is no evidence of statistical significance, and the $\overline{R}^2$s show that the explanatory power of SI is non-existent. It is clear that SI cannot predict returns at all in the 1973:1 to 2007:12 sample period.

We can further illustrate the importance of the year 2008 and hence the financial crisis for SI in predicting returns by turning to Panel C of Table 1 which reports the results for the 2008:1 to 2014:12 period. We report results using only a one month horizon to avoid problems of overlapping returns spanning the prior period. For this sample period, we find that SI can predict both excess and real returns. The estimated coefficient for excess returns is more than double that of the full sample at -1.04 and the monthly $\overline{R}^2$ is very large at 7.7%. Thus, in this sample period returns are highly predictable by SI. Panel D of Table 1 sheds further light on the question of how important 2008 is by reporting results for the 2009:1 to 2014:12 period. For this sample period, which admittedly has a small sample, we find that predictability is at its weakest: the estimated coefficient for excess returns is -0.07, the t-statistic is 0.10 and the $\overline{R}^2$ is -1.41. Recall that the full sample values are, respectively, -0.49, 2.49, and 1.00.

The findings presented in Table 1 tell us that the claim in RRZ that SI is "arguably the strongest known predictor of aggregate stock returns" is only true for twelve months of the five hundred and four months, or two percent of the sample. SI cannot predict stock returns either before 2008 or after 2008. This raises serious concerns regarding RRZ's claim of a information based explanation of stock return predictability where investors who are shorting the market have information about future stock returns that has not been incorporating into market prices correctly, at least outside of the year 2008.

2.2 Macroeconomic Variables, Short Interest, and Stock Returns

As well as claiming that SI is the best predictor of stock returns based on its performance over the entire sample period, RRZ also claim SI out-performs a set of thirteen financial market based variables and macroeconomics variables that are examined in Goyal and Welch (2008). It is well known that the thirteen variables used in Goyal and Welch (2008) are poor post mid 1970s oil price crisis predictors of stock returns, that is the conclusion from Goyal and Welch (2008). It is not so much that SI out-performs all the Goyal and Welch (2008) predictor variables, it is more accurate to say that in general this set of variables cannot predict returns at all.

It is interesting to dwell on the issue of the predictability of stock returns with macroeconomic variables. The issue of comparing variables like SI against financial and macroeconomic variables is more than a simple horse race to find the best predictor of stock returns. RRZ note that SI's role as a predictor is consistent with an information based explanation of stock return predictability where informed investors short the market based on cash flow news that has not been incorporated into market prices yet. Macroeconomic variables in contrast are used to try and measure business conditions and therefore any time variation in expected returns that is a result of variations in, for example, risk aversion or the quantity of risk around good and bad economic times. Therefore, comparing SI and macroeconomic variables speaks to the debate as to whether evidence of predictability is due to time variation in risk, risk aversion, or prices of risk which would reflect rational variation in investors future expected returns, or whether it is due to short sellers ability to gather and process valuable information that the aggregate market does not have.

The choice by RRZ to use the predictor variables of Goyal and Welch (2008) matches the monthly frequency of SI. Unfortunately, this choice does limit a more thorough analysis of the relative performance of SI and macroeconomic variables and hence the chances of reaching a reliable conclusion as to the reason why stock returns are predictable, if they are at all. The reason for this is two fold. First, we know that the Goyal and Welch (2008) variables are poor predictors of future stock returns already. Second, some of the most successful macroeconomic predictors that are often theoretically derived are measured at a quarterly frequency. However, there is no reason why we can not measure SI at a quarterly frequency. In order to do this, we simply take the value of SI in March, June, September and December as the quarterly values.

The macroeconomic variables that we use are Lettau and Ludvigson's (2001) cay, Cochrane's (1991) investment to capital ratio, $\frac{i}{k}$, Santos and Veronesi's (2006) labour to consumption ratio slc, Cooper and Priestley's (2009) output gap, gap, and consumption volatility of Bansal, Khatchatrian, and Yaron (2005), σ_c. Rather than the ad hoc set of variables that Goyal and Welch (2008) consider, these variables are, with the exception of gap, theoretically motivated.

Table 2 reports a correlation matrix of the five macroeconomic variables and SI. The level of correlation between SI and the macroeconomic variables is low with the largest being between SI and gap at 0.29. All the other correlations of SI and the other macroeconomic variables are less than 0.1 in absolute terms. This suggests that SI and the short positions that this group of investors are taking are unrelated to macroeconomic conditions, at least at the quarterly frequency and as measured by these particular macroeconomic variables. The highest correlation between the macroeconomic variables is 0.75 between gap and $\frac{i}{k}$.

By using a different set of macroeconomic variables, Table 3 reports in-sample predictive regressions of quarterly excess returns on each of the macroeconomic variables as well as on SI.[2] We present results over the full sample period of 1973:Q1 to 2014Q4, using one, two, three and four quarterly horizons. At the one quarter horizon, the estimated coefficient on SI is

[2]From now on, we report only resuts for excess returns. Results for real returns are similar.

-1.603 which is very similar to the estimated coefficient of -1.628 in Table 1 for the three month returns and very similar to the estimate using three month returns in Table 3 of RRZ. The estimate with quarterly excess returns is statistically significant at the 1% level and the $\overline{R}^2$ is 2.93. Clearly, using quarterly returns produces similar results to RRZ's three month returns and our own three month returns in Table 1. This pattern in predictability is reflected in the two, three and four quarter horizons. There is a strong consistency between monthly returns over various horizons up to one year and quarterly returns for horizons up to one year.

The remainder of Table 3 reports the results for predicting stock returns with the macroeconomic variables. Note that all the macroeconomic variables are constructed to have a mean of zero and are standardized to have a standard deviation of one. Consequently, the size of the coefficients can be compared across all predictor variables. Starting with *cay*, it can predict excess returns at all four horizons. The estimates are statistically significant and are of around the same magnitude as that of SI. The $\overline{R}^2s$ are slightly less than for SI except at the four quarter horizon where it is slightly larger. So, over the entire sample period, *cay* looks to have similar forecasting power for excess returns as SI.

The next row of Table 3 reports the results for *gap* and shows that there is stronger evidence of predictability of excess returns with *gap* than with SI at all horizons. The coefficient estimates are larger, there are higher levels of statistically significance and larger $\overline{R}^2s$. For example, the $\overline{R}^2s$ are 4.4 (2.9), 7.8 (5.4) , 11.5 (8.5), and 13.8 (9.7) per cent for *gap* (SI). The next row shows the results when predicting excess returns with $\frac{i}{k}$. The evidence for predictability is somewhat weaker in this case. The size of the coefficients are smaller than the three previous predictor variables and are statistically significant at the 10% level except for the two quarter horizon where it is statistically significant at the 5% level. The $\overline{R}^2s$ are around half of SI and *cay*. Consumption volatility, σ_c cannot predict excess returns at the one month horizon but has statistically significant coefficient estimates at the ten per cent level for the two, three and four quarter horizons, although the $\overline{R}^2s$ are relatively small at around two for these three horizons. The final row of Table 3 reports predictability results when using the share of labour income in consumption, *slc*. There is no evidence of predictability with this variable.

Table 3 provides evidence that contradicts RRZ's conclusion that SI "outperforms a host of popular return predictors". At least when looking at their stand-alone performance, both *cay* and *gap* have similar predictive power to SI when comparing the size of the estimated coefficient, the level of statistical significance and the explanatory power as measured by the $\overline{R}^2$. To a lesser extent $\frac{i}{k}$ can also predict excess returns at horizons up to one year, although the evidence here is weaker than for SI.

In an attempt to assess the relative predictive power of SI and the macroeconomic variables, in Table 4, we report the results of various regressions. First, we regress excess returns on both SI and one of the macroeconomic variables:

$$r_t = \alpha + \beta_{SI} * SI_{t-1} + \beta_i * Z_{i,t-1} + u_t \tag{2}$$

where Z_i is one of the five macroeconomic variables. This regression could reveal information about the relative importance of the two variables. Panel A of Table 4 shows that *cay*, *gap*, and $\frac{i}{k}$ retain their level of economic and statistical significance even in the presence of SI. Including both SI and one of these three macroeconomic variables increases the $\overline{R}^2$ from around 3% with only SI to between 4.7 and 5.5. However, it is interesting to see that in the case when both SI and *gap* are included, the estimated coefficient on SI falls from -1.6 to -1.1 and the t-statistic on SI is now statistically significant at the 10% level rather than the 1% level. Thus, it is not obvious that even over the entire sample that SI is the best predictor of returns. The estimated coefficients on σ_c and *slc* are not statistically significant in the presence of SI. However, recall that they were not even statistically significant on their own.

It is possible that the correlation between SI and the macroeconomic variables, although small, makes relative comparisons in multivariate regressions difficult. To guard against this, we also undertake two further regressions for each of the variables. First, we regress excess returns on SI

$$r_t = \alpha + \beta_{SI} * SI_{t-1} + e_{SI,t} \tag{3}$$

and subsequently regress the residuals from this regression on the macroeconomic variables:

$$e_{SI,t} = a + \beta_i * Z_{i,t-1} + v_t \tag{4}$$

Panel B of Table 4 reports the coefficient estimates on the five macroeconomic variables. In the case of *cay*, *gap*, and $\frac{i}{k}$ they all record statistically significant coefficients. Macroeconomic variables have a role in predicting stock returns even after first allowing for predictability with SI. Next, we regress excess returns on the macroeconomic variables first:

$$r_t = \alpha + \beta_i * Z_{i,t-1} + e_{i,t} \tag{5}$$

and subsequently regresses the residuals from this regression on SI:

$$e_{i,t} = a + \beta_{SI} * SI_{i,t-1} + v_t \tag{6}$$

In Panel C which reports these results, we find that SI is still statistically significant in all cases, albeit only marginally for *gap* indicating that *gap* leaves little return left that could be explained by SI. Furthermore, the increase in $\overline{R}^2$ is only 1% here. When we regress returns on all macroeconomic variables in a multivariate regression and then the residuals from this regression on SI, SI is no longer statistically significant. The results in Table 4 provide evidence that even over the entire sample period SI is not the best predictor of stock returns as claimed by RRZ and after accounting for all the macroeconomic variables in a single regression, SI cannot predict what the macroeconomic variables cannot predict.

We now turn to examining the predictability of quarterly excess returns in the sample period 1973:Q1 to 2007:Q4. Table 5 reports the results when regressing excess returns separately on SI and on each of the five macroeconomic variables. The first row of results confirm the findings with monthly returns that SI cannot predict returns in this sample period before the financial crisis at any of the quarterly horizons. The t-statistics are one or lower, the coefficient estimates are small and the $\overline{R}^2$ negative or small. For example, the one quarter estimate is -0.76, the t-statistic is 1.00 and the $\overline{R}^2$ is -0.11. Recall, at the three month horizon, as reported in Panel B of Table 1, the estimate is -0.71 with a t-statistic of 1.14 and a $\overline{R}^2$ of 0.42. Similar results and comparisons are recorded for the two, three and four quarter horizons. Thus, the monthly and quarterly results are entirely consistent with each other in that there is no evidence at these four horizons that SI can predict stock returns in the 1973 to 2007 sample, which is the vast majority of the period considered.

In contrast to the results that SI cannot predict returns in this sample period, Table 5 shows that of the five macroeconomic variables both *cay* and *gap* can predict returns up until the end of 2007. *cay* has slightly better predictive power in this sample period as compared to the full sample period at the one quarter horizon in terms of a larger estimated coefficient (1.99 compared to 1.41) a larger t-statistic (2.91 compared to 2.16) and a larger $\overline{R}^2$ (5.24 compared to 2.15). These differences are also present at the other three horizons. *gap* has slightly worse predictive power in this sample period compared to the full sample period at the one quarter horizon in terms of a smaller estimated coefficient (-1.42 compared to -1.87) a smaller t-statistic (2.07 compared to 3.03) and a smaller $\overline{R}^2$ (2.14 compared to 4.37). These differences are also present at the other three horizons. However, there is evidence of predictability in both sample periods for both variables. Therefore, unlike SI the predictive power of *cay* and *gap* is not confined to a sample period that includes the financial crisis. In the shorter sample period that runs to the end of 2007, it does appear that $\frac{i}{k}$ loses its predictive power in the pre-crisis period and that σ_c can predict in the pre-crisis period. There is no evidence that *slc* can predict in the pre-crisis period.[3]

Overall this section of the paper has confirmed that SI cannot predict quarterly stock returns in the pre-financial crisis period. More importantly, we have shown that there are a set of macroeconomic variables that can predict stock returns in both the pre-financial crisis period and the entire sample period.

3 Out-of-Sample Evidence

RRZ report extensive out-of-sample tests of return predictability. Dealing with out-of-sample analysis and claiming that this is an indiction of what an actual investor could have done in real time in terms of a trading strategy is not straightforward. This is because predictor variables sometimes require the estimation of coefficients and they often include data that is subsequently revised. Take, for example, short interest which has a linear trend removed by RRZ for their in-sample analysis through a full sample estimation process. In their out-of-sample tests which predict returns from 1990 to the end of the sample they use a recursively estimated linear trend

[3] Due to the finding that SI cannot predict returns in the 1973Q1 to 2007Q4 period, we do not repeat the analysis performed in Table 4. Furthermore, we do not report results for the 2009 to 2014 period for quarterly regressions given that we only have 24 observations. It is clear from Panel D of Table 1 that SI cannot predict returns in the post financial crisis period.

adding one month at a time from 1990.

The choice of removing a linear trend is probably taken after looking at the entire time series of short interest. This can been seen from looking again at Figure 1 that plots the actual time series of short interest. However, it is not entirely obvious looking from 1973 to 1989 that there is a strong linear trend in short interest. From 2000 it becomes much more obvious that there is an upward trend until 2008. However, it's not obvious that an investor would have picked out a linear trend in 1990 when looking back at the data from this point in time and subsequently used this type of trend month by month to detrend short interest. Certainly after 2007, its not clear that an investor would think there is a linear trend. Therefore, it is neither obvious that an investor would have observed a linear trend prior to the start of their trading rule, nor moreover, known that it would have continued to the end of the sample. This is important because Figure 2 shows detrended, standardized, short interest that is actually used in the in-sample and out-of-sample tests. It follows a much more cyclical pattern than actual short interest.

The point of this discussion is to illustrate that short interest is not necessarily a variable that could have been used to trade on. However, this does not mean that we cannot learn something about the mechanism of short interest and its potential signal of information about aggregate prices, it just means we need to be careful regarding claims about profitable trading opportunities. This problem also arises for the macroeconomic variables for three reasons. First, many of the macroeconomic variables use revised data that does not necessarily represent the actual data that was available in real time.[4] Second, a number of macroeconomic variables are constructed through the estimation of parameters. It is not possible to ascertain if investors know the functional form of the relation between the variables, or whether the estimated parameters are reflective of what investor's actually had (see, for example, Nagel and Xu (2019)). Third, the out-of-sample tests ignore costs involved in setting up a trading policy. In light of these three reasons, we view the out-of-sample analysis as supporting evidence for in-sample tests, albeit with lower power (Inoue and Kilian (2005)). Alternative definitions,

[4] However, it is not clear that using vintage data is more appropriate than revised data. For example, consumption that is used in *cay* is revised from its vintage publication. It might well be the case that the investor has a better estimate of actual consumption than the first vintage publication and that the investors estimate is closer to consumption reported in revised data. In this case it would be appropriate to use revised data for out-of-sample tests.

economic models, detrending and estimation mechanisms, data and assumptions about timing might well lead to different out-of-sample results across all predictor variables including SI.

We try and follow the extant literature as closely as possible in our use of variables to make out-of-sample forecasts. For SI, we follow RRZ and detrend SI period by period with a linear trend. For *cay*, we use the full sample estimates and revised data as recommended by Lettau and Ludvigson (2001, 2004, 2005) in their out-of-sample tests. For *gap*, we follow the methodology in Cooper and Priestley (2009) in their out-of-sample tests and use vintage data and a recursively estimated quadratic trend. For $\frac{i}{k}$ and *slc* that did not explicitly consider out-of-sample tests, we use the in-sample, revised data to construct them. For consumption volatility we use the in-sample revised data method based on a rolling estimate.

We use two well known metrics to judge out-of-sample performance. The first is the out-of-sample R^2 statistic of Campbell and Thompson (2008) which measures the proportional reduction (or increase) in the MSE of the unrestricted model relative to the MSE of the prevailing mean benchmark forecast. The R^2_{OOS} statistic is measured in units that are comparable to the in-sample R^2. The R^2_{OOS} takes positive (negative) values when the predictive regression model predicts better (worse) than the historical mean. The second is the *MSE-F* statistic of McCracken (2007) which tests the null hypothesis that the restricted forecasting model has a mean squared error (MSE) that is less than or equal to that of the unrestricted forecasting model; the alternative is that the unrestricted model has a smaller MSE.

Table 6 examines the out-of-sample predictability of $S\dot{I}$ and the macroeconomic variables using quarterly data so we can make easy comparisons across the variables. Panel A reports the results that forecast out-of-sample from 1990:1 to 2014:12 and hence are comparable to those in RRZ. We find very similar results to those reported by RRZ. For example, we report out-of-sample R^2s ranging from around 5.9 to 13.9 from the one to four quarter horizons. These are similar to the values at three and twelve month horizons in RRZ of 6.5 to 13.24 and similar to our own unreported results using monthly data. We also report the Clarke and McCracken (2001) MSE-F test for equality of MSEs. We find that the MSE of the forecasting regression based on SI is always smaller than when using the historic mean as a forecast for next periods return.

As in the case for the in-sample results, *cay*, *gap*, and $\frac{i}{k}$ all produce statistically significant out-of-sample forecasting power in the full sample. In terms of the size of the out-of-sample $\overline{R}^2$, SI appears to have the best predictive power, followed by gap, $\frac{i}{k}$ and then cay. However, the differences are not large. For example, the R^2_{OOS} at the four quarter horizon are 13.9 for SI, 7.65 for cay, 11.03 for gap, and 8.61 for $\frac{i}{k}$. In all four cases the MSE-F test statistic is significant at the 1% level. The out-of-sample predictability tends to increase with the horizon for all four variables that can predict out-of-sample, just dropping off slightly between the third to the fourth quarter for SI.

Moving to the sample period 1990-2007, Panel B of Table 6 shows that SI has no out-of-sample forecasting ability when using quarterly data in the sample period that is restricted to end in 2007:4. The R^2_{OOS} is 0.06 at the one quarter horizon and negative at the remaining horizons. Although this is not a surprising result given the in-sample results, it confirms that SI's predictive ability is limited to the sample including 2008.

In the shorter out-of-sample sample period of 1990:1 to 2007:4, cay, gap, and $\frac{i}{k}$ and now σ_c have out-of-sample forecasting power in this period. The predictive power of cay is a slightly higher in the period prior to the financial crisis. For example, the R^2_{OOS} is 2.6% in the period up to the end of 2007 and 1.4% for the period ending 2014. These difference in the two periods are also observed at each horizon where the R^2_{OOS} is 10.8 in the period up to the end of 2007 and 7.7% for the period ending 2014 at the four quarter horizon. The opposite pattern is present for gap, and $\frac{i}{k}$, consistent with the in-sample evidence.

In summary, the out-of-sample tests provide consistent support for the in-sample results that SI can only predict returns in a sample that includes 2008. This is not the case for some of the macroeconomic variables that can predict out-of-sample both in a sample before the financial crisis in 2008 and in a sample that includes the financial crisis. These two findings provide enough evidence to question RRZ's two first claims that, first, "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date", and second, that it "outperforms a host of popular return predictors". Both out-of-sample and in-sample tests simply do not support RRZ's claims.

4 Combining Forecasts of Macroeconomic Variables

RRZ claim that "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date". We have raised considerable concerns about this claim. So, what is the best predictor of the equity premium identified to date and can our results using macroeconomic variables say anything about this? In this section of the paper, we move away from looking a SI and present new results focussing on the macroeconomic variables. We follow Rapach, Strauss and Zhou (2009) who provide a thorough motivation for combining forecasts and show that this is potentially very useful for macroeconomic variables. This could be particularly useful in our analysis because it is evident that the predictive ability of the macroeconomic variables is sometimes stronger in one period relative to another period. For example, there is evidence of predictability before the financial crisis and not after (σ_c), some evidence that there is no predictability before the financial crisis but there is when the financial crisis is included ($\frac{i}{k}$), and evidence that cay and gap can predict returns in both the full sample and restricted sample, but the evidence is stronger either when the financial crisis is included or excluded. One way to gather the information across different macroeconomic variables is to combine forecasts and diversify across the uncertainty of individual forecasts with the aim of establishing whether a stable prediction of the equity premium is possible.

To assess whether we get more stability in the forecasts, we calculate out-of-sample $\overline{R}^2$s of forecasts from a simple equal weighted forecast combination:

$$\widehat{f_c} = 0.2 * \widehat{f}_{cay} + 0.2 * \widehat{f}_{gap} + 0.2 * \widehat{f}_{\frac{i}{k}} + 0.2 * \widehat{f}_{\sigma_c} + 0.2 * \widehat{f}_{slc} \tag{7}$$

where $\widehat{f_c}$ is the equal weight combination forecast, $\widehat{f_i}$ is the forecast based on macroeconomic variable i.[5] We use the out-of-sample forecasts from each individual predictor variable and then combine them to calculate the out-of-sample $\overline{R}^2$ in the 1974-2007 period and the 1974-

[5]Note that we include all five of the macroeconomic variables in the forecast combination even though we know from the in-sample regressions that some of them have no in-sample forcasting power. This should reduce data snooping concerns.

2014 period.[6] We repeat our emphasis that this is not meant to be able to reflect the optimal trading strategy of a market timing investor. Rather it is meant to provide some evidence to support the in-sample results that the macroeconomic variables are related to variations in expected returns that are different from that of SI. We believe this is important because macroeconomic variables and SI have very different interpretations in terms of what forces are affecting the equity premium.

Table 7 reports the out-of-sample $\overline{R}^2$s for the combined forecasts which are very similar across the sample before the financial crisis and the sample that includes the financial crisis. For example, at the one quarter horizon for the period up to the financial crisis, the $\overline{R}^2$ is 2.13. For the period that extends to the end of the sample, the $\overline{R}^2$ is 2.65. The $\overline{R}^2$s are comparable right up to the four quarter horizon being 7.81 for the sample period up to the financial crisis and 8.48 for the full sample. Combining forecast as suggested by Rapach, Strauss and Zhou (2009) does lead to more stable and consistent forecasts across the two sample periods than the forecasts based on individual macroeconomic variables. Therefore, arguably the best forecast to date of the equity market premium is a simple weighted average combination of macroeconomic forecasts.

5 Cash flows News and Short Interest

RRZ explain the role of short interest in predicting stock returns through a cash flow channel. The basic intuition is that the group of investors who are involved in short selling are informed about the future level of cashflows in the aggregate economy and that the rest of the market has not recognized or incorporated this news into market prices. In order to test this intuition, RRZ use the Campbell and Shiller (1988) log linearization of stock returns to decompose stock returns into news about future discount rates and news about future cash flows.

Consider Campbell's (1991) decomposition of unexpected returns from the present value

[6] We also calculate the economic value of the combined forecasts by computing the certainty equivalent return (CER) for an investor with mean-variance preferences who allocates across stocks and risk-free bills using the time-varying expected returns model relative to the historical mean return forecast. To do this, we follow Campbell and Thompson (2008). The findings from this are entirely consistent with the findings that use the out-of-sample $\overline{R}^2$.

model (see Campbell and Vuolteenaho (2004) also):

$$
\begin{aligned}
r_{t+1} - E_t(r_{t+1}) &= (E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^i \Delta d_{t+1+j} - (E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i} \\
&= N_{CF,t+1} - N_{DR,t+1}
\end{aligned}
\tag{8}
$$

where N_{CF} and N_{DR} are news about future dividend growth (cash flows) and future returns (discount rates) respectively. To implement (8) Campbell and Vuolteenaho (2004) follow Campbell (1991) and estimate a VAR to obtain $E_t(r_{t+1})$ and $(E_{t+1} - E_t) \sum_{i=1}^{\infty} \rho^i r_{t+1+i}$. These are then plugged into equation (8), which can then be solved for $(E_{t+1} - E_t) \sum_{j=0}^{\infty} \rho^i \Delta d_{t+1+j}$. Assuming the data are generated by a first order VAR:

$$
\mathbf{z}_t = \mathbf{A}\mathbf{z}_{t-1} + \mathbf{u}_t \tag{9}
$$

then Campbell and Vuolteenaho (2004) show that the news terms are given by

$$
\begin{aligned}
N_{CF,t} &= (\mathbf{e}_1' + \mathbf{e}_1' \boldsymbol{\lambda})\mathbf{u}_t \\
N_{DR,t} &= \mathbf{e}_1' \boldsymbol{\lambda} \mathbf{u}_t
\end{aligned}
\tag{10}
$$

where $\mathbf{e}_1$ is a vector that picks out the first element from $\mathbf{z}_t$, which is returns in Campbell and Vuolteenaho (2004), and $\boldsymbol{\lambda} = \rho \mathbf{A}(\mathbf{I} - \rho \mathbf{A})^{-1}$.

The estimation of the cash flow news requires that we specify a VAR that includes variables that predict stock returns. RRZ estimate various VARs that use the dividend price ratio along with one of Goyal and Welch's (2008) predictor variables as predictor variables. We consider five separate VARs specified as: $\mathbf{z}_t' = [r_t \quad dp_t \quad Z_{i,t}]$ where for each one, in addition to the dividend price ratio, we include one of the macroeconomic variables. Once the VAR is estimated we construct $N_{CF,t} = (\mathbf{e}_1' + \mathbf{e}_1' \boldsymbol{\lambda})\mathbf{u}_t$ and then follow RRZ and regress

$$
N_{CF,t} = a + b * SI_{t-1} + u_t \tag{11}
$$

to assess whether SI captures information about future cash flows.

Table 8 reports the results from estimating equation (11) for the five VARs that we estimate. The second column of the Table confirms RRZ's findings that SI does forecast changes in cash flow news in the 1973Q1 to 2014Q4 period. However, the third column indicates that this is not the case when the sample ends just before the financial crisis in 2007Q4. This results is entirely consistent with all the findings in the paper that SI's predictive ability is tied very closely with the financial crisis. It also allows us to question the third claim in RRZ that short interest predicts returns "through a cash flow channel" and that short sellers are "able to anticipate changes in future aggregate cash flows and associated changes in future market returns". At least as far as SI is concerned, our evidence does not favour an information based explanation for stock return predictability through a cash flow channel. It is also plausible that since cash flow news is backed out from a forecast of future stock returns in the VAR, the cash flow news inherits the large unexpected negative returns in this period mechanically and the relationship between cash flow news and short interest is even spurious in 2008.

6 Conclusion

In this paper, we have raised considerable doubt as to the role of short interest in predicting stocks returns and, therefore, its interpretation to motivate an information based explanation for stock return predictability. RRZ's evidence suggests that short sellers have information that is important for aggregate stock prices and the way that this works is through a cash flow channel where informed short sellers recognize the market is over-priced at certain times because cash flow forecasts are too high. This group of investors short stocks that are overpriced due to biased cash flow forecasts and earn returns for doing so when market prices are corrected for the mispricing. Evidence to support this is based upon the ability of SI to predict stocks returns and cash flow news. It is further strengthened by RRZ's accompanying evidence that SI outperforms thirteen other macroeconomic and financial market based variables in terms of predicting stock returns.

We have provided evidence that questions RRZ's three main claims that first, "short interest... is arguably *the* strongest predictor of the equity risk premium identified to date", second, that it "outperforms a host of popular return predictors" and third, that short interest predicts returns "through a cash flow channel" where short sellers are "able to anticipate changes in future aggregate cash flows and associated changes in future market returns". These conclusions depend crucially on the inclusion of the calendar year 2008 being present in the data. In a sample before 2008 and a sample after 2008 SI cannot predict stock returns. Clearly, 2008 is crucial to all the three claims in RRZ.

We find some new evidence of stable predictive power of aggregate returns amongst five macroeconomic variables that are not included in RRZ. This stability is enhanced when following Rapach, Strauss and Zhou's (2009) suggestion that combining forecasts acts like a diversification mechanism across forecasts. Combined forecasts based on five macroeconomic variables provide very similar performance both in a period before the financial crisis and a period that also includes the financial crisis. This finding leads to a reversal of RRZ's conclusion of an information explanation for the predictability of the aggregate market returns. Our results suggests rational variation in future expected returns is driven by business conditions as measured by macroeconomic variables.

Our results also illustrate a general point that it is important to fully take account of the impact of outliers, or spikes in data in predictive regressions and VAR estimation. Our findings show that it takes only a very few observations to ensure statistical significance of estimated coefficients over long sample periods. However, we show that this does not necessarily mean that a causal effect is present over an entire sample period.

7 References

Akbas, F, E. Boehmer, B. Erturk, and S. Sorescu, 2017, Short interest, returns, and fundamentals, Financial Management 46, 455-486.

Bansal, R., Yaron, A., 2004. Risks for the Long Run: A Potential Resolution of Asset Pricing Puzzles. Journal of Finance 59, 1481-1509.

Bansal, R, V. Khatchatrian, and A. Yaron, 2005, Interpretable asset markets? European Economic Review 49, 531–560.

Boehmer, E., C.M. Jones, and X. Zhang, 2008. Which shorts are informed? Journal of Finance 63, 491–527.

Campbell, J.Y., 1991. A variance decomposition for stock returns. Economic Journal 101, 157–179.

Campbell, J.Y. and R.J. Shiller, 1988, The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors, Review of Financial Studies 1, 195–228.

Campbell, J.Y., Cochrane, J.H., 1999. By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behaviour. Journal of Political Economy 107, 205-251.

Campbell J.Y. and T. Vuolteenaho, 2004, Bad Beta, Good Beta. American Economic Review 94, 1249-1275.

Campbell, J.Y. and S.B Thompson, 2008, Predicting excess stock returns out of sample: can anything beat the historical average? Review of Financial Studies 21, 1509–1531.

Clark, T.E. and M.W. McCracken, 2001, Tests of equal forecast accuracy and encompassing for nested models. Journal of Econometrics 105, 85–110.

Cochrane J.H., 1991, Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations, The Journal of Finance 46, 209-237.

Cochrane, J.H., 2017. Macro-Finance. Review of Finance 21, 945-985.

Constantinidies, G.M, D. Duffie, 1996, Asset Pricing with Heterogeneous Consumers, Journal of Political Economy 104, 219-240.

Cooper, I and R. Priestley, 2009, Time-Varying Risk Premia and the Output Gap, Review of Financial Studies 22, 2801–2833.

Engelberg, J.E., A.V. Reed, and M.C. Ringgenberg, 2012, How are shorts informed? Short sellers, news, and information processing. Journal of Financial Economics 105, 260–278.

Gârleanu N, and A. Panageas, 2015, Young, old, conservative, and bold: the implications of heterogeneity and finite lives for asset pricing, Journal of Political Economy 123, 670-685.

Goyal, A., I. Welch, 2008, A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies 21, 1455–1508.

Inoue A. and L. Kilian, 2005, In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use?, Econometric Reviews 23, 371-402.

Karpoff, J.M. and X. Lou, 2010, Short sellers and financial misconduct. Journal of Finance 65, 1879–1913.

Lettau, M, and S. Ludvigson, 2001, Consumption, Aggregate Wealth, and Expected Stock Returns, Journal of Finance 54, 815–849.

Lettau, M, and S. Ludvigson, 2004, Understanding Trend and Cycle in Asset Values: Reevaluating the Wealth Effect on Consumption, American Economic Review 94, 279-299.

Lettau, M, and S. Ludvigson, 2005, Tay is a good as cay: Reply, Finance Research Letters 2, 15-22.

McCracken, M.W., 2007, Asymptotics for out of sample tests of Granger causality. Journal of Econometrics 140, 719–752.

Nagel, S. and Z. Xu, 2019, Asset pricing with fading memory, Working Paper, University of Chicago.

Rapach, D.E, M.C. Ringgenberg, and G. Zhou, 2016, Short Interest and Aggregate Stock Returns, Journal of Financial Economics 121, 46–65.

Rapach, D.E., J.K. Strauss, and G. Zhou, 2010,. Out-of-sample equity premium prediction: combination forecasts and links to the real economy. Review of Financial Studies 23, 821–862.

Reitz, T.A., 1988, The equity premium puzzle: a solution, Journal of Monetary Economics 22, 117-131.

Santos T. and P. Veronesi, 2006, Labor Income and Predictable Stock Returns, Review of Financial Studies 19, 1-44.

Table 1
Predicting Stock Returns with Short Interest

The table reports ordinary least squares estimates from a regression of the S&P 500 excess (real) returns on a constant and the first lag of linearly detrended short interest, SI. SI is standardized to have a standard deviation of one. We report results using one, three, six and twelve month overlapping returns. β_{SI} is the estimated coefficient and $\overline{R}^2$ is the adjusted R^2 statistic. Newey-West t-statistics are reported in parenthesis and are adjusted for a lag length of two times the horizon. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. The data are sampled monthly. The sample periods vary according to the Panel. Panel A reports results for the sample period 1973:1 to 2014:12. Panel B reports results for the sample period 1973:1 to 2007:12. Panel C reports results for the sample period 2008:1 to 2014:12. Panel D reports results for the sample period 2009:1 to 2014:12.

Panel A: 1973:1 - 2014:12

	1 month		3 month		6 month		12 month	
	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$
Excess Returns	−0.486	0.97	−1.628	3.99	−3.273	7.55	−6.058	12.08
	(2.49)***		(2.69)***		(2.49)***		(2.57)***	
Real Returns	−0.488	0.96	−1.612	3.85	−3.258	7.32	−6.279	12.31
	(2.51)***		(2.70)***		(2.43)***		(2.56)***	

Panel B: 1973:1 - 2007:12

	1 month		3 month		6 month		12 month	
	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$	β_{SI}	$\overline{R}^2$
Excess Returns	−0.218	−0.05	−0.714	0.42	−1.340	0.86	−2.972	2.24
	(0.95)		(1.14)		(0.99)		(0.98)	
Real Returns	−0.258	0.00	−0.831	0.61	−1.609	1.62	−3.713	3.27
	(1.11)		(1.29)		(1.14)		(1.13)	

Panel C: 2008:1 - 2014:12

	1 month	
	β_{SI}	$\overline{R}^2$
Excess Returns	−1.037	7.66
	(2.22)**	
Real Returns	−1.031	7.74
	(2.36)**	

Panel D: 2009:1 - 2014:12

	1 month	
	β_{SI}	$\overline{R}^2$
Excess Returns	−0.068	−1.41
	(0.10)	
Real Returns	−0.128	−1.36
	(0.18)	

Table 2
Correlation Matrix

This table reports the correlation coefficients between short interest, SI, and the macroeconomic variables. The macroeconomic variables are Lettau and Ludvigson's (2001) cay, Cochrane's (1991) investment to capital ratio, $\frac{i}{k}$, Santos and Veronesi's (2006) labour to consumption ratio slc, Cooper and Priestley's (2009) output gap, gap, and consumption volatility of Bansal, Khatchatrian, and Yaron (2005), σ_c. The data are sampled quarterly and the sample period is 1973:1 to 2014:4.

	SI	cay	gap	$\frac{i}{k}$	σ_c	slc
SI	1.000	0.077	0.294	-0.031	-0.042	-0.096
cay		1.000	-0.168	0.057	-0.226	-0.097
gap			1.000	0.752	-0.219	-0.059
$\frac{i}{k}$				1.000	-0.126	0.198
σ_c					1.000	0.327
slc						1.000

Table 3
Predicting Stock Returns with Short Interest and Macroeconomic Variables: 1973:1 to 2014:4

The table reports ordinary least squares estimates from separate regressions of the S&P 500 excess returns on a constant and the first lag of linearly detrended short interest, SI, *cay*, the investment to capital ratio, $\frac{i}{k}$, the labour to consumption ratio *slc*, the output gap, *gap*, and consumption volatility σ_c. The data are sampled quarterly. All variables are standardized to have a standard deviation of one. We report results using one, two, three and four quarter overlapping returns. β is the estimated coefficient and $\overline{R}^2$ is the adjusted R^2 statistic. Newey-West t-statistics are reported in parenthesis and are adjusted for a lag length of two times the horizon. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. The sample period is 1973:1 to 2014:4

	1 Quarter		2 Quarter		3 Quarter		4 Quarter	
Variable	β	$\overline{R}^2$	β	$\overline{R}^2$	β	$\overline{R}^2$	β	$\overline{R}^2$
SI	−1.603	2.93	3.116	5.41	−4.743	8.50	−5.829	9.71
	(2.52)***		(2.22)**		(2.39)**		(2.35)**	
cay	1.409	2.15	2.783	4.28	4.369	7.34	5.867	10.29
	(2.16)**		(2.26)**		(2.46)***		(2.82)***	
gap	−1.878	4.37	−3.607	7.83	−5.275	11.45	−6.572	13.78
	(3.03)***		(3.00)***		(3.00)***		(3.01)***	
ik	−1.213	1.47	−2.318	2.90	−3.294	4.14	−4.129	5.14
	(1.89)*		(1.96)**		(1.83)*		(1.76)*	
σ_c	−0.877	0.48	−1.991	1.98	−2.511	2.13	−3.091	2.61
	(1.19)		(1.74)*		(1.78)*		(1.82)*	
sv	−0.509	−0.24	−0.892	−0.09	−1.287	0.09	−1.522	0.15
	(0.63)		(0.50)		(0.62)		(0.61)	

Table 4
Comparing Short Interest and Macroeconomic Variables: 1973:1 to 2014:4

The table reports ordinary least squares estimates from various regressions using one or more of the following predictor variables: linearly detrended short interest, SI, *cay*, the investment to capital ratio, $\frac{i}{k}$, the labour to consumption ratio *slc*, the output gap, *gap*, and consumption volatility σ_c. The data are sampled quarterly. All variables are standardized to have a standard deviation of one. We report results using one, two, three and four quarter overlapping returns. β_i is the estimated coefficient and $\overline{R}^2$ is the adjusted R^2 statistic. Newey-West t-statistics are reported in parenthesis and are adjusted for a lag length of two times the horizon. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. The sample period is 1973:1 to 2014:4

Panel A

$$r_t = \alpha + \beta_{SI} * SI_{t-1} + \beta_i * Z_{i,t-1} + u_t$$

	β_{SI}	β_{cay}	β_{gap}	β_{ik}	β_{σ_c}	β_{sw}	$\overline{R}^2$
r	−1.686 (2.67)***	1.502 (2.46)***					5.49
r	−1.153 (1.71)*		−1.551 (2.31)**				5.48
r	−1.652 (2.68)***			−1.275 (2.00)**			4.66
r	−1.647 (2.68)***				−0.951 (1.42)		3.63
r	−1.683 (2.67)***					−0.699 (0.93)	3.02

Panel B

$$r_t = \alpha + \beta_{SI} * SI_{t-1} + e_{SI,t}$$

$$e_{SI,t} = a + \beta_i * Z_{i,t-1} + v_t$$

	β_{cay}	β_{gap}	β_{ik}	β_{σ_c}	β_{sw}	$\overline{R}^2$
res_{SI}	1.497 (2.42)***					2.62
res_{SI}		−1.423 (2.26)**				2.35
res_{SI}			−1.273 (1.99)**			1.77
res_{SI}				−0.949 (1.42)		0.72
res_{SI}					−0.689 (0.91)	0.09

Panel C

$$r_t = \alpha + \gamma_i * Z_{i,t-1} + e_{i,t}$$

$$e_{i,t} = a + \beta_i * SI_{i,t-1} + v_t$$

	β_{SI}	β_{cay}	β_{gap}	β_{ik}	β_{σ_c}	β_{sw}	$\overline{R}^2$
res_{cay}	-1.681 (2.654)***						3.98
res_{gap}	-1.058 (1.69)*						1.01
res_{ik}	-1.650 (2.66)***						3.23
res_{σ_c}	-1.643 (2.69)***						3.16
res_{sv}	-1.662 (2.61)***						3.22
res_{all}	-0.900 (1.46)						0.59

Table 5
Predicting Stock Returns with Short Interest and Macroeconomic Variables: 1973:1 to 2007:4

The table reports ordinary least squares estimates from separate regressions of the S&P 500 excess returns on a constant and the first lag of linearly detrended short interest, SI, *cay*, the investment to capital ratio, $\frac{i}{k}$, the labour to consumption ratio *slc*, the output gap, *gap*, and consumption volatility σ_c. The data are sampled quarterly. All variables are standardized to have a standard deviation of one. We report results using one, two, three and four quarter overlapping returns. β is the estimated coefficient. $\overline{R}^2$ is the adjusted R^2 statistic. Newey-West t-statistics are reported in parenthesis and are adjusted for a lag length of two times the horizon. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level. The sample period is 1973:1 to 2007:4

	1 Quarter		2 Quarter		3 Quarter		4 Quarter	
Variables	β	$\overline{R}^2$	β	$\overline{R}^2$	β	$\overline{R}^2$	β	$\overline{R}^2$
SI	−0.763	−0.11	−1.245	0.02	−2.195	0.79	−2.791	1.13
	(1.00)		(0.77)		(0.89)		(0.81)	
cay	1.995	5.24	3.435	7.76	5.015	11.35	6.528	12.92
	(2.91)***		(2.66)***		(2.65)***		(2.92)***	
gap	−1.422	2.14	−2.559	3.71	−3.674	5.38	−4.518	6.33
	(2.07)**		(1.95)**		(1.97)**		(1.93)**	
$\frac{i}{k}$	−0.971	0.41	−1.717	0.91	−2.276	1.31	−2.792	1.63
	(1.35)		(1.16)		(1.03)		(0.97)	
σ_c	−0.953	0.59	−2.455	3.47	−3.408	4.75	−4.185	5.64
	(1.52)		(2.12)**		(2.34)**		(2.37)**	
slc	−0.543	−0.33	−1.034	−0.06	−1.546	0.26	−1.860	0.36
	(0.62)		(0.63)		(0.66)		(0.66)	

Table 6
Out-of-Sample Tests

This table reports the results of out-of-sample forecast comparisons of the excess return on the S&P500 Index. The comparisons are of forecasts of excess returns based on a constant (the restricted model) and forecasts based on a constant and a predictor variable (the unrestricted model). We report comparisons based on forecasting one quarter ahead using one-, two-, three, and four-quarter returns. "MSE-F" gives the F-test of McCracken (2007), which tests the null hypothesis of equal MSEs against the alternative that the MSE from the unrestricted model is smaller. R^2_{OOS} is the out-of-sample R^2■. Panel A reports results for the out-of-sample forecasting period of 1990:1 to 2014:4. Panel B reports results for the out-of-sample forecasting period of 1990:1 to 2007:4. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level.

Panel A: 1990:1-2014:4

Variables		$h=1$	$h=2$	$h=3$	$h=4$
SI	$MSE-F$	6.337***	12.195***	16.744***	16.205***
	R^2_{OOS}	5.95	11.43	14.34	13.94
cay	$MSE-F$	1.412**	2.568**	6.267***	8.291***
	R^2_{OOS}	1.39	2.50	5.89	7.65
gap	$MSE-F$	3.163**	7.314***	9.749***	12.394***
	R^2_{OOS}	3.07	6.82	8.88	11.03
$\frac{i}{k}$	$MSE-F$	1.160*	4.432***	7.346***	9.422***
	R^2_{OOS}	1.14	4.24	6.84	8.61
σ_c	$MSE-F$	0.472	0.021	0.487	0.826*
	R^2_{OOS}	0.47	0.02	0.48	0.81
slc	$MSE-F$	-1.565	-1.855	-2.170	-2.505
	R^2_{OOS}	-1.59	-1.89	-2.22	-2.57

Panel B: 1990:1-2007:4

Variables		$h=1$	$h=4$	$h=3$	$h=4$
SI	$MSE-F$	0.046	-0.294	-3.142	-5.234
	R^2_{OOS}	0.06	-0.41	-4.56	-7.84
cay	$MSE-F$	1.967**	2.802**	7.023***	8.697***
	R^2_{OOS}	2.65	3.75	8.89	10.78
gap	$MSE-F$	0.555	1.936**	2.618**	3.652***
	R^2_{OOS}	0.76	2.62	3.51	4.83
$\frac{i}{k}$	$MSE-F$	-1.308	-0.087	1.638**	2.961**
	R^2_{OOS}	-1.85	-0.12	2.22	3.95
σ_c	$MSE-F$	1.816**	2.609***	3.520***	4.549***
	R^2_{OOS}	2.50	3.50	4.66	5.94
slc	$MSE-F$	-1.325	-1.803	-2.204	-2.531
	R^2_{OOS}	-1.87	-2.56	-3.15	-3.64

Table 7
Forecast Combinations

This table reports the out-of-sample R^2, R^2_{OOS}, from combining the five forecasts of returns from the macroeconomic variables into one equal weighted forecast. The out-of-sample forecasting periods are from 1990:1 to 2014:4 and 1990:1 to 2007:4.

		$h=1$	$h=2$	$h=3$	$h=4$
1990:1 to 2014:4	R^2_{OOS}	2.65	5.19	7.32	8.48
1990:1 to 2007:4	R^2_{OOS}	2.13	4.53	6.77	7.81

Table 7
Predicting Cash flow News

This table reports results from regressing cash flow news on the first lag of short interest. r is the return on the S&P500 index, dp is the dividend price ratio, cay, the investment to capital ratio, $\frac{i}{k}$, the labour to consumption ratio slc, the output gap, gap, and consumption volatility σ_c. *** indicates significant at the 1% level, ** indicates significant at the 5% level, and * indicates significant at the 10% level.

	1973:1 to 2014:4	1973:1 to 2007:4
VAR variables	$\widehat{\beta}_{CF}$	$\widehat{\beta}_{CF}$
r dp cay	-0.010 (1.92)*	-0.003 (0.69)
r dp gap	-0.011 (2.55)***	-0.007 (1.23)
r dp ik	-0.012 (2.61)***	-0.010 (1.33)
r dp σ_c	-0.014 (2.60)***	-0.008 (1.58)
r dp sw	-0.009 (2.31)**	-0.002 (0.54)

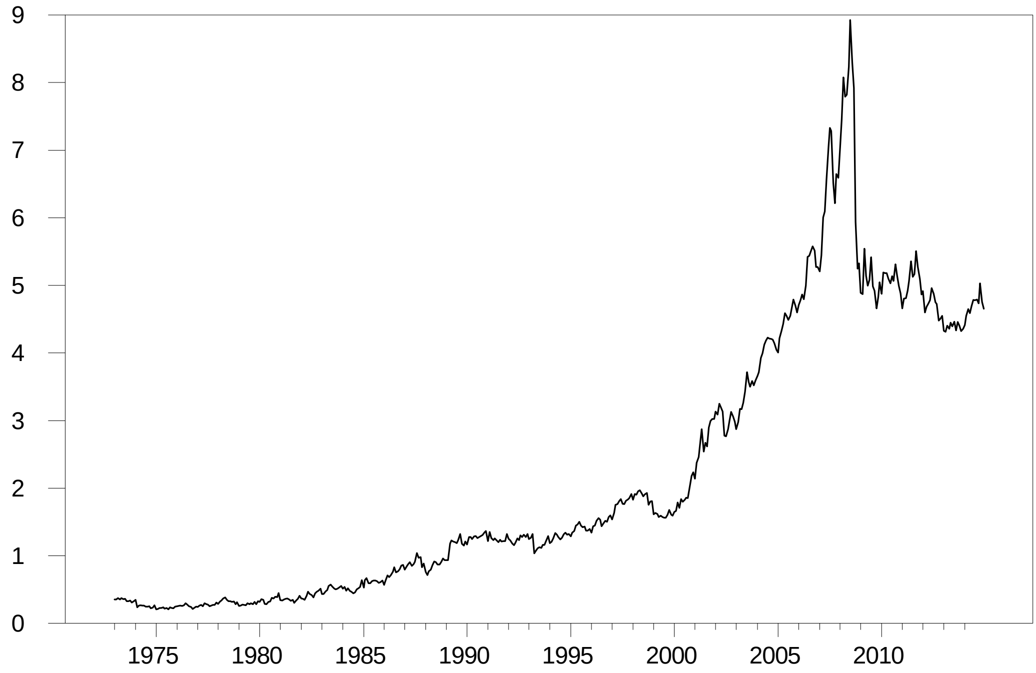

Figure 1: Actual Short Interest. This figure plot an equal weighted index of short interest. The sample period is January 1974 to December 2014.

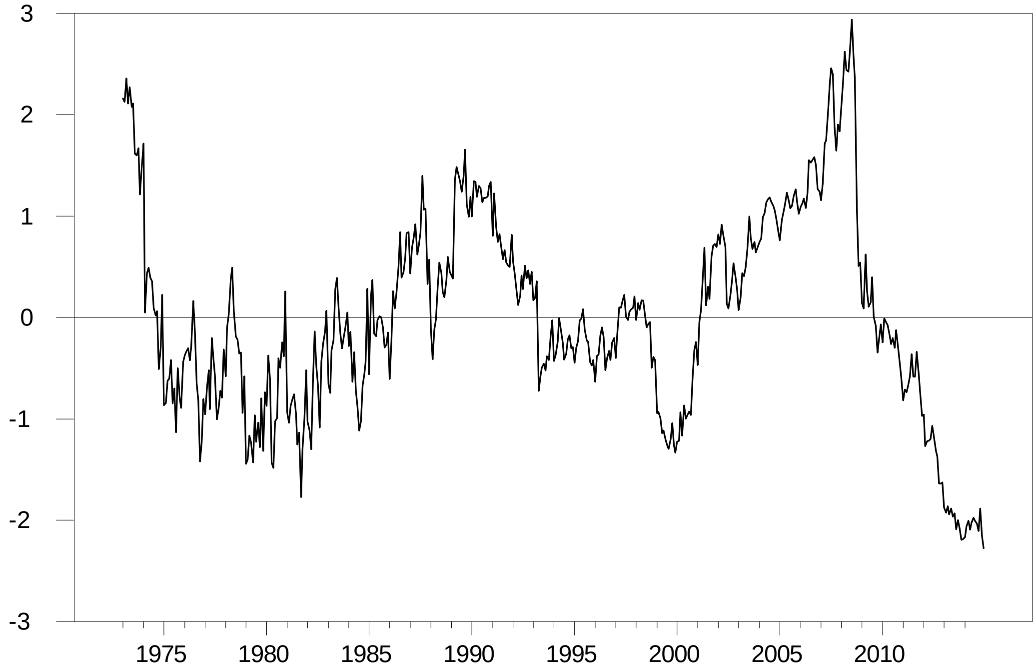

Figure 2: Linearly Detrended Short Interest. This figure plot an equal weighted index of short interest that has been detrended with a linear time trend. The sample period is January 1974 to December 2014.