Short Selling and Attention around the Business Cycle

PETER N. DIXON AND ERIC K. KELLEY*

July 11, 2017

ABSTRACT

We show that firm-level short interest predicts negative returns for individual stocks during economic expansions, while aggregate short interest predicts negative market returns during recessions. Viewing short sellers as informed traders, these findings are consistent with Kacperczyk, Van Nieuwerburgh, and Veldkamp's (2016) model in which rational yet cognitively constrained traders optimally allocate attention among firm-specific and systematic signals. In their model, traders collect aggregate (firm-specific) information in recessions (expansions) because these times are marked by higher (lower) aggregate volatility and price of risk.

JEL Codes: G10, G12, G14

Keywords: Short Selling, Rational Inattention, Inattention, Business Cycles, Asset Pricing, Return Predictability

---

* Both authors are from Haslam College of Business, University of Tennessee. We thank Andy Puckett and seminar participants at University of Mississippi and University of Tennessee for comments and Tyler Henry for help with the short interest data. Kelley acknowledges support from the Home Federal Bank Scholar Award. All errors are our own. Please address correspondence to Eric Kelley, Haslam College of Business, University of Tennessee, 916 Volunteer Blvd, Knoxville TN 37996; phone: 865-974-8353; fax 865-974-1716; email: ekk@utk.edu.

I. Introduction

When faced with information processing constraints, even the most sophisticated and capital rich investor must allocate the scarce resource of attention. The resulting allocation choices directly influence the composition and performance of managed portfolios. More broadly, since information acquisition—or the lack thereof—drives price efficiency (e.g., Grossman and Stiglitz (1980)), attention allocation has implications for the welfare of market participants, the severity and duration of mispricing, and the extent to which stock prices may guide firms' real investment decisions (Dow and Gorton (1997), Chen, Goldstein, and Jiang (2007)).

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016), hereafter KVV, model a multi-asset framework in which rational yet cognitively constrained traders optimally choose which types of information to observe prior to forming portfolios. Signals that are either systematic or firm-specific in nature represent these different types of information. Since recessions coincide with greater aggregate volatility and an elevated price of risk, constrained information processors allocate relatively more attention to signals affecting all firms than to signals affecting only a single firm. The opposite prediction holds for expansionary times. In short, the marginal benefit of collecting systematic (as opposed to idiosyncratic) signals is greatest during recessions, and rational agents respond accordingly.

We offer a novel test of the rational inattention model by analyzing the trading decisions of short sellers. This laboratory is appealing because empirical evidence portrays short sellers as informed investors. First, Saffi and Sigurdsson (2010) and Boehmer and Wu (2012) show that stocks with lower shorting constraints and higher shorting activity, respectively, have more efficient prices. These findings are consistent with a Grossman and Stiglitz (1980) world in which short sellers represent informed traders. Second, a large literature relates shorting activity to low future stock returns, again suggesting short sellers possess information relevant to future prices. Most of this work uses cross-sectional tests to show that stocks with greater short selling experience lower future returns than those with less shorting. Prominent studies that document this effect using monthly or bi-monthly short interest include Figlewski (1981) and Boehmer, Huszar, and Jordan (2010), hereafter BHJ. Those employing daily data on equity lending and shorting flow include Cohen, Diether, and Malloy (2007) and Diether, Lee, and Werner (2009). In addition, Boehmer, Jones, and Zhang (2008) and Kelley and Tetlock (2016) show that both institutional and retail short sellers correctly anticipate future negative returns. Recent work by Rapach, Ringgenberg, and Zhou (2016) complements the cross-sectional literature by demonstrating that short interest aggregated across stocks predicts market returns over the subsequent year. Short sellers' ability to anticipate aggregate cash flows primarily drives this predictability.

While the literature generally agrees that short sellers successfully anticipate stock returns, the timing and nature of this predictability is largely unexplored. We examine how short sellers' ability to predict aggregate and firm-specific stock returns varies across the business cycle and offer new insights into the attention allocation decisions of informed traders. To the extent that switching attention from aggregate to firm-specific signals drives time variation in short sellers' cross-sectional and aggregate return predictability, our two main results are consistent with the rational attention allocation theory of KVV. In our first set of tests, we examine a portfolio that is long stocks with low short interest and short stocks with high short interest. Consistent with prior literature, this portfolio has a positive alpha over the full time series from 1973 to August 2015. More importantly, the alpha is over twice as large in expansions as it is during recessions, suggesting that short sellers' trades convey less firm-specific information during recessions compared to expansions.

Our second set of tests examines the relation between Rapach, Ringgenberg, and Zhou's (2016) short interest index (*SII*) and future aggregate market returns. We show that aggregate short interest predicts future market returns economically and statistically more strongly during economic recessions than during economic expansions. Specifically, we find that during a recession (expansion), a one standard deviation increase in *SII* is associated with a future three-month excess return of -1.7% (-0.4%), -1.4% (-0.2%), and -1.3% (-0.2%) on the CRSP value weighted index, the CRSP equal weighted index, and the S&P 500 respectively. During recessions, the relation between each of the three indices and the SII is highly significant. However, for the S&P 500 and the CRSP value weighted index the observed relation is statistically insignificant during expansions. Taken as a whole, our results are consistent with one class of informed investors – short sellers – shifting their attention from firm-specific information in expansions to aggregate information in recessions.

These results are robust to a number of alternative specifications. First, our cross-sectional results hold when we allow factor loadings to vary with the business cycle and when we measure abnormal returns using Daniel, Grinblatt, Titman, and Wermers (1997) characteristic adjustments (DGTW). Second, our findings are robust to two alternative real-time recession indicators: the probability of recession based on the work of Chauvet and Piger (2008) and a measure based on the Chicago Fed's National Activity Index. Finally, we divide our sample in June 1988 and verify our results in both subsamples.

Our paper joins a budding empirical literature on rational attention allocation. Most closely related is the analysis in KVV. These authors test their model by examining the covariances between actively managed mutual funds' quarterly position changes and future aggregate and firm-level fundamentals. They find that during expansions, funds tilt their holdings in the cross-section of stocks toward those with strong future earnings. In contrast, during recessions, funds tend to shift into and out of equities in a manner that anticipates future aggregate earnings shocks. This evidence speaks directly to how certain traders allocate attention but is silent on the extent to which the attention reallocation is profitable. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014), in contrast, show certain funds switch from stock selection strategies in expansions to market timing strategies in recessions and that these particular funds generate positive alpha. In other words, these authors identify skilled investors as those who switch focus from firm-specific to aggregate information across the business cycle. Because we study short interest aggregated across all short sellers, we conduct no analysis at the trader level. Rather, in our analysis, we speak to business cycle variations in an entire class of investors' ability to identify firm-specific and market-wide mispricing.

Other authors provide empirical evidence that attention allocation matters for prices. Ben-Rephael, Da, and Israelsen (2016) show that institutional attention facilitates the incorporation of information in earnings announcements and analyst recommendation changes. In a similar vein, DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2009) show that markets respond sluggishly to earnings announcement information when investors are likely distracted by other stimuli. A key difference between these studies and ours is that they relate attention to efficient incorporation of *public* information. We consider how informed traders allocate attention by observing the manner in which their trades convey *private* information and predict returns.

Our analysis also suggests potential real implications of rational attention allocation. Kempf, Manconi, and Spalt (2016) argue that investors who allocate attention elsewhere play a diminished monitoring role. Firms with such "distracted" shareholders are more likely to announce value-destroying acquisitions, cut dividends, and retain CEOs in the wake of poor performance.

Other work shows short sellers are effective monitors. For example, Karpoff and Lou (2010) show that short sellers are able to identify financial misconduct well in advance of other market participants and Fang, Huang, and Karpoff (2015) relate short-selling constraints to greater earnings management. As short-sellers allocate attention away from firm-specific signals in recessions, managers may engage in more value-destroying and nefarious behavior in these states of the world. This is particularly concerning in recessions because some combination of greater operating and financial leverage, weak fundamental performance, and underdiversified managers may facilitate inefficient outcomes ranging from excessive risk-taking to underinvestment (e.g., Jensen and Meckling, (1976); Myers, (1984)).

II. Hypothesis Development

In KVV's model, investors make two rounds of choices. In the first, they allocate attention amongst firm-specific and aggregate signals. In the second, they form portfolios. While this model is static in nature, its rich predictions highlight how investors optimally reallocate attention across the business cycle as the price of risk and volatility evolve. In particular, since aggregate volatility and the price of risk both tend to rise during recessions[1], investors in this model find it more valuable to allocate attention to aggregate (firm-specific) signals in recessions (expansions). Intuitively, recessions are times when aggregate shocks have the greatest effects on overall portfolios, and it is during these times when investors most value the reduction in risk that results from learning aggregate signals. Since attention is a scarce resource in the model, investors who learn more about aggregate signals must necessarily learn less about firm-specific signals.

[1] KVV summarize this literature in their Section 3.2.

In standard information asymmetry models (e.g, Kyle (1985)), informed traders gain at the expense of the uninformed. KVV's model implies the nature of these gains varies across the business cycle. This reasoning leads to our main hypotheses regarding short sellers' ability to predict future stock returns which we refer to as the *Stock Selection Hypothesis* and the *Market Timing Hypothesis*. According to the *Stock Selection Hypothesis*, short interest will be a stronger cross-sectional predictor of stock returns during expansions than recessions. During expansions, informed traders, as proxied by short-sellers, should allocate attention to firm-specific signals, and the profitability of their trading strategies should manifest cross-sectionally via the stocks they trade. According to the *Market Timing Hypothesis*, short interest will be a stronger time-series predictor of stock returns during recessions than expansions. This is because during recessions, informed traders should reallocate attention to aggregate signals, and their trading should better predict future aggregate stock returns.

III. Data

We analyze short interest data for NYSE, AMEX, and NASDAQ listed stocks as compiled and reported by the exchanges from 1973 to 2015. Exchanges reported outstanding short interest once per month (as of the 15th) from 1973 through August, 2007 and twice per month (as of the 15th and 30th) from September, 2007 until present. We limit our analysis to the mid-month reports for consistency over the entire time series. We obtain these data primarily from Compustat, which provides short interest data for NYSE and AMEX listed firms from 1973 to 2015 and for NASDAQ listed firms from 2004 to 2015.We supplement the Compustat data with monthly short interest for

NASDAQ-listed securities obtained directly from NASDAQ for the years 1988-2003.[2] For each stock-month, we normalize short interest by computing the fraction of shares held short as the number of shares held short divided by the number of shares outstanding. Henceforth, we refer to this fraction as short interest.

We obtain stock specific information on shares outstanding, returns, delisting returns, price, and trading volume from CRSP. We consider only ordinary common stocks that have traded for at least one year and require non-missing data for return, trading volume, shares outstanding, and share price. To measure recessions, we use official business cycle dates published by the National Bureau of Economic Research (NBER). Since the NBER establishes these dates *ex post* and our hypotheses describe real-time attention allocation decisions of short-sellers, we employ two real-time business cycle measures similar to those used in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014). The first is the probability of recession (*Pr_REC*), as estimated by Chauvet and Piger (2008) using a dynamic-factor-Markov-switching model applied to four monthly macroeconomic variables. We obtain the time series of recession probabilities from Marcelle Chauvet's website.[3] The second alternative measure for the business cycle is based on the Chicago Fed's National Activity Index (*CFNAI*).

In Table 1 we present descriptive statistics for our sample. In our descriptive statistics, we split our sample into two periods with the first period beginning in January 1973 and ending in May 1988 and the second period beginning in June 1988 and running through August 2015. This partition ensures that both periods have approximately the same number of recession months (34 in the first period and 38 in the second period). We also note that since the NASDAQ short interest

[2] The NASDAQ short interest dataset is not perfectly complete as noted also by Chen and Singal (2003) and Boehmer, Huszar, and Jordan (2010) data is missing for February and July of 1990.
[3] https://sites.google.com/site/marcellechauvet/u-s-probabilities-of-recession-chauvet-and-piger-2008

data begins in June 1988, our subsample procedure facilitates a cursory analysis of the exclusion of NASDAQ securities.

Insert Table 1 Here

In Panel A of Table 1, we present descriptive statistics for the 25th, 50th, and 75th percentiles, as well as the mean value of short interest for the two time periods considered. In Panels B and C, we present similar statistics for stock price and market cap (in thousands) for the two periods. Panel D presents other statistics, including the average number of stocks with zero and non-zero reported short interest each month and the number of NBER recession months in a given subsample. From Table 1 we observe that average short interest has increased over time. Further, the median stock price declines in the latter period coincident with the addition of NASDAQ securities. Also, we find that the addition of NASDAQ securities increases our average number of observations each month from just over a thousand to over four thousand.

IV. Empirical Analysis

In our empirical analysis, we test the *Stock Selection* and *Market Timing Hypotheses* by examining how the relation between short selling and future returns varies with the business cycle. We proceed with a cross-sectional analysis of the information content of short sales around the business cycle. This analysis follows the established literature documenting that in the cross section of stocks, high short selling conveys information about low future returns of individual stocks.[4] We then consider the relation between short interest and aggregate stock returns by building on the recent work of Rapach, Ringgenberg, and Zhou (2016) who document that detrended aggregate short interest strongly predicts future returns on the S&P 500 index.

a. Cross Sectional Results

Our first set of analysis tests the *Stock Selection Hypothesis*. Specifically, we assess how short sellers' ability to explain the cross-section of individual security returns varies around the business cycle. A large literature documents the informed nature of short sells, and our tests most closely follows those relating the cross-section of short interest to future stock returns such as Figlewski (1981), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), and BHJ. To test the hypothesis that short interest better predicts firm-specific returns during expansions than during recessions, we begin with the framework of BHJ. They find that a portfolio with long exposure to lightly shorted stocks and short exposure to highly shorted stocks earns a positive abnormal return over the subsequent month during the 1988 to 2005 time period.

We sort stocks each month according to short interest on the 15th of the prior month. We then form portfolios of lightly and heavily shorted stocks as those with short interest below (above) some extreme threshold percentile in the prior month's cross-sectional short-interest distribution. Following BHJ, we consider the 10th, 5th, and 1st percentiles as the thresholds for lightly shorted stocks and the 90th, 95th, and 99th percentiles as thresholds for heavily shorted stocks. We then compute equal-weighted returns for the three lightly and heavily shorted stock portfolios over the

[4] See for example Figlewski (1981), BHJ, Cohen, Diether, and Malloy (2007) , Diether, Lee, and Werner (2009), Boehmer, Jones, and Zhang (2008), and Kelley and Tetlock (2016)

h months following the formation month. For h > 1, we overlap returns in calendar time as in Jegadeesh and Titman (1993). Lastly, we compute three spread portfolio returns corresponding to portfolios that buy and sell the 10th and 90th short interest percentile portfolios, the 5th and 95th short interest percentile portfolios, and the 1st and 99th short interest percentile portfolios.

We evaluate the profitability of these strategies using the Carhart (1997) four-factor model augmented with a recession dummy:

$$ret_{t+1:t+h}^{p} = \alpha_e + \alpha_r Rec_t + \beta MKTRF_t + \; sSMB_t + hHML_t + mMOM_t + \varepsilon_t \qquad (1)$$

The dependent variable $ret_{t+1:t+h}^{p}$ corresponds to the excess return on portfolio p where p indexes the percentile $p\ \varepsilon\ (10,5,1,90,95,99, 10-90,5-95, 1-99))$. The indicator variable Rec_t equals 1 during NBER recession months and 0 during expansion months. The variables $MKTRF_t$, SMB_t, HML_t, and MOM_t correspond to the monthly factors in the Carhart (1997) four factor model.[5] The coefficient α_e denotes the four-factor alpha for the given portfolio during an expansion. The coefficient α_r indicates the incremental four-factor alpha during a recession. The sum of $\alpha_e + \alpha_r$ indicates the alpha of the portfolio during a recession.

To establish a baseline and connect with prior literature, we first estimate the model under the restriction $\alpha_r = 0$ and report the results in Table 2. Columns one through three contain results corresponding to one-month calendar time portfolio returns (h = 1), and columns four through six contain the results for three-month calendar time portfolio returns (h = 3). These unconditional results cohere with prior findings. First, across all six models, the spread portfolios produce significantly positive alphas; lightly-shorted firms tend to out-perform heavily-shorted firms on a risk-adjusted basis. Second, portfolios formed using more extreme short interest cutoffs experience

[5] We obtain the monthly market, SMB, HML, and momentum factors as well as the risk-free rate from Ken French's website.

more extreme alphas. Specifically, we find that for one (three) month calendar time portfolios the alphas are 1.8 (1.7), 2.1 (2.1), and 2.9 (2.6) percent monthly for portfolios that are long and short stocks in the most extreme 10%, 5%, and 1% of high and low short interest respectively. These findings also demonstrate that the alphas decay in event time as in every case the alphas for the portfolios with three month holding periods produces smaller risk adjusted alphas than their corresponding one month portfolios. Finally, the significantly negative market betas for the spread portfolios are consistent with the known finding that investors tend to short high-beta stocks.

Insert Table 2 Here

We present our main cross-sectional results in Table 3. Across all six specifications in Table 3 we observe that the expansion alpha is positive and significant at the one-percent level. In column 1 (4) the monthly alpha generated by the one- (three-) month calendar time portfolio that goes long stocks below the 10^{th} percentile and short stocks above 90^{th} percentile is 2.0 percent (2.0 percent). Similarly, in column 2 (5) the monthly alpha generated by the one (three) month calendar time portfolio that goes long stocks below the 5^{th} percentile and short stocks above 95^{th} percentile is 2.3 percent (2.3 percent). Lastly, in column 3 (6) we observe the monthly alpha generated by the one (three) month calendar time portfolio based on the most extreme short interest cutoffs is 3.1 percent (2.9 percent). These results suggest that during an expansion the trades of short sellers in individual securities contain significant information about future firm-specific returns. Moreover, these findings are consistent with the unconditional results from Table 2 and prior literature. This is not surprising given the U.S. economy has experienced far more months in expansions than recessions over the sample period.

Insert Table 3 Here

Examining the point estimate on the *Rec* variable, we observe that in each of the six specifications, alpha diminishes significantly during recession months. These findings provide strong support for the *Stock Selection Hypothesis*. The decrease in alpha is economically meaningful as point estimates decrease by about one-half during recessions. For the one-month calendar time portfolios, monthly alpha falls from 2.0 percent, 2.3 percent, and 3.1 percent in expansions to 0.8 percent, 0.9 percent, and 1.6 percent in recessions. The changes in point estimates for the three-month calendar time portfolios are similar. Figure 1 summarizes these results. The blue bars represent spread portfolio alphas for one-month calendar time portfolios, and the green bars represent those for the three-month calendar time portfolios. The dark bars indicate the expansion alpha as indicated by the coefficient α_e from Equation (1), and the light bars indicate the recession alpha computed as the sum of the coefficients $\alpha_e + \alpha_r$ from Equation (1).

Insert Figure 1 Here

We next investigate separately each leg of the spread portfolio to better describe how short sellers reallocate attention across the business cycle. The attention theory suggests that highly shorted stocks should drive business cycle variation in alpha. High shorting activity in a stock implies attention; however, this attention may reflect the collection of either aggregate or firm-specific signals. Theory predicts the type of signals collected will vary with the business cycle. In contrast, low or zero shorting activity is more difficult to interpret. On the one hand, low shorting may reflect inattention. On the other hand, it may reflect attentive investors who have observed positive signals, potentially either aggregate or firm-specific in nature.[6] Thus, during a recession, as short sellers shift their attention from firm specific to macro information we expect that the individual short sales will become less informed about firm specific information, and alphas become smaller in magnitude for the portfolio of stocks with high short interest. It is not clear what, if any effect a recession will have on the alphas in the portfolios of lightly shorted stocks.

We study the effect of a recession on the alphas of heavily and lightly shorted stocks in Table 4. In this analysis, we employ the same specification from Equation (1) with the returns on the lightly and heavily shorted portfolios. In Panel A, we present the results for the portfolios of heavily shorted securities. Across all specifications, the portfolios of highly shorted stocks produce a significantly negative four-factor alpha during expansions. This alpha diminishes significantly, and in some cases, disappears entirely, during a recession. For example, in column 4, the expansion alpha for the three-month calendar time returns for the portfolio of heavily shorted stocks is a statistically significant -0.8 percent. Thus, stocks with high short interest during expansions subsequently experience low future returns. However, the alpha for the high short interest portfolio during recessions is -0.8 + 1.0 = 0.2 percent. An *F*-test fails to reject the null hypothesis that $\alpha_e + \alpha_r = 0$ (p=0.72). Similar *F*-tests for each of the other five specifications in Panel A also fail to reject the null hypothesis of zero recession alpha at the 10% level or better. These findings bolster our interpretation that short sellers pay more attention to macro information than firm-specific information during recessions.

[6] As discussed by BHJ, a low level of short interest may indicate that there is a consensus among market participants that a stock is not overpriced, and thus not worth shorting. These lightly shorted stocks would therefore be less likely to experience negative future returns, and BHJ demonstrate that a portfolio of lightly shorted stocks does produce positive four factor alpha.

Insert Table 4 Here

In Table 4 Panel B, we present results for lightly shorted stocks. In these specifications, we find, consistent with the unconditional results of BHJ, that the portfolios of lightly shorted stocks produce significant four factor alphas across all six specifications during expansions. The intercept in each of our specifications is significantly positive. Moreover, these alphas generally do not significantly change during recessions.

In sum, our findings demonstrate that high short interest is only an effective predictor of future firm-specific returns during economic expansions. During recessions, high short interest has no measurable ability to predict future stock returns. Consequently, the alphas on an arbitrage portfolio that is long low short interest stocks and short high short interest stocks is cut approximately in half during recessions. These finding are consistent with short sellers devoting less attention to firm-specific information during recessions than during expansions.

b. Aggregate Returns

According to the attention allocation theory of KVV, informed investors reallocate attention away from firm-specific signals and toward aggregate signals during recessions. Our results in the prior section are consistent with the first part of this theory; short interest does not correctly predict the cross-section of future stock returns during recessions. We now turn to the second part of the theory and examine how the relation between aggregate short interest and future market returns varies with the business cycle. If informed traders are reallocating attention to aggregate signals during recessions, we expect their positions to better predict aggregate market returns during these periods. This is the essence of the *Market Timing Hypothesis*.

Compared to the vast literature relating short selling to the future returns of individual stocks, few authors have examined short sellers' ability to anticipate aggregate returns. Rapach, Ringgenberg, and Zhou (2016) offer the first analysis covering a long time series. They construct a detrended aggregate short interest index (*SII*) that predicts future aggregate stock returns. They show that the *SII*'s ability to predict returns surpasses that of other variables widely studied in the literature (e.g., Welch and Goyal, 2008). The short interest index offers an ideal environment for testing whether investors shift from firm-specific signals to macroeconomic signals because the index aggregates the trading behavior of short sellers across stocks. If short sellers are, as an investor class, observing aggregate signals during recessions and firm-specific signals during expansions, then we expect *SII* to correlate more strongly with future market returns during recessions than during expansions. We construct *SII* as in Rapach, Ringgenberg, and Zhou (2016). We first restrict the sample to stocks with price exceeding $5 and those with market capitalization above the NYSE 5th percentile. Since the index is based on an equal-weighted average, these filters reduce the influence of the disproportionate number of stocks with little or no short interest, especially early in the time series. We then compute the equal weighted average short interest across all stocks each month ($EWSI_t$), leaving us with a monthly time series from 1973 through 2015. This series has a strong linear trend, so we detrend the series using the following regression:

$$\log(EWSI_t) = a + bt + u_t \tag{2}$$

We divide the time series of residuals u_t by their standard deviation σ_{u_t} to create the final *SII*. In Figure 2, we present the computed *SII* time series from January 1973 through August 2015.

Insert Figure 2 Here

Rapach, Ringgenberg, and Zhou (2016) demonstrate that *SII* has strong predictive properties for future realizations of the S&P 500 index by estimating the predictive regression:

$$ret_{t+1:t+h}^{S\&P500} = \alpha + \beta SII_t + \varepsilon_{t+1:t+h}, \qquad (3)$$

where $ret_{t+1:t+h}^{S\&P500} = \left(\frac{1}{h}\right)\left(ret_{t+1}^{S\&P500} + \cdots + ret_{t+h}^{S\&P500}\right)$. In this specification, the coefficient β measures the relation between *SII* in month *t* and the S&P500 over the subsequent *h* months. In Table 4 we perform a similar analysis except that we allow the relation between the *SII* and future returns to vary with the state of the market. We augment Equation (3) with the *Rec* dummy and its interaction with *SII*:

$$ret_{t+1:t+h}^{m} = \alpha + \beta SII_t + \beta_r SII_t * Rec_t + \gamma Rec_t + \varepsilon_{t+1:t+h} \qquad (4)$$

As before, the indicator variable Rec_t equals one during months identified by the NBER as recession months and zero otherwise. The variable $ret_{t+1:t+h}^{m}$ is the return on either the CRSP equal weighted index, the CRSP value weighted index, or the S&P 500. The coefficient β measures the relation between the *SII* and future aggregate returns during expansions, and the coefficient β_r measures the effect that being in a recession has on the relation between the *SII* and future returns. Because the *SII* is high when short interest is high, the *Market Timing Hypothesis* predicts β_r will be negative.

We estimate Equation (4) using future one-month and three-month market returns (*h* = 1, 3) and present the results in Table 5. In Panels A, B, and C the dependent variable is the return on the S&P 500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The first and third models restrict $\beta_r = 0$ to compare our results to Rapach, Ringgenberg, and Zhou (2016). Consistent with their findings, our unconditional models show a negative relation between *SII* and future market returns. This holds for one-month and three-month market returns and for all three market indices.

Insert Table 5 here

Turning to our models that include the recession indicator, we observe that in Column (2) in all three panels the coefficient on *SII* is statistically significant, indicating that we cannot reject the null hypothesis of no relation between *SII* and one month returns during expansion times. In contrast, during recessions, the relation between *SII* and future returns is negative and statistically significant. While β_r itself is not significant, the effect of *SII* during recessions, measured as the sum of the coefficient on the *SII* plus the interaction term $\beta + \beta_r$ is significant at the 5% level. This result holds when measuring the aggregate market with the S&P 500 as well as the equal and value weighted CRSP indices.

In Column (4), in which *SII* predicts three-month market returns, the results are statistically stronger. In particular, the coefficient on the interaction term is statistically significant in each of the three Panels. That is, for all three market indices, we observe a statistically significant increase in the magnitude of the relation between *SII* and aggregate returns during recessions. Moreover, for the S&P500 and the CRSP value weighted index, the relation between *SII* and the market return does not appear to be statistically significant during expansions.

We summarize how the relation between *SII* and future market return changes over the business cycle in Figure 3. We plot the various coefficients from Columns (2) and (4) for the three measures of market returns. The blue bars present coefficients using one-month returns and the green bars present coefficients for the specifications using three-month returns. The lighter bars present the coefficient β, which indicates the relation between the *SII* and future returns during expansions. The darker bars present the sums of coefficients $\beta + \beta_r$ which represent the relation between the *SII* and future returns during expansions. For the analysis employing the S&P 500 index and the CRSP value weighted index, the observed relation between the *SII* and future one-month and three-month returns is four to six times stronger during recession months compared to expansion months. For the equal weighted index the relation between the *SII* and future returns is two to four times larger during recession months than during expansion months.

Insert Figure 3 Here

The impact of the state of the market on the relation between the *SII* and future returns can also be seen by analyzing the increase in adjusted *R*-squared in the various regressions. For the three-month returns, adjusted *R*-squared nearly doubles across all three indices by allowing the relation between *SII* and future returns to be conditional on the state of the economy.

The results from this analysis suggest that the aggregate positions of short sellers, as an investor class, better anticipate aggregate market returns during recessions compared to expansions. This finding is consistent with the notion that short sellers allocate more attention to aggregate signals during recessions than during expansions. This result complements the analysis in the prior section to support the rational attention theory of KVV.

V. Robustness

In this section, we explore the robustness of the results obtained in Section IV. We first examine the robustness of our cross-sectional results from Section IV part (a) to alternative methods of risk adjusting returns. We then explore the robustness of both the cross-sectional and aggregate stock return results to two alternative measures of recession and to various sub-periods of the data.

a. Alternative Model Specification

The analysis in Section IV Part (a) demonstrates that a portfolio that purchases stocks with low short interest and sells stocks with high short interest generates positive four-factor alpha during expansions and that this alpha diminishes significantly, or disappears, during recessions. One potential concern with this approach is that factor loadings may change around the business cycle. In principle, factor loadings could change due to either changes in portfolio composition or time variation in stocks' factor loadings. Either way, if portfolio factor loadings systematically changes during recessions, then unconditional estimation of Equation (1) may produce biased estimates of the effect of a recession on alpha.

We address this potential issue in two ways. First, we estimate a variation of the four-factor model where each of the factors is interacted with the recession indicator *Rec*, which allows the relation between factors and returns to vary across the business cycle. Second, we use characteristic based benchmarks to adjust the returns of the stocks in each of our long-short portfolios based on a procedure similar to Daniel, Grinblatt, Titman, and Wermers (1997). In this procedure, we assign each stock to one of 125 benchmark portfolios formed using dependent sorts on firm size, book-to-market, and prior eleven-month return.[7] Since these benchmarks are

[7] Each June, we update size as June market equity and book-to-market as the ratio of the prior December market equity to prior year book equity. We update prior return each calendar quarter as the 11-month return ending the month prior to the calendar quarter end. Since our calendar-time analysis uses equal-weighted portfolios, we compute benchmarks as equal weighted returns as well.

estimated each month and the stock assignments are updated frequently, the characteristic-adjusted returns should account for dependency between factor sensitivity and the business cycle.

Insert Table 6 Here

Table 6 Panel A contains results from the four-factor model with time-varying factor loadings. As in Table 3, the dependent variable is the return on an equally weighted portfolio that purchases low short interest stocks and sells high short interest stocks. Columns one through three present the results from regressions with one month returns for portfolios that are long and short stocks in the lowest and highest 10, 5, and 1 percentiles respectively. Columns four through six present the results for three-month calendar time portfolios. Only the HML loading changes over the business cycle, and the interaction coefficients for this factor are modest at best. More importantly, in all cases the alphas for expansions and recessions are quite close to their values in the unconditional estimation from Table 3. Consequently, allowing the factor loadings to vary over the business cycle does not significantly affect the finding that portfolios that buy low short interest stocks and sell high short interest stocks produces positive alpha during expansion.

We present similar results using the characteristic-adjusted abnormal returns in Table 6 Panel B. These results are also consistent with the inferences from Table 3. Each of the six specifications produces a positive expansion alpha. The one (three) month calendar time portfolios produce positive monthly alpha of 1.4 (1.3), 1.7 (1.6), and 2.5 (2.1) percent respectively. These quantities are somewhat smaller than what is obtained using the four-factor regression framework but still reasonably similar. Further, one (three) month abnormal returns decrease in recessions a statistically significant 1.3 (1.2), 1.7 (1.4), and 1.8 (1.6) percent. In every case, an *F*-test fails to reject the null hypothesis that the characteristic-adjusted alpha is equal to zero during recessions.

b. Alternative Recession Variables

The underlying theory for our analysis describes how short sellers' attention allocation decisions change in real-time with the business cycle. As such, our utilizing NBER business cycle indicators, which are determined *ex post*, may overstate traders' abilities to optimally reallocate attention. To alleviate such concerns, we employ two alternative definitions of recession that can be estimated in real-time. The first is the probability of recession, *Pr_Rec*, studied by Chauvet and Piger (2008). This measure employs a dynamic-factor-Markov-switching model applied to four monthly macroeconomic variables to produce a variable ranging from zero to one indicating the likelihood of a recession. This metric has the advantage that it is a continuous time variable derived directly from time series of macro variables that are available in a timelier manner than are the official NBER recession turning points. Further, because this variable is a probability, we can substitute it in our prior regressions in place of the recession indicator without changing the inference of the coefficients.

The second alternative measure is based on the Chicago Fed's National Activity Index (CFNAI), which aggregates data from 85 macroeconomic time series. It is constructed to be mean zero and standard deviation of one such that a high value indicates economic output is 'high'. Because our main goal is to study the interaction between states of the world where economic output is abnormally 'low' and the nature of information contained in short sales, we set the indicator variable *CFNAI_Rec* to one if the value of the CFNAI is one standard deviation below the mean and zero otherwise. The pairwise correlations between the NBER *Rec* indicator and each of these alternatives are 0.87 and 0.79, respectively. In Figure 4 we present the time series of *Pr_Rec* and *CFNAI_Rec* along with shaded bars denoting NBER recessions.

Insert Figure 4 Here

We first repeat the calendar-time portfolio analysis from Table 3 using the two alternative recession variables. Table 7 presents point estimates for the spread portfolios with long exposure to low short interest stocks and short exposure to high short interest stocks. Panel A uses *Pr_Rec*, and Panel B uses *CFNAI_Rec*. In both Panel A and Panel B, we observe similar patterns as those described in Table 3. The spread portfolio alphas are positive and significant during expansions as denoted by the positive and significant intercepts. Across all specifications in Panel A, the alphas of the portfolios diminish significantly as the probability of recession increases. For both the 10%-90% and the 5%-95% short interest portfolios, alpha declines about 40% (80%) when the probability of recession is 0.5 (1.0). For the 1%-99% short interest portfolio, the decline is smaller but still economically meaningful.

Insert Table 7 Here

Panel B documents a similar pattern based on *CFNAI_Rec*. For both the 10%-90% and the 5%-95% one-month short interest portfolios, alpha declines about 50% when the *Rec* indicator equals one. For the one-month 1%-99% short interest portfolio, the point estimate for the recession is negative, consistent with prior results, but not statistically significant. For the three-month calendar time portfolios, the recession point estimates are negative, but they are not statistically significant in the 5%-95% and the 1%-99% portfolios. It is perhaps not surprising that the CFNAI results are slightly weaker than those in Table 3 and Table 7, Panel A; since it indicates economic output of one standard deviation below normal, the CFNAI dummy is a less extreme definition of recessions than our other two measures.

Insert Table 8 Here

In Tables 8 and 9 we perform similar robustness tests for the analysis of *SII* and aggregate stock market returns. In Table 8 we present results of a specification that interacts *SII* with *Pr_Rec*. Table 9 contains results from the same analysis employing *CFNAI_Rec* in place of the recession indicator. We observe in Table 8 that using the probability of recession to interact with *SII* as opposed to the NBER recession indicator strengthens the result that the relation between *SII* and aggregate returns strengthens as the economy heads towards recession. In each specification in Table 8, the interaction term between *SII* and the probability of recession is always negative and statistically significant, and the magnitude of the coefficient is larger than in the initial regressions.

In Table 9, we present results based on *CFNAI_Rec*. In all specifications, the interaction between the recession indicator and *SII* is negative, but the statistical significance of the point estimates are somewhat weaker than in the analysis employing the NBER recession dates or the probability of recession. Across all three measures of aggregate market returns, the interaction terms indicating how the relation between *SII* and future returns changes when *CFNAI_Rec* equals one are statistically significant when predicting three-month returns but insignificant when predicting future one-month returns. However, for the one month returns, *F*-tests for the joint significance of the *SII* and *SII* x *CFNAI_Rec* indicate that for each of the three indices the negative relation between *SII* and future one-month aggregate returns is statistically significant. Overall, the results employing either real-time measure – the probability of recession or the CFNAI index – are consistent with the main findings from Table 5.

Insert Table 9 Here

c. Subsamples

We next examine the robustness of our findings to different time periods. Since recessions are not evenly distributed across the sample, we split our sample in May 1988 so that approximately half of the recession months are in the first period (January 1973 through May 1988), and half of the recession months are in the second period (June 1988 through August 2015). We also note that since the NASDAQ short interest data begins in June 1988, our subsample procedure facilitates a cursory analysis of the exclusion of NASDAQ securities.

In Table 10, we report results from our main calendar-time analysis for each subperiod. Panel A of Table 10 presents four-factor regression results using the period of January 1973 through May 1988; Panel B present results for the period beginning June 1988. Across all specifications in both subperiods, the intercept, indicating the alpha during expansions, is positive and significant at the 1% level and the coefficient estimates for the *Rec* indicator variable are negative. The statistical significance of the decline in alpha during recessions is diminished relative to the whole sample analysis presented in Table 3, particularly in the early period. For the earlier sub-sample, two of the six *Rec* coefficients are significantly negative, while four of six are significantly negative in the later time period.

Insert Table 10 Here

The decline in statistical significance is not surprising given that the time series was already relatively short, and therefore dividing the sample results in a material loss in statistical power. *F*-tests in each of the six specifications in the earlier time period fail to reject the null hypothesis that the alpha of the long short portfolio during recession months is different from zero. The pattern of results presented in Table 10 are consistent with the decline in alpha during recessions existing in both sub-samples.

Insert Table 11 Here

We next explore the robustness of the relation between *SII* and future returns. In Table 11, we present the results for regressions estimating the relation between *SII* and future aggregate stock returns for the 1973-1988 sub-sample. Table 12 presents the same analysis for the latter sub-sample. Overall, our results from Table 5 hold in both subsamples. The *Rec* x *SII* interaction coefficient estimates are uniformly negative. As in the full sample, the interactions are generally only statistically significant for models predicting future three-month returns. Only one three-month return model, Table 11 Panel C, fails to find a statistically significant interaction coefficient. Taken as a whole, the results presented in Tables 11 and 12 document that the relation between the SII and future aggregate stock returns strengthens during recessions and that this relation appears to exist in both sub-samples.

Insert Table 12 Here

VI. Conclusion

Sophisticated market participants play the important role of discovering and trading on private valuation signals. This activity provides a social good that can result in positive effects on real outcomes: it may lower firms' cost of capital, improve CEO incentives, and provide useful feedback in managerial decision making. Further, traders who discover and trade on private signals provide an additional source of external monitoring. Observing signals necessarily requires the scarce resource of attention (Kahneman, 1973); however, existing research offers few empirical explorations of factors influencing how large groups of traders allocate attention. We partially fill this void by studying the trading choices of short sellers, a group largely viewed as sophisticated, and the nature of how their revealed beliefs predict future stock returns.

Our findings that short sellers better anticipate firm-level returns during economic expansions and aggregate market returns during economic recessions are consistent with the rational attention allocation theory of Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). In short, their model predicts informed traders will shift their focus from firm-specific to aggregate signals during recessions because greater aggregate volatility and a higher price of risk increase the marginal benefit of collecting information that affects large portfolios during these times.

Works Cited

Asquith, P., Pathak, P., & Ritter, J. (2005). Short interest, institutional ownership, and stock returns. *Journal of Financial Economics*, 243-276.

Ben-Rephael, A., & Israelsen, R. (2016). It Depends on Where You Search: Institutional Investor Attention and Under-Reaction to News. *Working Paper*.

Boehmer, E., & Wu, J. (2012). Short selling and the price discovery process. *Review of Financial Studies*, 287-322.

Boehmer, E., Huszar, Z., & Jordan, B. (2010). The good news in short interest. *Journal of Financial Economics*, 80-97.

Boehmer, E., Jones, C., & Zhang, X. (2008). Which shorts are informed? *Journal of Finance*, 491-527.

Carhart, M. (1997). On persistence in mutual fund performance. *Journal of Finance*.

Chauvet, M., & Piger, J. (2008). A comparison of the real-time performance of business cycle dating methods. *Journal of Business and Economic Statistics*, 42-49.

Chen, H., & Singal, V. (2003). Role of speculative short sales in price formation: the case of the weekend effect. *Journal of Finance*, 685-705.

Chen, Q., Goldstein, I., & Jiang, W. (2007). Price informativeness and investment sensitivity to stock price. *Review of Financial Studies*, 619-650.

Cohen, L., Diether, K., & Malloy, C. (2007). Supply and demand shifts in the shorting market. *Journal of Finance*, 2061-2096.

Daniel, K., Grinblatt, M., Titman, S., & Wermers, R. (1997). Measuring mutual fund performance with characteristic-based benchmarks. *Journal of Finance*, 1035-1058.

DellaVigna, S., & Pollet, J. (2009). Investor inattention and Friday earnings announcements. *Journal of Finance*, 709-749.

Desai, H., Ramesh, K., Thiagarajan, S., & Balachandran, B. (2002). An investigation of the informational role of short interest in the Nasdaq market. *Journal of Finance*, 2263-2287.

Diether, K., Lee, K., & Werner, I. (2009). Short-sale strategies and return predictability. *Review of Financial Studies*, 575-607.

Dow, J., & Gorton, G. (1997). Stock market efficiency and economic efficiency: Is there a connection? *Journal of Finance*, 1087-1129.

Fang, V., Huang, A., & Karpoff, J. (2015). Short selling and earnings management: a controlled experiment. *Journal of Finance*.

Figlewski, S. (1981). The informational effects of restrictions on short sales: Some empirical evidence. *Journal of Financial and Quantitative Analysis*, 463-476.

Grossman, S., & Stiglitz, J. (1980). On the Impossibility of Informationally Efficient Markets. *American Economic Review*.

Hirshleifer, D., Lim, S., & Teoh, S. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance*, 2289-2325.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance*, 65-91.

Jensen, M., & Meckling, W. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, 305-360.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2014). Time-Varying Fund Manager Skill. *Journal of Finance*, 1455-1484.

Kacperczyk, M., Van Nieuwerburgh, S., & Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, 571-626.

Kahneman, D. (1973). *Attention and effort.* Englewood Cliffs, NJ: Prentice-Hall.

Karpoff, J., & Lou, X. (2010). Short sellers and financial misconduct. *Journal of Finance*, 1879-1913.

Kelley, E., & Tetlock, P. (2016). Retail short selling and stock prices. *Review of Financial Studies*.

Kempf, E., Manconi, A., & Spalt, O. (2016). Distracted shareholders and corporate actions. *Review of Financial Studies*.

Kyle, A. (1985). Continous Auctions and Insider Trading. *Econometrica*, 1315-1335.

Myers, S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 187-221.

Rapach, D., Ringgenberg, M., & Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 46-65.

Saffi, P., & Sigurdsson, K. (2010). Price efficiency and short selling. *Review of Financial Studies*, 821-852.

Table 1

Summary Statistics

This table presents summary statistics for the short interest data employed in this study. Short interest is reported as shares held short and is reported once per month. We divide shares outstanding (from CRSP) to compute the short interest ratio (*SIR*) as the fraction of shares held short divided by the total shares outstanding. We divide our descriptive statistics into two periods, the first beginning in January 1973 and ending in May 1988 and the second beginning in June 1988 and continuing through August 2015. Since we only have short interest data for Nasdaq securities beginning in June 1988, this bifurcation separates our data into the two periods where we have only NYSE and Amex listed securities, and where we have NYSE, Amex, and Nasdaq securities. Panel A presents summary statistics for *SIR*. Panels B and C presents summary statistics for stock price and market capitalization. Panel D presents various other statistics.

Panel A: Short Interest

	1973-May 1988	June 1988-Aug 2015
25th Percentile	0.04%	0.07%
Median	0.12%	0.65%
Mean	0.44%	2.45%
75th Percentile	0.37%	2.87%

Panel B: Price

	1973-May 1988	June 1988- Aug 2015
25th Percentile	9.88	4.59
Median	19.25	12.71
Mean	23.85	19.75
75th Percentile	31.88	25.95

Panel C: Market Cap (Thousands)

	1973-May 1988	June 1988-Aug 2015
25th Percentile	36,226	36,561
Median	164,456	156,969
Mean	883,753	2,294,219
75th Percentile	690,652	796,248

Panel D: Other Statistics

	1973-May 1988	June 1988-Aug 2015
Average number of stocks with zero short interest per month	1	199
Average number of stocks with short interest data per month	1,017	4,674
Number of NBER Recession Months	34	38

Table 2

Calendar Time Analysis of Short Interest Portfolios

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR1*%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.624***	-0.676***	-0.753***	-0.664***	-0.730***	-0.814***
	(-18.83)	(-17.75)	(-12.69)	(-21.89)	(-21.14)	(-15.43)
SMB	-0.365***	-0.491***	-0.556***	-0.407***	-0.549***	-0.600***
	(-7.77)	(-9.09)	(-6.60)	(-9.45)	(-11.20)	(-8.02)
HML	0.152***	0.165***	0.252***	0.102**	0.106**	0.105
	(2.95)	(2.79)	(2.73)	(2.16)	(1.98)	(1.28)
MOM	0.0227	0.0389	0.0744	0.0395	0.0451	0.0685
	(0.70)	(1.04)	(1.28)	(1.33)	(1.33)	(1.32)
Intercept	1.809***	2.119***	2.896***	1.750***	2.080***	2.674***
	(12.40)	(12.64)	(11.08)	(13.08)	(13.67)	(11.50)
N	512	512	512	510	510	510
Adj. R^2	0.553	0.547	0.393	0.622	0.627	0.468

* p<.01 **p<.05 ***p<.01

Table 3

Calendar Time Analysis of Short Interest Portfolios in Expansions and Recessions

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.636***	-0.691***	-0.770***	-0.675***	-0.742***	-0.826***
	(-19.19)	(-18.18)	(-12.90)	(-22.21)	(-21.43)	(-15.57)
SMB	-0.357***	-0.481***	-0.545***	-0.400***	-0.541***	-0.593***
	(-7.64)	(-8.97)	(-6.49)	(-9.33)	(-11.09)	(-7.92)
HML	0.144***	0.155***	0.241***	0.0950**	0.0988*	0.0974
	(2.81)	(2.64)	(2.62)	(2.02)	(1.85)	(1.19)
MOM	0.0146	0.0288	0.0638	0.0325	0.0375	0.0606
	(0.45)	(0.78)	(1.10)	(1.10)	(1.11)	(1.17)
Rec	-1.182***	-1.482***	-1.546**	-1.027***	-1.115***	-1.158*
	(-2.93)	(-3.20)	(-2.13)	(-2.78)	(-2.65)	(-1.79)
Intercept	1.989***	2.345***	3.131***	1.907***	2.251***	2.850***
	(12.65)	(12.99)	(11.07)	(13.21)	(13.70)	(11.31)
N	512	512	512	510	510	510
Adj. R^2	0.560	0.555	0.397	0.627	0.631	0.471

* p<.01 **p<.05 ***p<.01

Table 4

Calendar Time Analysis of High and Low Short Interest Portfolios in Expansions and Recessions

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Panel A analyzes equal weighted portfolios of heavily shorted stocks which have *SIR* above the 90th, 95th, or 99th percentiles. Panel B analyzes equal weighted portfolios of lightly shorted stocks which have *SIR* below the 10th, 5th, or 1st percentiles. The first three columns consider a one month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Heavily Shorted Stocks

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	SIR 90%	*SIR* 95%	*SIR* 99%	*SIR* 90%	*SIR* 95%	*SIR* 99%
MKTRF	1.283***	1.308***	1.335***	1.242***	1.263***	1.315***
	(49.28)	(43.32)	(27.00)	(45.45)	(38.76)	(26.03)
SMB	0.975***	1.053***	1.128***	0.967***	1.066***	1.084***
	(26.58)	(24.76)	(16.19)	(25.10)	(23.21)	(15.21)
HML	0.161***	0.140***	0.0863	0.213***	0.197***	0.209***
	(3.99)	(3.00)	(1.13)	(5.05)	(3.91)	(2.67)
MOM	-0.125***	-0.144***	-0.156***	-0.139***	-0.161***	-0.162***
	(-4.92)	(-4.90)	(-3.23)	(-5.23)	(-5.07)	(-3.29)
Rec	0.806**	0.930**	0.738	0.981***	0.839**	1.377**
	(2.54)	(2.53)	(1.23)	(2.95)	(2.12)	(2.24)
Intercept	-0.893***	-1.054***	-1.667***	-0.825***	-1.015***	-1.646***
	(-7.23)	(-7.36)	(-7.11)	(-6.36)	(-6.56)	(-6.86)
N	512	512	512	510	510	510
Adj. R^2	0.896	0.874	0.737	0.881	0.850	0.715

Panel B: Lightly Shorted Stocks

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	SIR 10%	*SIR* 5%	*SIR* 1%	*SIR* 10%	*SIR* 5%	*SIR* 1%
MKTRF	0.647***	0.616***	0.566***	0.533***	0.505***	0.472***
	(23.53)	(21.05)	(13.79)	(20.51)	(17.95)	(11.93)
SMB	0.618***	0.572***	0.583***	0.548***	0.481***	0.502***
	(15.96)	(13.87)	(10.09)	(14.94)	(12.12)	(9.00)
HML	0.305***	0.295***	0.328***	0.277***	0.267***	0.283***
	(7.17)	(6.52)	(5.17)	(6.89)	(6.15)	(4.63)
MOM	-0.110***	-0.115***	-0.0918**	-0.0890***	-0.116***	-0.108***
	(-4.12)	(-4.04)	(-2.30)	(-3.51)	(-4.21)	(-2.81)
Rec	-0.376	-0.551	-0.808	0.111	0.0631	0.159
	(-1.12)	(-1.55)	(-1.62)	(0.35)	(0.18)	(0.33)
Intercept	1.096***	1.291***	1.464***	1.059***	1.156***	1.278***
	(8.40)	(9.29)	(7.53)	(8.58)	(8.66)	(6.80)
N	512	512	512	510	510	510
Adj R^2	0.687	0.635	0.441	0.634	0.564	0.378

* p<.01 **p<.05 ***p<.01

Table 5

Short Selling Index and Aggregate Return Predictability

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month *t* is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.200	-0.413***	-0.202
	(-1.84)	(-0.91)	(-3.56)	(-1.59)
SII_t * Rec_t		-0.741		-1.063***
		(-1.45)		(-3.61)
Rec_t		-0.705		-0.187
		(-1.23)		(-0.57)
Intercept	0.245	0.368*	0.263**	0.322***
	(1.25)	(1.74)	(2.30)	(2.64)
N	512	512	510	510
Adj. R^2	0.005	0.009	0.022	0.046

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.225	-0.450***	-0.218
	(-1.96)	(-1.00)	(-3.69)	(-1.62)
SII_t * Rec_t		-0.831		-1.207***
		(-1.57)		(-3.89)
Rec_t		-0.542		0.0114
		(-0.91)		(0.03)
Intercept	0.497**	0.600***	0.519***	0.553***
	(2.45)	(2.75)	(4.31)	(4.32)
N	512	512	510	510
Adj. R^2	0.006	0.009	0.024	0.050

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.442	-0.620***	-0.392**
	(-2.20)	(-1.58)	(-3.80)	(-2.18)
SII_t * Rec_t		-0.579		-1.324***
		(-0.89)		(-3.18)
Rec_t		-0.0681		0.849*
		(-0.09)		(1.82)
Intercept	0.339	0.367	0.776***	0.697***
	(1.36)	(1.36)	(4.82)	(4.05)
N	512	512	510	510
Adj. R^2	0.007	0.005	0.026	0.044

* p<.01 **p<.05 ***p<.01

Table 6

Calendar Time Analysis with Time Varying Factor Exposure

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with each factor loading interacted with the NBER recession indicator in Panel A. In Panel B, all returns are characteristic adjusted with benchmarks based on size, book-to-market, and prior 11-month return. *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Recession Varying Factor Loadings

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.617***	-0.669***	-0.706***	-0.673***	-0.736***	-0.818***
	(-15.90)	(-15.04)	(-10.07)	(-18.90)	(-18.12)	(-13.09)
*MKTRF * Rec*	-0.0249	-0.0139	-0.235*	0.0388	0.0360	-0.00446
	(-0.32)	(-0.15)	(-1.66)	(0.54)	(0.44)	(-0.04)
SMB	-0.336***	-0.439***	-0.569***	-0.378***	-0.513***	-0.610***
	(-6.57)	(-7.48)	(-6.15)	(-8.03)	(-9.56)	(-7.39)
*SMB * Rec*	0.00972	-0.0997	0.208	-0.0265	-0.0526	0.172
	(0.07)	(-0.66)	(0.87)	(-0.22)	(-0.38)	(0.80)
HML	0.216***	0.239***	0.235**	0.149***	0.150**	0.0747
	(3.61)	(3.49)	(2.18)	(2.72)	(2.40)	(0.78)
*HML * Rec*	-0.261**	-0.289**	0.0387	-0.197*	-0.177	0.0824
	(-2.23)	(-2.16)	(0.18)	(-1.84)	(-1.45)	(0.44)
MOM	-0.0140	-0.0130	0.0334	0.00746	0.000508	0.0236
	(-0.36)	(-0.29)	(0.47)	(0.21)	(0.01)	(0.38)
*MOM * Rec*	0.0905	0.119	0.0479	0.0938	0.126	0.143
	(1.20)	(1.37)	(0.35)	(1.35)	(1.59)	(1.17)
Rec	-1.131***	-1.378***	-1.731**	-0.961**	-1.051**	-1.286*
	(-2.76)	(-2.94)	(-2.34)	(-2.56)	(-2.46)	(-1.95)
Intercept	1.968***	2.324***	3.118***	1.902***	2.252***	2.885***
	(12.39)	(12.77)	(10.87)	(13.03)	(13.55)	(11.27)
N	512	512	512	510	510	510
Adj. R^2	0.563	0.560	0.397	0.630	0.633	0.469

Panel B: Characteristic-adjusted returns

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
Rec	-0.814**	-1.166**	-1.240*	-0.714**	-0.920**	-0.994
	(-2.13)	(-2.57)	(-1.72)	(-1.99)	(-2.19)	(-1.54)
Intercept	1.212***	1.469***	2.221***	1.072***	1.295***	1.782***
	(8.44)	(8.65)	(8.22)	(7.98)	(8.20)	(7.34)
N	512	512	512	510	510	510
Adj. R^2	0.310	0.262	0.121	0.331	0.305	0.168

*p<.01 **p<.05 ***p<.01

Table 7

Calendar Time Analysis with Alternative Recession Metrics

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one-month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. In Panel A, the variable *Pr_Rec* is equal to the probability of recession in a given month as computed by Chauvet and Piger (2008). In Panel B the variable *CFNAI_Rec* is equal to one if the value of the Chicago Fed National Activity Index is less than one standard deviation below the mean and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: Probability of Recession

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.633***	-0.688***	-0.763***	-0.673***	-0.740***	-0.824***
	(-19.12)	(-18.12)	(-12.81)	(-22.21)	(-21.45)	(-15.57)
SMB	-0.359***	-0.482***	-0.549***	-0.401***	-0.542***	-0.594***
	(-7.67)	(-9.00)	(-6.52)	(-9.35)	(-11.12)	(-7.93)
HML	0.143***	0.153***	0.242***	0.0934**	0.0968*	0.0956
	(2.79)	(2.61)	(2.62)	(1.99)	(1.81)	(1.17)
MOM	0.0122	0.0250	0.0630	0.0296	0.0339	0.0574
	(0.37)	(0.67)	(1.08)	(0.99)	(1.00)	(1.10)
Pr_Rec	-1.537***	-2.033***	-1.662	-1.452***	-1.632***	-1.631*
	(-2.67)	(-3.09)	(-1.61)	(-2.76)	(-2.73)	(-1.78)
Intercept	1.969***	2.330***	3.068***	1.901***	2.250***	2.843***
	(12.55)	(12.96)	(10.87)	(13.23)	(13.76)	(11.33)
N	512	512	512	510	510	510
Adj. R^2	0.558	0.555	0.395	0.627	0.631	0.471

Panel B: CFNAI Index Measure

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.628***	-0.680***	-0.756***	-0.668***	-0.733***	-0.817***
	(-19.01)	(-17.92)	(-12.72)	(-22.04)	(-21.23)	(-15.47)
SMB	-0.361***	-0.486***	-0.553***	-0.404***	-0.546***	-0.597***
	(-7.71)	(-9.04)	(-6.56)	(-9.39)	(-11.15)	(-7.97)
HML	0.138***	0.149**	0.241***	0.0899*	0.0956*	0.0941
	(2.66)	(2.51)	(2.60)	(1.90)	(1.77)	(1.14)
MOM	0.0128	0.0279	0.0675	0.0314	0.0378	0.0610
	(0.39)	(0.74)	(1.15)	(1.05)	(1.11)	(1.17)
CFNAI_Rec	-0.974**	-1.094**	-0.685	-0.802**	-0.718	-0.744
	(-2.28)	(-2.23)	(-0.89)	(-2.05)	(-1.61)	(-1.09)
Intercept	1.945***	2.271***	2.991***	1.862***	2.181***	2.777***
	(12.39)	(12.59)	(10.59)	(12.93)	(13.29)	(11.06)
N	512	512	512	510	510	510
Adj. R^2	0.557	0.551	0.393	0.625	0.628	0.469

* p<.01 **p<.05 ***p<.01

Table 8

Aggregate Return Predictability and the Probability of Recession

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Pr_Rec_t is equal to the probability of recession in a given month as computed by Chauvet and Piger (2008). The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.140	-0.413***	-0.150
	(-1.84)	(-0.65)	(-3.56)	(-1.20)
$SII_t * Pr\_Rec_t$		-1.618**		-1.919***
		(-2.39)		(-4.96)
Pr_Rec_t		-0.424		0.142
		(-0.53)		(0.31)
Intercept	0.245	0.301	0.263**	0.267**
	(1.25)	(1.44)	(2.30)	(2.22)
N	512	512	510	510
Adj. R^2	0.005	0.013	0.022	0.064

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.148	-0.450***	-0.157
	(-1.96)	(-0.66)	(-3.69)	(-1.20)
$SII_t * Pr\_Rec_t$		-1.850***		-2.157***
		(-2.65)		(-5.31)
Pr_Rec_t		-0.122		0.457
		(-0.15)		(0.95)
Intercept	0.497**	0.527**	0.519***	0.495***
	(2.45)	(2.44)	(4.31)	(3.93)
N	512	512	510	510
Adj. R^2	0.006	0.015	0.024	0.073

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.323	-0.620***	-0.301*
	(-2.20)	(-1.17)	(-3.80)	(-1.71)
SII_t * Pr_Rec_t		-1.756**		-2.446***
		(-2.04)		(-4.50)
Pr_Rec_t		0.681		1.836***
		(0.67)		(2.86)
Intercept	0.339	0.293	0.776***	0.624***
	(1.36)	(1.09)	(4.82)	(3.70)
N	512	512	510	510
Adj. R^2	0.007	0.012	0.026	0.072

* p<.01 **p<.05 ***p<.01

Table 9

Aggregate Return Predictability and CFNAI Recessions

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable $CFNAI\_Rec_t$ is equal to one if the value of the Chicago Fed National Activity Index is less than one standard deviation below the mean and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.363*	-0.261	-0.413***	-0.242*
	(-1.84)	(-1.20)	(-3.56)	(-1.92)
SII_t * $CFNAI\_Rec_t$		-0.658		-1.046***
		(-1.25)		(-3.44)
$CFNAI\_Rec_t$		0.543		0.600*
		(0.90)		(1.74)
Intercept	0.245	0.191	0.263**	0.208*
	(1.25)	(0.91)	(2.30)	(1.72)
N	512	512	510	510
Adj. R^2	0.005	0.005	0.022	0.044

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.399*	-0.274	-0.450***	-0.259*
	(-1.96)	(-1.23)	(-3.69)	(-1.96)
SII_t * $CFNAI\_Rec_t$		-0.838		-1.193***
		(-1.54)		(-3.75)
$CFNAI\_Rec_t$		0.913		0.891**
		(1.48)		(2.47)
Intercept	0.497**	0.400*	0.519***	0.430***
	(2.45)	(1.85)	(4.31)	(3.39)
N	512	512	510	510
Adj. R^2	0.006	0.010	0.024	0.054

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.553**	-0.473*	-0.620***	-0.429**
	(-2.20)	(-1.72)	(-3.80)	(-2.45)
SII_t * $CFNAI\_Rec_t$		-0.711		-1.338***
		(-1.07)		(-3.17)
$CFNAI\_Rec_t$		1.976***		2.146***
		(2.60)		(4.48)
Intercept	0.339	0.107	0.776***	0.533***
	(1.36)	(0.40)	(4.82)	(3.17)
N	512	512	510	510
Adj. R^2	0.007	0.018	0.026	0.071

* p<.01 **p<.05 ***p<.01

Table 10

Calendar Time Analysis: Subperiods

This table presents monthly returns based on short interest as a fraction of total shares outstanding (*SIR*) according to short interest reports from the 15th of the prior month for two sub-samples of the data. Panel A presents the analysis for the period of January 1973-May 1988, and panel B presents the analysis for the period of June 1988-August 2015. Lightly shorted stocks correspond to those with *SIR* below the 10th, 5th, or 1st percentiles; heavily shorted stocks corresponding to those with *SIR* above the 90th, 95th, or 99th percentiles. Spread portfolios purchase an equal weighted portfolio of lightly shorted stocks and sell an equal weighted portfolio of highly shorted stocks. The first three columns consider a one- month calendar-time analysis. The second three columns consider a three-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Numbers in the table contain factor loadings and intercepts estimated using the Carhart (1997) four-factor model with *t*-statistics in parenthesis. The indicator variable *Rec* equals one if the given month is identified as a NBER recession month and zero otherwise. The regressions begin in January 1973 and run through August 2015. One, two, and three stars indicates statistical significance at the ten, five, and one percent levels, respectively.

Panel A: 1973-1988

		Ret_{t+1}			$Ret_{t+1:t+3}$	
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.460***	-0.505***	-0.585***	-0.547***	-0.626***	-0.665***
	(-10.41)	(-8.57)	(-5.37)	(-13.96)	(-12.21)	(-6.82)
SMB	-0.257***	-0.380***	-0.304*	-0.380***	-0.522***	-0.436***
	(-3.64)	(-4.04)	(-1.74)	(-6.04)	(-6.35)	(-2.79)
HML	0.274***	0.290***	0.628***	0.199***	0.202**	0.364**
	(3.67)	(2.92)	(3.42)	(3.01)	(2.33)	(2.21)
MOM	-0.0716	-0.0607	0.0661	-0.0389	-0.0467	-0.0812
	(-1.40)	(-0.89)	(0.52)	(-0.86)	(-0.79)	(-0.72)
Rec	-0.897*	-1.269**	-1.753	-0.609	-0.837	-0.922
	(-1.91)	(-2.03)	(-1.51)	(-1.46)	(-1.54)	(-0.89)
Intercept	1.725***	2.008***	2.222***	1.507***	1.849***	2.141***
	(7.64)	(6.69)	(4.00)	(7.51)	(7.04)	(4.29)
N	185	185	185	183	183	183
Adj. R^2	0.594	0.517	0.320	0.715	0.669	0.384

Panel B: 1973-1988

	Ret_{t+1}			$Ret_{t+1:t+3}$		
	(1)	(2)	(3)	(4)	(5)	(6)
	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%	*SIR*10%-*SIR*90%	*SIR*5%-*SIR*95%	*SIR*1%-*SIR*99%
MKTRF	-0.766***	-0.828***	-0.888***	-0.762***	-0.814***	-0.914***
	(-16.38)	(-16.31)	(-12.34)	(-17.27)	(-16.90)	(-14.27)
SMB	-0.436***	-0.560***	-0.710***	-0.429***	-0.572***	-0.719***
	(-7.26)	(-8.59)	(-7.67)	(-7.56)	(-9.23)	(-8.73)
HML	0.0819	0.0968	0.0501	0.0567	0.0643	-0.0291
	(1.22)	(1.33)	(0.49)	(0.90)	(0.93)	(-0.32)
MOM	0.0183	0.0339	0.0500	0.0373	0.0522	0.0990*
	(0.45)	(0.76)	(0.79)	(0.96)	(1.24)	(1.77)
Rec	-1.528**	-1.706**	-1.268	-1.363**	-1.243*	-1.127
	(-2.49)	(-2.56)	(-1.34)	(-2.35)	(-1.96)	(-1.34)
Intercept	2.174***	2.566***	3.545***	2.140***	2.472***	3.179***
	(10.73)	(11.66)	(11.36)	(11.19)	(11.84)	(11.45)
N	327	327	327	327	327	327
Adj. R^2	0.582	0.601	0.479	0.606	0.621	0.549

*p<.1 **p<.05 ***p<.01

Table 11

Short Selling Index and Aggregate Return Predictability: 1973-1988

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month t is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in January 1973 and run through May 1988. t-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.605	-0.454	-0.570**	-0.307
	(-1.39)	(-0.95)	(-2.28)	(-1.13)
$SII_t * Rec_t$		-1.299		-1.719**
		(-1.04)		(-2.43)
Rec_t		-1.134		-0.686
		(-1.05)		(-1.12)
Intercept	-0.220	-0.0858	-0.207	-0.181
	(-0.58)	(-0.21)	(-0.95)	(-0.76)
N	185	185	185	185
Adj. R^2	0.005	0.002	0.022	0.043

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.858*	-0.724	-0.793***	-0.524*
	(-1.91)	(-1.46)	(-3.04)	(-1.85)
$SII_t * Rec_t$		-1.225		-1.764**
		(-0.95)		(-2.39)
Rec_t		-1.182		-0.706
		(-1.06)		(-1.10)
Intercept	0.107	0.254	0.132	0.160
	(0.27)	(0.59)	(0.58)	(0.65)
N	185	185	185	185
Adj. R^2	0.014	0.010	0.043	0.062

Panel B: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-1.432**	-1.554**	-1.450***	-1.300***
	(-2.56)	(-2.52)	(-4.18)	(-3.41)
$SII_t * Rec_t$		0.487		-0.802
		(0.30)		(-0.81)
Rec_t		-0.416		0.0330
		(-0.30)		(0.04)
Intercept	-0.283	-0.177	0.390	0.336
	(-0.58)	(-0.33)	(1.29)	(1.01)
N	185	185	185	185
Adj. R^2	0.029	0.021	0.082	0.077

*p<.1 **p<.05 ***p<.01

Table 12

Short Selling Index and Aggregate Return Predictability: 1988-2015

This table presents time series regressions of aggregate stock market returns on the short selling index (*SII*) of Rapach, Ringgenberg, and Zhou (2016). The dependent variable for the columns (1) and (2) is the future one-month return. The dependent variable for columns (3) and (4) is the future three-month return. The indicator variable Rec_t equals one when month t is an NBER recession month and zero otherwise. The return variables in Panels A, B, and C are the return on the S&P500 index, the CRSP value weighted index, and the CRSP equal weighted index, respectively. The regressions begin in June 1988 and run through August 2015. *t*-statistics appear in parenthesis, and one two and three stars indicates statistical significance at the ten, five, and one percent levels respectively.

Panel A: S&P 500 Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.361*	-0.157	-0.452***	-0.225
	(-1.65)	(-0.66)	(-3.51)	(-1.63)
$SII_t * Rec_t$		-1.234		-1.820***
		(-1.53)		(-3.98)
Rec_t		0.0915		1.080*
		(0.08)		(1.71)
Intercept	0.473**	0.569**	0.515***	0.567***
	(2.04)	(2.36)	(3.81)	(4.11)
N	327	327	325	325
Adj. R^2	0.005	0.012	0.034	0.080

Panel B: CRSP Value Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.294	-0.0765	-0.391***	-0.147
	(-1.30)	(-0.31)	(-2.85)	(-1.01)
$SII_t * Rec_t$		-1.500*		-2.110***
		(-1.81)		(-4.35)
Rec_t		0.482		1.478**
		(0.42)		(2.21)
Intercept	0.636***	0.719***	0.679***	0.719***
	(2.66)	(2.89)	(4.72)	(4.91)
N	327	327	325	325
Adj. R^2	0.002	0.011	0.021	0.074

Panel C: CRSP Equal Weighted Index

	Ret_{Mt+1}		$Ret_{Mt+1:t+3}$	
	(1)	(2)	(3)	(4)
SII_t	-0.324	-0.0855	-0.354*	-0.0809
	(-1.18)	(-0.29)	(-1.93)	(-0.42)
SII_t * Rec_t		-2.705***		-3.415***
		(-2.69)		(-5.33)
Rec_t		2.635*		3.760***
		(1.90)		(4.26)
Intercept	0.530*	0.519*	0.831***	0.773***
	(1.82)	(1.71)	(4.32)	(4.00)
N	327	327	325	325
Adj. R^2	0.001	0.017	0.008	0.084

*p<.1 **p<.05 ***p<.01

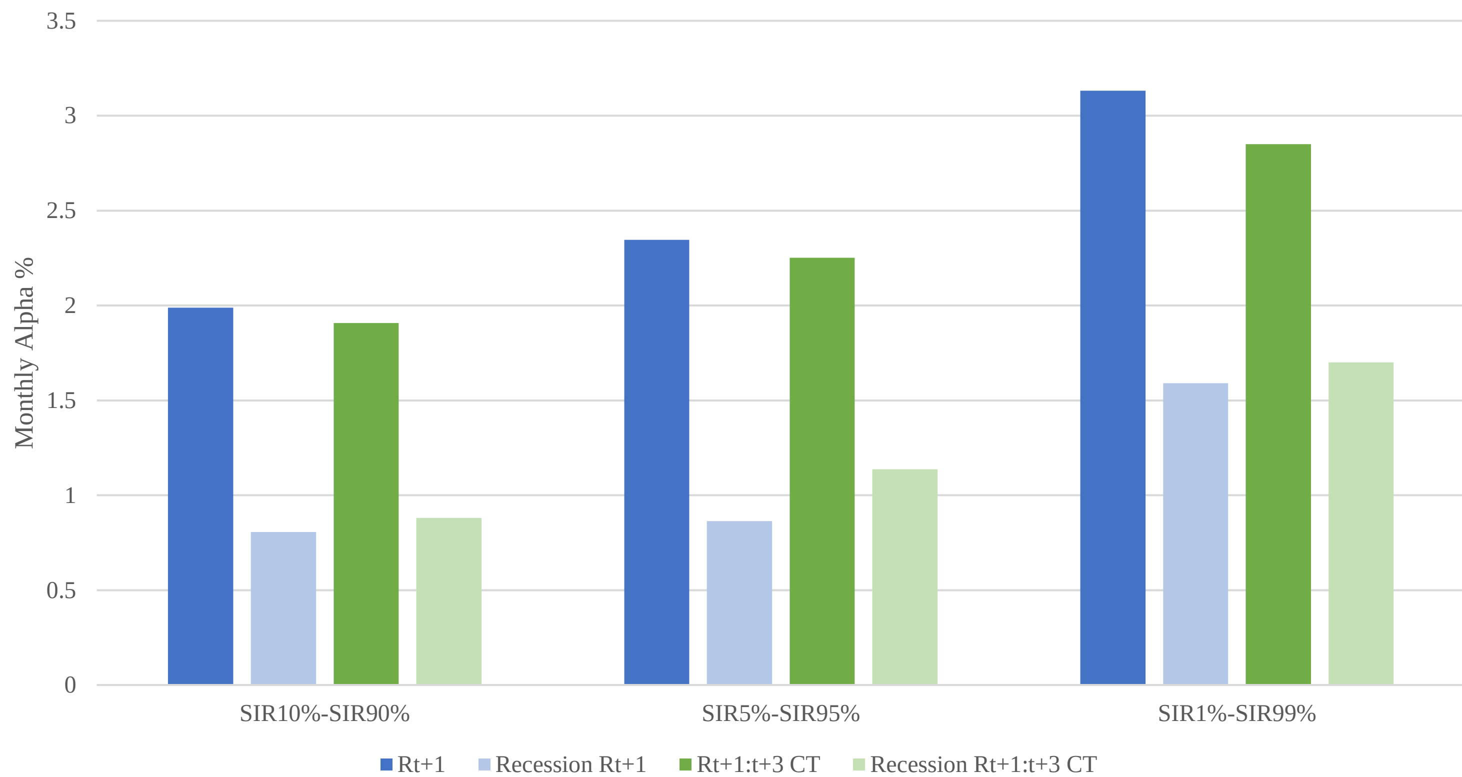

Figure 1: Four Factor Alpha During Recessions and Expansions. This figure presents the monthly alphas from Carhart (1997) four-factor regressions which include an additional intercept for recession months as in Equation (1). The first set of bars presents the monthly alphas from regressions where the dependent variable is either the one-month or three-month return on a calendar time portfolio that buys stocks with short interest below the 10th percentile, and sells stocks with short interest above the 90th percentile. The middle and rightmost set of bars present the results for similar portfolios with thresholds for the long and short portfolios being 5% and 95% respectively for the middle set of bars, and 1% and 99% respectively for the rightmost set of bars. The green bars identify three-month calendar time portfolios and the blue bars one-month calendar time portfolios. The darkly shaded bars present the observed value of the coefficient α_e from Equation (1) which indicates the four-factor alpha for the given arbitrage portfolio during expansions. The darkly shaded bars present the observed value of the sum of coefficients $\alpha_e + \alpha_r$ from Equation (1) which indicates the magnitude of the four-factor alpha for the given arbitrage portfolio during NBER recession months.

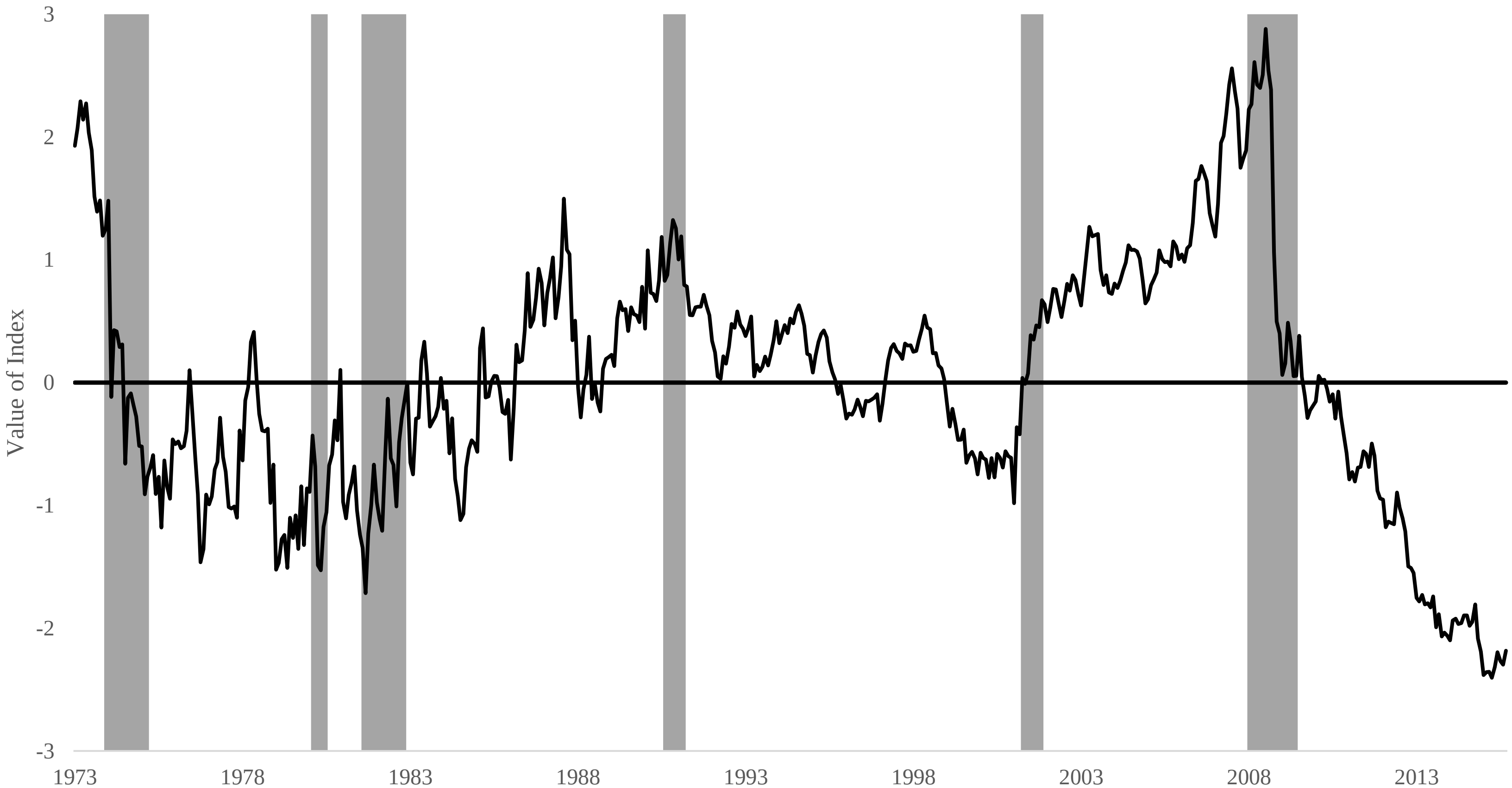

Figure 2: Short Interest Index from 1973-2015. This figure presents the monthly Short Interest Index as developed by Rapach, Ringgenberg, and Zhou (2016). Each month short interest is calculated for each stock as the number of shares held short divided by the number of shares outstanding. The long of the equally weighted average of short interest across all stocks is computed and the time trend is removed. The remaining series is divided by its standard deviation to produce the aggregate short interest index (*SII*). This figure presents the aggregate short interest index from 1973-2015. Recession bars are in grey.

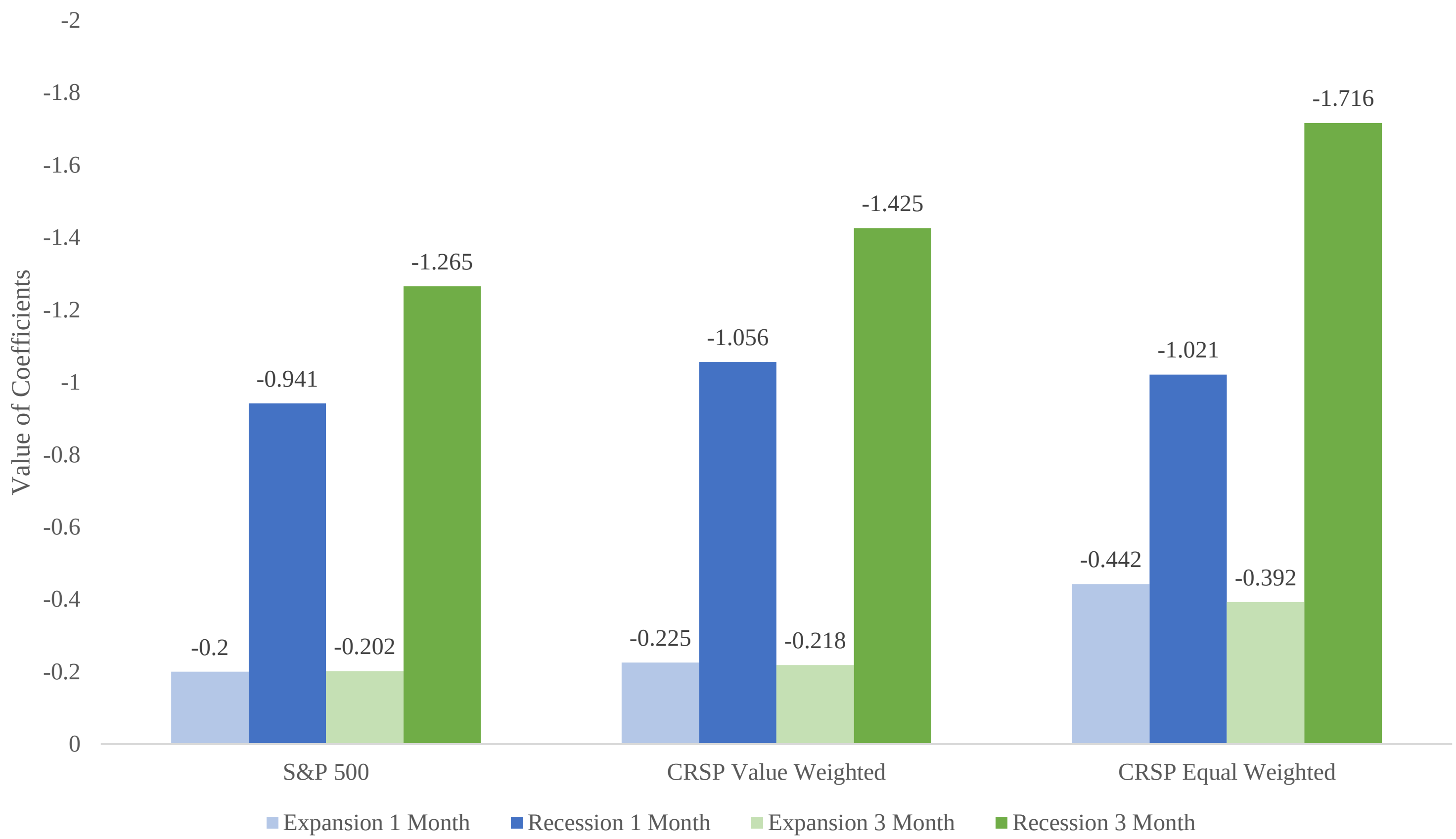

Figure 3: Relation Between SII and Aggregate Stock Returns During Recessions and Expansions. This Table presents a graphical description of the coefficients indicating the relation between *SII* and future aggregate stock returns from Equation (4). The first, second, and third set of bars present the results where the dependent variable is either the one-month or three-month return on the S&P 500 index, CRSP Value Weighted index, or the CRSP Equal Weighted index. The blue (green) bars correspond to specifications where the dependent variable is the one-month (three-month) return on the given index. The lightly shaded bars present the observed value of the coefficient β from Equation (4) which indicates the relation between *SII* and future returns during expansion periods, and the darkly shaded bars present the observed value of the sum of coefficients $\beta + \beta_r$ which indicates the magnitude of the relation between *SII* and future aggregate returns during NBER recession months.

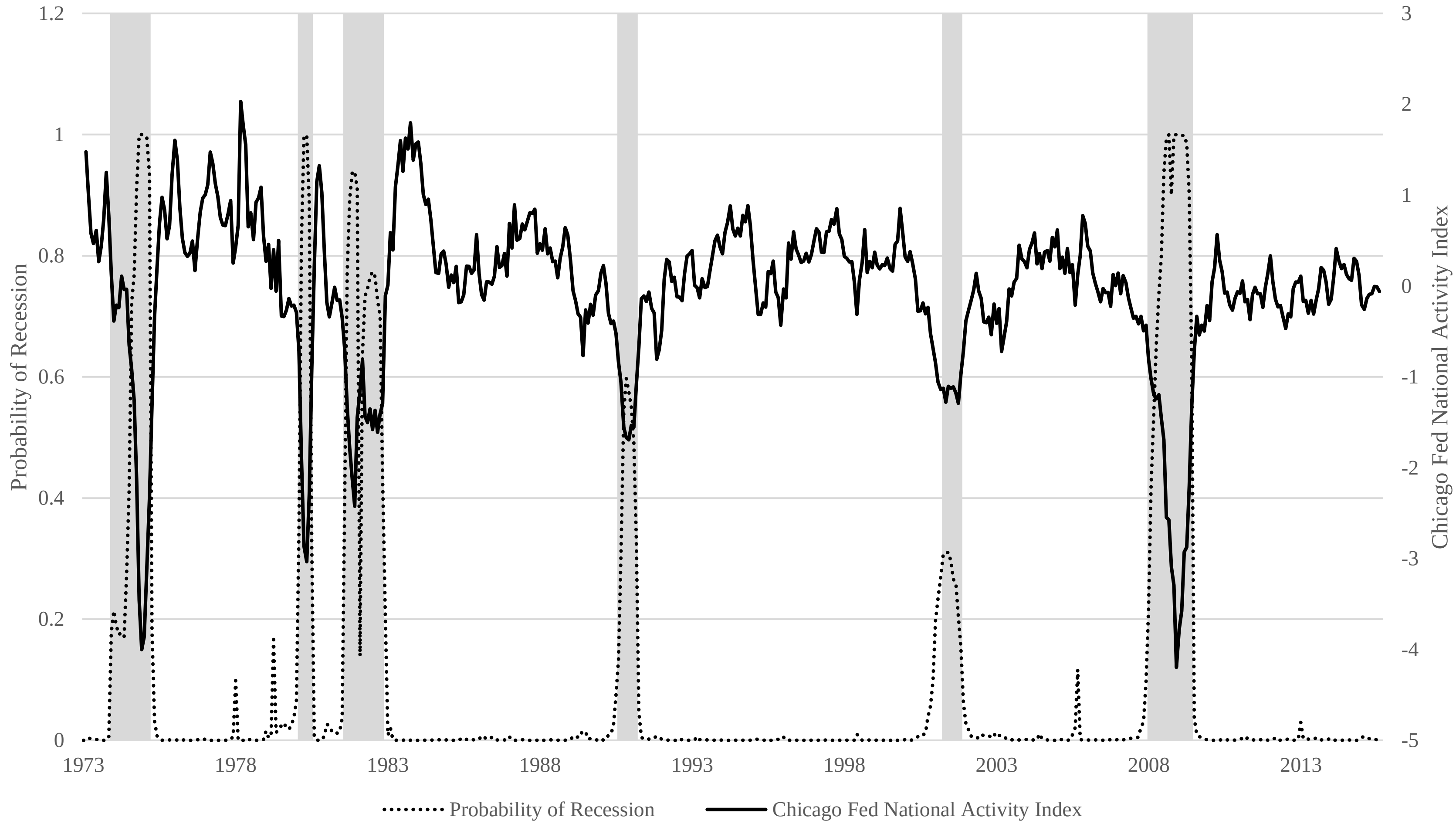

Figure 4: Alternative Recession Measures. This figure presents two alternative recession indicators. The dotted line indicates the probability of recession as described by Chauvet and Piger (2008). The solid line is the Chicago Fed National Activity Index (CFNAI). The grey bars indicate NBER recession dates.