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Business Cycle Variation in Short Selling Strategies: Picking During Expansions and Timing During Recessions

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Abstract

We present evidence that short sellers alternate between stock picking during expansions and market timing during recessions. First, firm-level short interest is a much stronger negative predictor of the cross-section of stock returns during expansions than it is during recessions. High short interest also only predicts negative future earnings announcement returns during expansions. We attribute these findings to short sellers' emphasis on collecting firm-specific signals. Second, short sellers appear to make factor bets more so during recessions than during expansions. These bets tend to pay off as we observe a strong negative relation between the betas of highly shorted stocks and future stock market returns, a result that disappears during expansions. Together, these findings are consistent with theories of information acquisition under attention constraints, endogenous information production, as well as theories of time variation in aggregate overconfidence amongst traders.

I. Introduction

In a world with scarce attention and arbitrage capital, dynamic information production, and an evolving investor population, short sellers – a class of investors widely characterized as sophisticated – face complex tradeoffs when gathering information. Which signals do they choose to learn? Which do they ignore? And how do they allocate effort to study firms, industries, and entire economies? The ramifications of these choices strike the core of how information is discovered in financial markets and when it is revealed in prices. While the vast empirical research on short selling offers mostly unconditional analyses that relate shorting activity to

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future stock returns and a host of other outcomes,[1] theory suggests the answers to these questions may vary conditionally with the business cycle.

Kacperczyk, Van Nieuwerburgh, and Veldkamp (KVV) (2016) model rational yet cognitively constrained traders who allocate limited information gathering resources (i.e., attention) across firm-specific and systematic signals prior to forming portfolios. KVV argue that the marginal benefit of collecting firm-specific signals is greatest during expansions because these periods coincide with lower aggregate volatility and a reduced price of risk. If short sellers possess scarce information-processing capacity, KVV's model suggests they will better resemble stock pickers in expansions and market timers in recessions. In addition, Veldkamp (2005) argues information production increases in expansions as the accompanying real investment endogenously generates signals that are inexpensive to replicate. Moreover, in the model of Van Nieuwerburgh and Veldkamp (2006), information signals are more precise in expansions as well. To the extent that short sellers' advantage stems from superior *processing* of information signals (Engelberg, Reed, and Ringgenberg (2012)), these models suggest their stock-picking abilities may strengthen during expansions.

Theories of overconfidence reinforce the notion that short-sellers may be better stock pickers in expansions than in recessions. Most relevant to our work are models associating overconfidence with stock market mispricings. Two prominent examples are Daniel, Hirshleifer, and Subrahmanyam (1998) and Odean (1998), who link overconfidence to stock price overreactions and the delayed incorporation of rational traders' beliefs into prices.[2] Gervais and Odean (2001) model traders who learn about their own abilities and tend to become overconfident after experiencing success. They argue that since the average trader has long exposure, aggregate overconfidence will fluctuate with stock price levels. Thus, short sellers' opportunities to exploit their overconfident trading counterparts may be more prevalent in economic expansions, which are marked by generally rising stock prices.

Whether short sellers gather different types of information during expansions and contractions is ultimately an empirical question. We offer several pieces of evidence that they do. First, a portfolio of the most highly shorted stocks performs differently in expansions than in recessions. Specifically, a strategy that shorts stocks having short interest above the 95th percentile ("high short interest stocks") and purchases stocks having short interest below the 5th percentile ("low short interest stocks") earns a statistically significant 4-factor alpha of 1.7% per month

[1]Shorting activity is a robust negative predictor of the cross-section of returns (Figlewski (1981), Desai, Ramesh, Thiagarajan, and Balachandran (2002), Asquith, Pathak, and Ritter (2005), and Boehmer, Huszar, and Jordan (BHJ) (2010)). Firm-level short interest also correctly anticipates the revelation of financial misconduct (Karpoff and Lou (2010), Fang, Huang, and Karpoff (2015)), analyst downgrades (Christophe, Ferri, and Hsieh (2010)), bond rating downgrades (Henry, Kisgen, and Wu (2015)), earning surprises (Christophe, Ferri, and Angel (2005), Berkman and McKenzie (2012)), private placements (Berkman, McKenzie, and Verwijmeren (2017)), and earnings restatements (Desai, Krishnamurthy, and Venkataraman (2006)). In addition, Rapach, Ringgenberg, and Zhou's (2016) link a systematic component of short interest to future market-wide returns.

[2]Both papers also provide detailed reviews of the large empirical literature documenting that people display overconfidence in a variety of settings.

during expansions but an insignificant alpha of 0.37% during recessions. This finding that a portfolio mimicking the disclosed positions of short sellers resembles successful stock-picking in expansions alone is novel to the literature and is robust to a host of factor models with time varying loadings as well as to the use of alternative measures of economic recessions.

While consistent with these traders collecting firm-specific signals in expansions, the evidence is indirect; it does not connect shorting behavior to the realization of firm-specific signals. Our second piece of evidence does. On average, stocks with high short interest exhibit negative subsequent earnings announcement returns. Like the alpha result, the earnings disappointments for these stocks are much sharper in expansions than in recessions. During expansions, the average 3-day market-adjusted return around earnings announcements for high short interest stocks (stocks with short interest above the 95th percentile) is −0.59% and statistically significant. The same statistic during recessions is an insignificant 0.16%. These results are particularly useful because the stock price reaction to an earnings release captures the value-relevance of the firm-specific signal revealed by the announcement.

Third, the factor exposure of high short interest stocks varies over the business cycle in an interesting manner as well. Short sellers who collect aggregate signals will tilt their positions toward stocks with similar exposure to a given factor at the same time. Empirically, the resulting factor bets will manifest in a portfolio of high short interest stocks in two ways: i) across months, variation in average factor loadings will be high; ii) within a given month, cross-stock dispersion in factor loadings will be low. Each effect will be particularly acute during recessions if that is when short sellers most actively gather aggregate information. Our results, most salient for CAPM beta, are once again consistent. The month-to-month volatility in the beta of the high short interest stock portfolio is about 30% greater in recessions than expansions. Moreover, during an average recession month, the standard deviation of beta across high short interest stocks decreases to about 0.66, down from 0.76 during expansions. Differences from both these tests are statistically significant.

Fourth, a portfolio of high short interest stocks performs like a successful factor-timing strategy. Again, the results are most striking for timing the aggregate stock market. Using a framework akin to Jiang, Yao, and Yu's (2007) mutual fund market timing test, we find a negative relation between the high short interest portfolio's CAPM beta and future aggregate market returns, which indicates short sellers tend toward higher beta stocks prior to low market returns. And consistent with greater focus on aggregate signals, this relation is strongest during recessions. Importantly, this result is largely orthogonal to the relation between Rapach et al.'s (2016) short interest index and future market returns, and it persists alongside the aggregate stock market predictors studied by Welch and Goyal (2008).

In sum, short positions reflect new firm-specific information in expansions and aggregate information in recessions. We conclude our analysis with a simple thought experiment that illustrates the value of firm-specific and aggregate signals imbedded in short interest. We consider four simple investing strategies: holding the S&P 500, stock picking based on average short interest, market timing based on the betas of highly shorted stocks, and a strategy that alternates between stock picking during expansion months and market timing during recession months. The wealth paths obtained from this thought experiment show that over the 1974–2017 period both the market timing and the stock picking strategies outperform the S&P 500, but the simple switching strategy outperforms the other three. This pattern bolsters the argument that short sellers may be acting optimally by alternating which signals they collect and trade on across the business cycle.

Our paper contributes to multiple strands of research. First, we join authors who explore what short sellers know. While prior literature offers evidence of specific pieces of firm-specific information that short sellers understand, we are the first to suggest the nature of this understanding may vary with the business cycle. This result informs our view of how short sellers contribute to price efficiency in financial markets (Saffi and Siggurdson (2010), Boehmer and Wu (2013)). For instance, our evidence is consistent with information and attention allocation theories which suggest, albeit for different reasons, that short sellers impound less firm-specific information into stock prices during recessions. This effect would render public announcements more valuable and could help explain recent findings in Loh and Stulz (2018) and Schmalz and Zhuk (2018) who show that prices respond more to analyst revisions and earnings news respectively during downturns than during upturns.[3]

Other authors contend that short sellers act as valuable external monitors of the firm (e.g., Fang, Huang, and Karpoff (2015), Massa, Zhang, and Zhang (2015)). If short sellers learn less firm specific information during recessions about individual firms, whether due to attention allocation or diminished signal quality, then their value as monitors of the firm may likewise diminish during down economic times. To the extent that less monitoring creates opportunities for nefarious behavior, fraud may become more likely during economic downturns.[4] This view is nearly universally held by certified fraud examiners (Association of Certified Fraud Examiners (ACFE) (2009)), but stands in contrast to the theoretical predictions of Povel, Singh, and Winton (2007) who argue that monitoring will intensify during down times because of the increased likelihood that a given firm is bad.

Lastly, to the extent that our results are driven by attention allocation, this study suggests business cycle variation in an entire class of investors' ability to identify firm-specific and market-wide mispricing. This finding adds an additional dimension to the analysis by Kacperczyk, Van Nieuwerburgh, and Veldkamp (2014) who show that certain mutual 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. Our study compliments theirs because we analyze an entire class of investors – short sellers – rather than individual fund managers.

[3]For additional research indicating that investor attention affects how information is incorporated into prices see: DellaVigna and Pollet (2009), Hirshleifer, Lim, and Teoh (2009), and Ben-Rephael, Da, and Israelsen (2017).

[4]Cressey (1950) (1953) argues 3 interrelated factors (i.e., the fraud triangle) contribute to the likelihood of fraud: financial pressure, opportunity, and rationalization.

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II. Data

We analyze short interest data for NYSE, AMEX, and Nasdaq listed stocks as compiled and reported by the exchanges from 1974 to 2017.[5] Exchanges reported outstanding short interest once per month (as of the 15th) through Aug. 2007 and twice per month (as of the 15th and 30th) from Sept. 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 1974 to 2017 and for Nasdaq listed firms from 2004 to 2017. We supplement the Compustat data with monthly short interest for Nasdaq-listed securities downloaded directly from the Nasdaq website for the years 1988–2003.[6] 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 (SIR).

We obtain stock-specific information on shares outstanding, returns, delisting returns, price, and trading volume from CRSP. We include stocks that delist and adjust returns for delisting using the CRSP delisting returns in such cases. We consider only ordinary common stocks that have traded for at least 1 year, and we require nonmissing data for return, trading volume, shares outstanding, and share price. We measure recessions according to official business cycle dates published by the National Bureau of Economic Research (NBER). Since the NBER establishes these dates ex post and some of the theories behind our analysis imply real-time allocation decisions of short sellers, we also employ two real-time business cycle measures discussed in the robustness analysis below.

In Table 1, we present descriptive statistics. We split our sample into two periods with the first period beginning in Jan. 1974 and ending in May 1988 (Panel A) and the second period beginning in June 1988 and running through Dec. 2017 (Panel B). This partition ensures the periods have approximately the same number of recession months (37 in the first period and 34 in the second period). 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.

We present various percentiles and other distributional characteristics for short interest. In our analysis below, we identify "high short interest stocks" in a particular month using the 90th, 95th, or 99th percentile of SIR, with our main analysis using the 95th percentile. These breakpoints are the same as those in Boehmer et al. (2010). In the average month from the first period, those percentiles represent 1.0%, 1.8%, and 5.7% of shares outstanding, respectively. The breakpoints in the second subperiod, increase substantially to 8.0%, 12.2%, and 23.6% of shares outstanding, respectively, consistent with the general trend observed in the literature that typical firm-level short interest has increased over time (see, e.g., Rapach et al. (2016)). We also note the median short interest increased across the two sample periods from

[5]The reports begin in 1973, but we limit our cross-sectional analysis to the years 1974 and forward because the first year of data only cover a very small number of firms.

[6]The Nasdaq short interest data set is not perfectly complete as noted also by Chen and Singal (2003) and Boehmer et al. (2010) data is missing for February and July of 1990, these months are removed from the sample in all analysis.

TABLE 1

Summary Statistics

Table 1 presents summary statistics for data employed in this study. We divide our descriptive statistics into two periods, the first beginning in Jan. 1974 and ending in May 1988, presented in Panel A, and the second beginning in June 1988 and continuing through Dec. 2017 presented in Panel B. The Short Interest Ratio (SIR) is exchange reported short interest as of the 15th of the month scaled by shares outstanding from CRSP. We also present descriptive statistics for stock price (PRICE) and market capitalization (MKT_CAP) in thousands. We present the time-series average for the 1st, 5th, 10th, 25th, median, 75th, 90th, 95th, and 99th percentiles for each variable along with its time series mean. Panel C presents various other statistics.

	p1	p5	p10	p25	p50	Mean	p75	p90	p95	p99
Panel A. Earlier Period: Jan. 1974–May 1988										
SIR	0.001%	0.005%	0.010%	0.037%	0.125%	0.453%	0.380%	1.021%	1.837%	5.676%
PRICE	$1.13	$3.00	$4.75	$10.00	$19.50	$23.87	$32.00	$46.75	$58.88	$90.13
MKT_CAP	2,461	6,481	11,671	35,653	155,670	777,375	641,109	1,732,465	3,146,161	9,340,873
Panel B. Later Period June 1988–Dec. 2017										
SIR	0.001%	0.007%	0.020%	0.111%	0.912%	2.854%	3.387%	8.022%	12.159%	23.621%
PRICE	$0.30	$1.00	$1.81	$5.00	$13.63	$30.41	$27.45	$45.96	$61.60	$113.38
MKT_CAP	2,463	7,618	14,430	44,787	189,850	2,576,283	931,489	3,769,007	9,124,364	44,207,406

Panel C. Other Statistics

	1973–May 1988	June 1988–Dec. 2017
Average number of stocks with zero short interest per month	1	199
Average number of stocks with short interest data per month	1,084	4,343
Number of NBER recession months	34	38

0.1% to 0.9% of shares outstanding. For some of our analyses, we also identify "low short interest stocks", again following BHJ. For symmetry, we use the 10th, 5th, or 1st percentile of SIR each month. In both periods, these values are always below 0.1% of shares outstanding.

We present similar statistics for stock price and market cap (in thousands of dollars) for the two periods. Finally, we include the average number of stocks with zero and nonzero reported short interest each month and the number of NBER recession months. We observe that the median stock price is lower in the latter period, coincident with the inclusion of Nasdaq securities. Also, we find that the addition of Nasdaq securities increases the average number of observations each month from just over a 1,000 to 4,000.

III. Stock Picking and the Business Cycle

A. Calendar Time Return Analysis

For our cross-sectional analysis, we evaluate the profitability of strategies that purchase low short interest stocks and sell high short interest stocks. We identify short interest breakpoints each calendar month t and hold equal-weighted portfolios for either 1 or 3 subsequent months. For 3-month holding periods, we overlap returns in calendar time as in Jegadeesh and Titman (1993). Thus, when evaluating event months $\tau+1$ through $\tau+3$, the calendar month t portfolio return is the equal-weighted average return of the strategies formed based on short interest observed in calendar months $t-1$, $t-2$, and $t-3$.

We evaluate the profitability of these strategies using several factor models. The results are quite robust across models (shown in Table 5). In general, we estimate alpha each month $t+1$ for portfolio p as

$$\alpha_{p,t+1} = r_{p,t+1} - \sum_{k=1}^{K} \beta_{p,t}^{k} F_{k,t+1}. \tag{1}$$

The variable r_{t+1}^{p} corresponds to the excess return in calendar month $t+1$ for portfolio p where p indexes the percentile $p\ \epsilon(99,95,90,10,5,1)$. The parameter $\beta_{p,t}^{k}$ is the loading of portfolio p on factor F_k estimated based on data leading up to and including month t. Since we use equal-weighted portfolios, this loading is the average of each individual stock's month t factor loading estimated using 60 month rolling regressions over the period $t-59$ to t.[7] The subscript on these parameters emphasizes that factor loadings vary from 1 month to the next as stocks enter and leave the extreme short interest portfolios of interest over time. Such time variation is critical in our estimation as we expect short sellers to tilt their factor exposures one way or another as they gather aggregate signals. We note that our calendar time

[7]Specifically, for a given K-factor model, we estimate for every stock i in each calendar month t, $r_{i,t-j} = a_{it} + \sum_{k=1}^{K} b_{i,t}^{k} F_{k,t-j} + e_{i,t-j}$ using $j=(0, \ldots, 59)$. This generates for each stock a unique estimate of each factor loading every month based on 60 months of data.

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TABLE 2

Calendar Time Analysis of Short Interest Portfolios

Panel A of Table 2 presents average time-varying 4-factor monthly alphas for equal-weighted portfolios that purchase lightly shorted stocks and short highly shorted stocks based on their short interest ratio (SIR). Panels B and C present the alphas for the short and long ends of the portfolio separately. The table also presents average factor loadings for MKTRF, SMB, HML, and MOM for the spread portfolios in Panel D. The sample period is Jan. 1974 to Dec. 2017. Lightly shorted stocks are those with SIR below the 10th, 5th, or 1st percentiles; heavily shorted stocks are those with SIR above the 90th, 95th, or 99th percentiles. All factor loadings are estimated stock-by-stock using rolling prior 60-month windows. Three-month alphas are computed using a 3-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Newey–West p-values with one and three lags for the 1- and 3-month regressions are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3
Panel A. Alphas for Long-Short Portfolios			
	SIR10%–SIR90%	SIR5%–SIR95%	SIR1%–SIR99%
1-Month alpha	1.328***	1.508***	2.274***
	(0.000)	(0.000)	(0.000)
3-Month alpha	1.264***	1.481***	2.017***
	(0.000)	(0.000)	(0.000)
Panel B. Alphas for Heavily Shorted Stocks			
	SIR90%	SIR95%	SIR99%
1-Month alpha	−0.175*	−0.323***	−0.966***
	(0.054)	(0.004)	(0.000)
3-Month alpha	−0.147	−0.331***	−0.871***
	(0.123)	(0.004)	(0.000)
Panel C. Alphas for Lightly Shorted Stocks			
	SIR10%	SIR5%	SIR1%
1-Month alpha	1.153***	1.184***	1.308***
	(0.000)	(0.000)	(0.000)
3-Month alpha	1.118***	1.150***	1.146***
	(0.000)	(0.000)	(0.000)
Panel D. Factor Loadings			
	SIR10%–SIR90%	SIR5%–SIR95%	SIR1%–SIR99%
MKTRF	−0.475***	−0.526***	−0.599***
	(0.000)	(0.000)	(0.000)
SMB	−0.318***	−0.392***	−0.410***
	(0.000)	(0.000)	(0.000)
HML	0.301***	0.308***	0.292***
	(0.000)	(0.000)	(0.000)
MOM	0.005	0.001	−0.035**
	(0.571)	(0.930)	(0.032)

results are quantitatively similar (not reported) using specifications with constant portfolio loadings through the full sample.

Table 2 presents average alphas from various spread portfolios that purchase low short interest stocks and sell high short interest stocks in Panel A; Panels B and C present estimates separately for high short interest and low short interest stocks. In each panel, the first row of alphas corresponds to 1-month calendar time portfolio returns using three different sets of extreme short interest breakpoints; the second row of alphas contains similar results based on 3-month calendar time portfolio returns. This analysis measures abnormal returns using the Carhart (1997) model, whose $K = 4$ factors are the three Fama and French (1993) factors (the overall stock market return in excess of the risk-free rate (RMRF), the return of a portfolio that purchases small stocks and sells big stocks (SMB), and the return of a portfolio that purchases high book-to-market stocks and sells low book-to-market stocks (HML)) along with a momentum factor that purchases recent winners and sells recent losers (UMD).[8] We report each portfolio's average factor loadings in Panel D, such that the factor-k loading is the average value of a portfolio's $\beta_{p,t}^{k}$ over the entire time series.

The initial results cohere with prior findings such as BHJ, who study the time period 1988 to 2005. First, across all models, lightly shorted firms tend to outperform heavily shorted firms (Panel A) where high short interest firms generate negative alphas (Panel B) and low short interest firms generate positive alphas (Panel C). Second, portfolios formed using more extreme short interest cutoffs experience more extreme alphas. Specifically, we find that alphas for 1 (3) month calendar time portfolios are 1.33 (1.26)%, 1.51 (1.48)%, and 2.27 (2.02)% monthly for portfolios that are long and short stocks in the most extreme 10%, 5%, and 1% of low and high short interest, respectively. These findings also demonstrate that the monthly alphas decay in event time as in every case the alphas for the portfolios with 3 month holding periods produce smaller risk-adjusted alphas than their corresponding 1-month portfolios. Finally, the significantly negative average market betas for the spread portfolios are consistent with the known finding that investors tend to short high-beta stocks (see, e.g., BHJ). We analyze how these betas vary over time in Section IV.

The negative relation between firm-level short interest and future stock returns presented in Table 2 is an unconditional, or "on average" result. However, our main hypotheses motivate a conditional analysis. Does the strength of the relation between firm-level short interest and future returns vary over the business cycle as would be expected if investors shift their focus from firm-specific to aggregate signals? Intuitively, if short sellers are primarily gathering firm-specific signals during expansions, firm-level short interest should be a more reliable predictor of future returns in expansions than in recessions. Hence, we expect the alphas from Table 2 to be larger in magnitude when the economy is expanding than when it is contracting. We test this prediction by estimating the alphas separately for expansions and recessions. Specifically, we regress the time series of $\alpha_{p,t+1}$ on a constant and the indicator variable REC_t that equals 1 when the short interest breakpoints are identified during months corresponding to an NBER recession and 0 otherwise[9]:

$$\alpha_{p,t+1} = \alpha_e + \alpha_r \text{REC}_t + \varepsilon_{p,t+1}. \tag{2}$$

We present estimates of equation (2) for spread portfolios in Panel A of Table 3. Across all six specifications, estimates of the expansion alpha are positive and significant at the 1% level. In column 1 (4), the monthly alpha generated by the 1- (3-) month calendar time portfolio that purchases stocks below the 10th short interest percentile and sells stocks above 90th percentile is 1.50% (1.40%). Similarly, in column 2 (5), the monthly alpha generated by the 1- (3-) month calendar time portfolio based on the 5th and 95th percentile cutoffs is 1.69% (1.65%). Lastly, in column 3 (6), we observe the monthly alpha generated by the 1- (3-) month calendar

[8]We obtain factors from Ken French's website.

[9]For the 3-month calendar time portfolios, the REC_t variable is the average of the recession dummy corresponding to each of the 3 months currently held in the time t portfolio. Thus, it may take the value of 0, 1/3, 2/3, or 1 depending on whether the portfolio formation months straddle a transition between a recession and expansion period.

TABLE 3

Calendar Time Analysis of Short Interest Portfolios in Expansions and Recessions

Table 3 presents average time varying 4-factor monthly alphas for expansions and recessions separately for equal weighted portfolios that purchase lightly shorted stocks and short highly shorted stacks based on their short interest ratio (SIR). All factor loadings are estimated stock-by-stock using rolling prior 60-month windows. EXPANSION_ALPHA indicates the average alpha during NBER expansion months. RECESSION_ALPHA indicates average alpha of the spread portfolios during NBER recession months. DIFFERENCE indicates the difference between EXPANSION_ALPHA_and RECESSION_ALPHA. The sample period is Jan. 1974 through Dec. 2017. Lightly shorted stocks are those with SIR below the 10th, 5th, or 1st percentiles; heavily shorted stocks are those with SIR above the 90th, 95th, or 99th percentiles. The first 3 columns consider a 1-month calendar-time analysis. The final 3 columns consider a 3-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Panel A presents the results for spread portfolios. Panel B presents the results for the portfolio of heavily shorted stocks. Panel C presents the results for the portfolio of lightly shorted stocks, Newey–West *p*-values with one and three lags for the 1- and 3-month regressions are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Return Horizon					
	1-Month			3-Month		
	1	2	3	4	5	6
Panel A. Spread Portfolio						
	SIR10%–SIR90%	SIR5%–SIR95%	SIR1%–SIR99%	SIR10%–SIR90%	SIR5%–SIR95%	SIR1%–SIR99%
EXPANSION_ ALPHA (α_e)	1.500***	1.685***	2.504***	1.402***	1.654***	2.242***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_ ALPHA ($\alpha_e+\alpha_r$)	0.233	0.371	0.801	0.373	0.364	0.562
	(0.631)	(0.475)	(0.278)	(0.457)	(0.514)	(0.413)
DIFFERENCE (α_r)	−1.267**	−1.314**	−1.703**	−1.029**	−1.290**	−1.680**
	(0.012)	(0.015)	(0.029)	(0.049)	(0.026)	(0.021)
Panel B. Heavily Shorted Stocks						
	SIR 90%	SIR 95%	SIR 99%	SIR 90%	SIR 95%	SIR 99%
EXPANSION_ ALPHA (α_e)	−0.255***	−0.411***	−1.131***	−0.218**	−0.427***	−1.021***
	(0.007)	(0.001)	(0.000)	(0.034)	(0.001)	(0.000)
RECESSION_ ALPHA ($\alpha_e+\alpha_r$)	0.338	0.242	0.092	0.311	0.290	0.100
	(0.218)	(0.482)	(0.873)	(0.21)	(0.367)	(0.864)
DIFFERENCE (α_r)	0.593**	0.653*	1.223**	0.529*	0.717**	1.121*
	(0.041)	(0.075)	(0.043)	(0.053)	(0.041)	(0.072)
Panel C. Lightly Shorted Stocks						
	SIR 90%	SIR 95%	SIR 99%	SIR 90%	SIR 95%	SIR 99%
EXPANSION_ ALPHA (α_e)	1.244***	1.274***	1.373***	1.185***	1.227***	1.221***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_ ALPHA ($\alpha_e+\alpha_r$)	0.570	0.613	0.892	0.685	0.653	0.662
	(0.219)	(0.214)	(0.172)	(0.174)	(0.241)	(0.268)
DIFFERENCE (α_r)	−0.674	−0.661	−0.481	−0.500	−0.574	−0.559
	(0.162)	(0.196)	(0.478)	(0.338)	(0.319)	(0.366)

time portfolio based on the most extreme short interest cutoffs is 2.50% (2.24%). These results suggest that during an expansion, short sellers' positions in individual securities contain meaningful information about future firm-specific returns. Moreover, these findings are consistent with the unconditional results from Table 2 and prior literature. The general agreement between expansion alphas and the unconditional alphas known to the literature is not surprising given the U.S. economy has experienced far more months of expansions than recessions over the sample period.

The point estimate on the REC variable represents the difference between the expansion alpha (α_e) and the recession alpha $(\alpha_e+\alpha_r)$. In each of the six specifications for the long-short portfolios, the statistically significant estimates for α_r indicate that alpha is indeed significantly smaller in magnitude when short interest breakpoints are identified during recession months. The deterioration in the link

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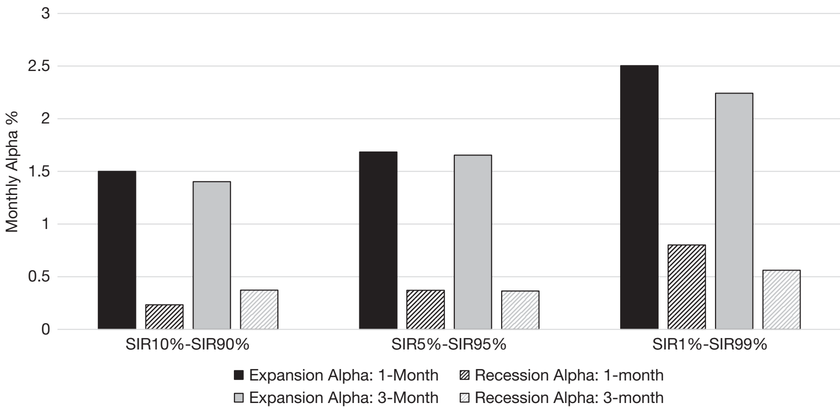
FIGURE 1

Time Varying 4-Factor Alpha During Expansions and Recessions

Figure 1 presents the monthly alphas from a time-varying Carhart (1997) model. The leftmost set of bars presents the monthly alphas during expansions and recessions derived from regressions where the dependent variable is either the 1-month or 3-month return on a calendar time portfolio that buys stocks with short interest below the 10th percentile and shorts 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% and 1% and 99%, respectively. The black bars indicate 1-month while the gray bars indicate 3-month calendar time portfolios. Solid bars indicate expansion alpha while the striped bars indicate the recession alphas.



between short interest and future returns is economically meaningful as point estimates fall by at least one-half during recessions. For the 1-month calendar time portfolios, monthly alpha falls from 1.50%, 1.69%, and 2.50% in expansions to 0.23%, 0.37%, and 0.80% in recessions. The changes in point estimates for the 3-month calendar time portfolios are similar. In all six cases, F-tests for the joint significance of $\alpha_e + \alpha_r$ fail to reject the null hypothesis of zero alpha during recessions at the 10% level or greater. The pattern for 3-month calendar time returns is similar. Figure 1 illustrates the magnitudes of these results. The black bars represent spread portfolio alphas for 1-month calendar time portfolios, and the gray bars represent those for the 3-month calendar time portfolios. The solid bars indicate the expansion alpha as indicated by the coefficient α_e from equation (2), and the striped bars indicate the recession alpha computed as the sum of the coefficients $\alpha_e + \alpha_r$ from equation (2).

We present the results for each leg of the portfolios separately in Panels B and C. While BHJ find a stronger unconditional result for lightly shorted stocks, we expect stronger time variation in the alphas of stocks with high short interest. High short interest in the cross-section of stocks is a rather unambiguous signal that informed traders anticipate low future firm-specific returns. Whether this results from greater attention to firm-specific information or greater opportunities to exploit less sophisticated traders, the various theories motivating our tests suggest these signals are stronger in expansions. In contrast, low or zero shorting activity is more difficult to interpret. Low shorting may reflect inattention to a particular stock, high shorting constraints, or the actions of investors who have observed positive signals. As such, the theory does not suggest a clear prediction of how the alphas of the portfolios of lightly shorted stocks will change across the business cycle.

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Panel B of Table 3 reveals that the portfolios of highly shorted stocks indeed produce a significantly negative 4-factor alpha during expansions. This alpha diminishes significantly during recessions. For example, in column 3, the expansion alpha for the 1-month calendar time returns for the portfolio of stocks with SIR above 99% is a statistically significant -1.13%. 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 $-1.13+1.22=0.09\%$. An F-test fails to reject the null hypothesis that $\alpha_e+\alpha_r=0$ ($p=0.87$). Similar F-tests for each of the other five specifications in Panel B also fail to reject the null hypothesis of zero recession alpha at the 10% level or better, and in each case, the difference is statistically significant. These findings bolster our interpretation that short sellers are less able to predict firm-specific returns during recessions. Panel C contains results for lightly shorted stocks. Consistent with the unconditional results of BHJ, we find that lightly shorted stocks produce significant 4-factor alphas across all six specifications during expansions. The intercept in each of our specifications is significantly positive. During recessions, the alphas of lightly shorted stocks drop and are statistically indistinguishable from zero – although we fail to reject the hypothesis of equality between the expansion and recession alpha.

For robustness, we employ two alternative definitions of recession that can be estimated in real-time. These measures have the advantage over NBER recessions in that they are not determined ex post and thus more accurately reflect information about the business cycle that short sellers would have when making investment decisions. The first measure is the probability of recession (PR_REC) studied by Chauvet and Piger (2008). This measure employs a dynamic-factor-Markov-switching model applied to 4 monthly macroeconomic variables to produce a variable ranging from 0 to 1 indicating the likelihood of a recession. This metric is a continuous variable derived directly from time series of macro variables that are available in a more timely 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 have mean 0 and standard deviation of 1 such that a high value indicates economic output is "high." To emphasize 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 1 if the value of the CFNAI is 1-standard-deviation below the mean and 0 otherwise. Figure 2 displays the time series of PR_REC and the 3-month moving average of CFNAI along with shaded bars denoting NBER recessions. The pairwise correlations between the NBER recession indicator and each of these alternatives are 0.87 and 0.79, respectively.

We repeat the calendar-time portfolio analysis from Panel A of Table 3 using the two alternative recession variables. Table 4 presents point estimates for the spread portfolios. Panel A uses PR_REC, and Panel B uses CFNAI_REC. In both panels, we observe patterns similar to those in Table 3. The spread portfolio alphas

FIGURE 2

Alternative Recession Measures

Figure 2 presents the time series of two alternative recession indicators. The dotted line indicates the probability of recession as described by Chauvet and Piger (2008). The solid line is the 3-month moving average of the Chicago Fed National Activity Index (CFNAI). The gray bars indicate NBER recession dates.

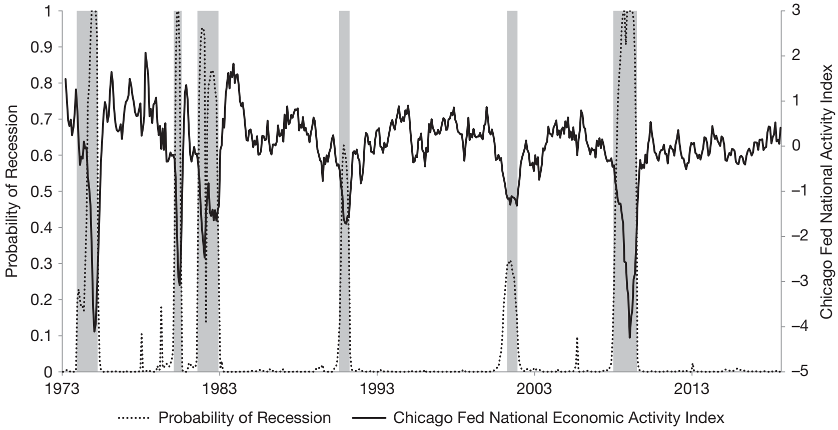

TABLE 4

Alternative Recession Measures

Table 4 presents average time-varying 4-factor monthly alphas for expansions and two alternative recession indicators for equal-weighted portfolios that purchase lightly shorted stocks and short highly shorted stacks based on their short interest ratio (SIR). All factor loadings are estimated stock-by-stock using rolling prior 60-month windows. In Panel A, expansions are identified using Chauvet and Piger's (2008) probability of recession. In Panel B, expansions are identified using an indicator that takes the value of 1 if the Chicago Fed National Economic Activity Index is below −1 and 0 otherwise. EXPANSION_ALPHA indicates the average alpha during identified expansion months. RECESSION_ALPHA indicates average alpha of the spread portfolios during identified recession months. DIFFERENCE indicates the difference between EXPANSION_ALPHA and RECESSION_ALPHA. The sample period is Jan. 1974 through Dec. 2017. Lightly shorted stocks are those with SIR below the 10th, 5th, or 1st percentiles; heavily shorted stocks are those with SIR above the 90th, 95th, or 99th percentiles. The first 3 columns consider a 1-month calendar-time analysis. The final 3 columns consider a 3-month calendar-time analysis with overlapping portfolios as in Jegadeesh and Titman (1993). Newey–West p-values with one and three lags for the 1- and 3-month regressions are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Return Horizon					
	1-Month			3-Month		
	SIR 90%	SIR 95%	SIR 99%	SIR 90%	SIR 95%	SIR 99%
	1	2	3	4	5	6
Panel A. Probability of Recession						
EXPANSION_ALPHA (α_e)	1.520***	1.700***	2.504***	1.423***	1.662***	2.230***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_ALPHA ($\alpha_e+\alpha_r$)	−0.531	−0.362	0.034	−0.278	−0.282	−0.052
	(0.477)	(0.644)	(0.976)	(0.711)	(0.740)	(0.958)
DIFFERENCE (α_r)	−2.051***	−2.062**	−2.470**	−1.701**	−1.944**	−2.282**
	(0.008)	(0.012)	(0.033)	(0.030)	(0.028)	(0.027)
Panel B. Chicago Fed National Economic Activity Index						
EXPANSION_ALPHA (α_e)	1.501***	1.688***	2.503***	1.377***	1.621***	2.186***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_ALPHA ($\alpha_e+\alpha_r$)	0.083	0.207	0.625	0.460	0.476	0.801
	(0.870)	(0.691)	(0.428)	(0.443)	(0.463)	(0.262)
DIFFERENCE (α_r)	−1.418***	−1.481***	−1.878**	−0.917	−1.145*	−1.385*
	(0.007)	(0.007)	(0.025)	(0.142)	(0.093)	(0.067)

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. Across all short interest portfolios, the decline in alpha averages around 60% when the probability of recession is 0.5. When the probability of recession is 1.0 the alpha further declines and generally becomes negative, but not statistically different from 0. Panel B documents a consistent pattern based on CFNAI_REC. For each of the 1-month calendar-time portfolios, alpha declines about 75% or more when the CFNAI_REC indicator equals 1 and is statistically indistinguishable from 0. It is unsurprising that the CFNAI results are slightly weaker than those in Table 3 and Panel A of Table 4; since it indicates economic output of 1-standard-deviation below normal, the CFNAI dummy is a less extreme definition of recessions than our other two measures.

In Table 5, we examine the robustness of our main finding to alternative abnormal return calculations. Specifically, we use: DGTW characteristic adjustments (Daniel, Grinblatt, Titman, and Wermers (1997)), CAPM, Fama and French

TABLE 5

Alternative Factor Loading Models

Table 5 presents average monthly alphas for expansions and recessions separately for an equal weighted portfolio that purchase stocks with SIR less than the 5th percentile and shorts stocks with SIR greater than the 95th percentile. All factor loadings are estimated stock-by-stock using rolling prior 60-month windows. The portfolio is a 3-month calendar time portfolio. EXPANSION_ALPHA indicates the average alpha during NBER expansion months. RECESSION_ALPHA indicates average alpha of the spread portfolios during NBER recession months. DIFFERENCE indicated the difference between EXPANSION_ALPHA and RECESSION_ALPHA. The sample period is Jan. 1974 through Dec. 2017. Alphas are computed using various methodologies: DGTW, CAPM, Fama–French 3-factor, Carhart 4-factor with Pastor and Stambaugh liquidity, and Fama–French 5-factor in columns 1 through 5 of Panel A respectively along with average factor loadings for the portfolio presented in Panel B. Newey–West *p*-values with three lags are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Dep Var: 3-Month Alpha for SIR5%–SIR95%				
	DGTW	CAPM	FF 3 Factor	4-Factor + PS Liquidity	FF 5 Factor
	1	2	3	4	5
Panel A. Alphas					
EXPANSION_ALPHA (α_e)	1.215***	1.896***	1.690***	1.651***	1.670***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_ALPHA ($\alpha_e + \alpha_r$)	−0.465	−0.225	−0.033	0.193	0.058
	(0.384)	(0.695)	(0.952)	(0.730)	(0.919)
DIFFERENCE (α_r)	−1.680***	−2.121***	−1.723***	−1.458**	−1.612***
	(0.003)	(0.000)	(0.003)	(0.013)	(0.007)
Panel B. Factor Loadings					
RMRF		−0.705***	−0.534***	−0.527***	−0.531***
		(0.000)	(0.000)	(0.000)	(0.000)
SMB			−0.386***	−0.376***	−0.372***
			(0.000)	(0.000)	(0.000)
HML			0.291***	0.316***	0.277***
			(0.000)	(0.000)	(0.000)
UMD				0.007	
				(0.459)	
PS_LIQUIDITY				0.042***	
				(0.000)	
RMW					−0.010
					(0.639)
CMA					0.166***
					(0.000)

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(1993) 3-factor, Carhart 4-factor augmented with the Pastor and Stambaugh (2003) liquidity factor, and Fama and French (2015) 5-factor. In each methodology, except for DGTW, we estimate factor loadings month by month as previously explained. Panel A presents abnormal returns, and Panel B presents the time-series average factor loadings. For brevity, we only include the 3-month calendar results for the *SIR*5%–SIR95% portfolio for each specification. In each specification, we observe a positive and statistically significant alpha during expansions, and smaller and statistically insignificant alpha during recessions, and the difference is statistically significant.

B. Earnings Announcements

Our maintained hypothesis is that short sellers gather more firm-specific signals in expansions than in recessions. While the calendar-time return evidence is consistent with this notion, portfolio alphas of highly shorted stocks imperfectly reflect the signals that short sellers collect. Consequently, we cannot be certain that the observed return performance manifests successful exploitation of information signals or something else like technical skills, liquidity provision, or model misspecification. An ideal test would more precisely emphasize the realization of signals that short sellers observe.

In this section, we isolate the realization of firm-specific signals acquired by short sellers by analyzing future earnings announcement returns of highly shorted stocks. Such a stock price reaction exposes the value-relevance of the signal revealed in the underlying earnings release. As such, it serves as a reasonable proxy for the realization of a formerly unobservable signal. Moreover, because firms report earnings on a quarterly basis, we can observe this proxy for the full cross-section of firms over regular intervals. Since daily returns are mostly idiosyncratic in nature, model misspecification is of minor concern. Finally, we prefer earnings announcement returns over analyst forecast errors or standardized unexpected earnings because the latter two rely on some subjective measure of expectations.

Prior literature establishes the use of earnings announcement returns to discern the sourceof investors' superior return performance. Most notably, Baker, Litov, Wachter, and Wurgler (2010) find that, for the average mutual fund, stocks with portfolio weight increases have higher future earnings announcement returns than those with portfolio weight decreases. These authors argue their results add clarity to the findings of others such as Chen, Jegadeesh, and Wermers (2000), who find that stocks heavily bought by mutual funds experience better future return performance than those that are heavily sold. Our analysis in this section parallels this approach.

We collect quarterly earnings announcement dates for all firms in Compustat and IBES, and we retain the trading day corresponding to the earlier of the two dates if they differ as "day 0". Following Baker et al. (2010), we then compute a 3-day return over trading days -1 through $+1$ and subtract the 3-day CRSP value-weighted return.[10] We refer to the resulting return, $\text{EARN\_RET}_{\text{it}}$, as the market-

[10]We find similar results using either 3-day returns or CAPM-adjusted CARs as the EARN_RET variable.

adjusted earnings announcement return or simply the earnings return for firm i observed in month t. We estimate a simple panel regression as in equation (3):

$$(3)\quad \text{EARN\_RET}_{i,t+1} = c_0 + c_1\text{HIGH\_SHORT}_{(x)_{i,t}} + c_2\text{HIGH\_SHORT}_{(x)_{i,t}} \times \text{REC} + c_3\text{REC}_t + e_{i,t+1}.$$

The dummy variable HIGH_SHORT(x) equals 1 if the firm had Short Interest above the x = 90th, 95th, or 99th percentile in the most recent mid-month short interest prior to the earning announcement date and 0 otherwise. As before, the dummy variable REC_t takes on the value of 1 if the short interest reporting month t is an NBER recession month and 0 otherwise. We cluster standard errors by stock and month.

Prior literature suggests a negative coefficient estimate for c_1. Christophe et al. (2005) report a negative relation between shorting activity and subsequent earnings announcements for Nasdaq firms in the Fall of 2000 (an expansionary period), and Boehmer, Jones, Wu, and Zhang (2020) report a similar negative relation for NYSE firms from 2000 to 2005 (which contains a 9-month recession). Our base specifications, which exclude the REC dummy, appear in the odd-numbered columns of Table 6. The results are consistent with prior literature as the b_1 coefficients corresponding to the various levels of high short interest are all negative and statistically

TABLE 6

Short Interest and Earnings Announcement Returns

Table 6 presents results from regressions presented in equation (3) estimating the relation between [−1,1] earnings announcement cumulative abnormal returns and high short interest across the business cycle. The variable HIGH_SHORT is an indicator variable equal to 1 if the stock's SIR was above a given percentile threshold as of the most recent mid-month reporting date prior to the earning announcement. Recession is an indicator variable that equals 1 if the month corresponding to the most recent short interest reporting period was an NBER recession month and 0 otherwise. Odd columns present the unconditional analysis and even columns present the analysis conditional on the state of the economy. For columns 1 and 2, the SIR threshold to identify highly shorted stocks is the 90th percentile. For columns 3 and 4 (5 and 6), the threshold is the 95th (99th) percentile. The top rows provide the individual coefficients while the bottom rows provide aggregated coefficients along with p-values from an F-test for joint significance. p-values estimated using standard errors that are clustered at the month and firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	SIR% 90		SIR% 95		SIR% 99	
	1	2	3	4	5	6
Coefficients						
HIGH_SHORT (c_1)	−0.614***	−0.655***	−0.777***	−0.828***	−1.171***	−1.292***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HIGH_SHORT × REC (c_2)		0.408*		0.499*		1.229*
		(0.054)		(0.058)		(0.064)
REC (c_3)		0.230		0.247		0.261
		(0.230)		(0.206)		(0.181)
INTERCEPT (c_0)	0.287***	0.263***	0.264***	0.237***	0.236***	0.208***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Combined coefficients for highly shorted stocks						
Expansion CAR ($c_0 + c_1$)		−0.392***		−0.591***		−1.084***
		(0.000)		(0.000)		(0.000)
Recession CAR ($c_0 + c_1 + c_2 + c_3$)		0.246		0.155		0.406
		(0.398)		(0.613)		(0.559)
Difference ($c_2 + c_3$)		0.638**		0.746**		1.49**
		(0.035)		(0.022)		(0.034)
N	532,320	532,320	532,320	532,320	532,320	532,320
Time/Firm clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

TABLE 7

Short Interest and Earnings Announcement Returns: Alternative Recession Variables

Table 7 presents results from regressions presented in equation (3) estimating the relation between [−1,1] earnings announcement cumulative abnormal returns and high short interest across the business cycle. The variable HIGH_SHORT in equation (3) is an indicator variable equal to 1 if the stock's SIR was above a given percentile threshold as of the most recent mid-month reporting date prior to the earning announcement. In columns 1–3, recessions are defined using the Chauvet and Piger (2008) probability of recession. In columns 4–6, recessions are identified using an index that takes the value of 1 if the Chicago Fed National Economic Activity Index is less than −1 and 0 otherwise. The 90th, 95th, and 99th percentiles are used to define highly shorted stocks. The table only presents the sum of coefficients indicating the expansion CAR, recession CAR, and the difference between the expansion and recession CARs, *p*-values estimated using standard errors that are clustered at the month and firm level are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	Probability of Recession			CFNAI		
	SIR% 90	SIR% 95	SIR% 99	SIR% 90	SIR% 95	SIR% 99
	1	2	3	4	5	6
EXPANSION_CAR (c_0+c_1)	−0.378***	−0.584***	−1.043***	−0.401***	−0.587***	−1.044***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RECESSION_CAR ($c_0+c_1+c_2+c_3$)	0.368	0.456	0.637	0.298*	0.103	0.010
	(0.171)	(0.265)	(0.472)	(0.077)	(0.672)	(0.987)
DIFFERENCE (c_2+c_3)	0.746***	1.040**	1.680*	0.699***	0.690***	1.054*
	(0.007)	(0.014)	(0.063)	(0.000)	(0.007)	(0.083)
N	532,320	532,320	532,320	532,320	532,320	532,320
Time/firm clustered SE	Yes	Yes	Yes	Yes	Yes	Yes

significant, and the point estimates increase in magnitude as the short interest threshold increases from about −0.61% for the 90th percentile threshold to −1.17% for the 99th percentile.

Our full specifications, appearing in the even-numbered columns of Table 6, reveal striking differences in earnings announcement returns for highly shorted stocks during expansions and recessions. The coefficient estimate for c_3, which reflects the marginal effect of recessions on the extreme short interest indicator, is uniformly positive and statistically significant indicating that the negative earnings announcement returns for high short interest stocks are muted during recessions. The magnitudes are illuminating as well; the c_2 coefficients are comparable to those for c_1. We present at the bottom of Table 6 the announcement returns for high short interest stocks separately in expansions (c_0+c_1) and recessions ($c_0+c_1+c_2+c_3$) along with tests for statistical differences. Across each high short interest definition, we observe that high short interest is associated with negative earnings returns in expansions only. That is, during recessions, the average earnings announcement return for high short interest stocks is statistically 0, and the expansion and recession earnings returns for highly shorted stocks are statistically different. For highly shorted stocks the expansion earnings returns are −0.39%, −0.59%, and −1.08% for the 90, 95, and 99% thresholds, respectively, and are each highly statistically significant. For recessions, the earnings return drops to a statistically insignificant 0.25%, 0.16%, and 0.41% for the respective thresholds. The differences in expansion and recession earnings returns for highly shorted stocks are statistically significant at the 5% level.

As with the prior analysis, and for the same reasons, we test the robustness of these findings to the alternative recession variables PR_REC and CFNAI_REC and present the results in Table 7. For brevity, we only show the combined coefficients indicating the expansion earnings return, recession earnings return, and the difference between the two as in the bottom portion of Table 6. For both the PR_REC and

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CFNAI_REC variables the pattern is the same as before. The earnings return for highly shorted stocks is negative and statistically significant during expansions, with the magnitude of the earnings return increasing with the short interest threshold. During the recession periods, the earnings returns are indistinguishable from 0 in five of the six specifications while in all six specifications the decline in the absolute magnitude of the earnings return is statistically significant.

IV. Market Timing and the Business Cycle

The evidence presented in the previous section suggests short sellers benefit from collecting firm-specific information during economic expansions. However, the inability of firm-level short interest to predict future returns and earnings surprises in recessions does not immediately imply that short sellers switch their efforts to collect aggregate signals at these times. Perhaps gathering and trading on firm-specific signals is simply more difficult during recessions than expansions. In that case, short sellers might either pull back their participation altogether, waiting for conditions to improve, or they might continue collecting and trading on firm-specific information albeit with less success. Consistent with this possibility, Schmalz and Zhuk (2018) observe the market responds more strongly to public information releases during recessions, which implies that less of the information had already been impounded into stock prices prior to the release. In contrast, Loh and Stulz (2018) find that analyst recommendations have a larger permanent price impact during recessions, which suggests that collecting firm-specific information during recessions is still possible and potentially very lucrative. This latter result begs the question: if firm-specific information is attainable in recessions, why do short sellers not act accordingly?

The theory that short sellers change behavior to collect aggregate, rather than firm specific, signals during recessions offers an explanation. According to this theory, short sellers collect fewer firm-specific signals during recessions not because these signals are nonexistent or are harder to collect, but rather because it is optimal to collect something else – aggregate signals. In this case, short interest will be less informative about the cross-section of returns during recessions, but it will convey more information about aggregate returns.

In this section, we explore the extent to which short sellers gather aggregate information and whether they do so more during recessions than during expansions. In general, traders collecting aggregate signals will make factor bets by tilting their positions to increase or decrease exposure according to expected future factor realizations (i.e., they will attempt to time factors). Consider, for example, a simple CAPM framework where aggregate signals predict future market portfolio returns. Upon collection of these signals, if short sellers anticipate negative future market returns next period, they will shift into high beta stocks this period; in contrast, if they anticipate positive future market returns, they will shift into lower beta stocks.

Three empirical implications follow from this factor bets hypothesis, expressed again using a CAPM framework. First, short sellers' collection of aggregate signals will create time-series volatility in the beta of a portfolio of highly shorted stocks. This occurs because short sellers will move together either into or out of high beta stocks in response to aggregate signals. And the volatility should weaken in expansions when short sellers are more focused on stock-picking; when a stock's beta plays a smaller role in investment decisions as short sellers pursue a host of cross-sectional strategies. Second, high short interest stocks will have similar betas to one another at the same time as short sellers make similar factor bets. Thus, the cross-sectional dispersion of beta across high short interest stocks will be lowest during recessions when short sellers are trying the hardest to time the market. Once again, this occurs because short sellers responding to aggregate signals will seek out stocks with similar factor loadings. Third, and perhaps most importantly, the portfolio of high short interest stocks will resemble a market-timing strategy, especially during recessions. Thus, the portfolio's beta will be relatively high prior to negative market returns and relatively low prior to positive market returns. While these predictions can generalize to a multifactor world, we emphasize the CAPM beta in our tests below as the market portfolio has near universal long-standing acceptance as a relevant factor for asset pricing and attempts to time this factor are immensely popular in practice.

A. Time Variation in Factor Exposure

The high short interest portfolio's factor exposure will change over time as short sellers shift their positions across stocks.[11] Our portfolio framework from Section III.A embraces this variation because we estimate loadings stock-by-stock each month and then compute the month t portfolio loading as the average loading across its component stocks. Since that section's focus was portfolio alpha while allowing for variation in factor loadings, we presented only the average factor loadings across the whole time series in Tables 2 and 5. We now emphasize the time-varying nature of these loadings. For this analysis, we use the 95th short interest percentile to define high short interest stocks. Results based on the 90th and 99th percentiles are qualitatively similar.

Our first prediction is that factor loadings of the high short interest portfolio will exhibit greater variation during recessions as short sellers move in and out of stocks with similar factor loadings in response to aggregate signals. We conduct a simple test for nonconstant volatility in the factor loadings of the high short interest portfolio following the method of Sensier and van Dijk (2004). In our context, this is a heteroscedasticity- and autocorrelation-consistent Wald test of whether $\delta_r > \delta_e$ in the regression

$$\sqrt{\frac{\pi}{2}}\left|\beta_t^k - \bar{\beta}^k\right| = \delta_r \mathrm{REC}_t + \delta_e(1 - \mathrm{REC}_t) + \varepsilon_t, \tag{4}$$

where π references the mathematical constant, β_t^k is the portfolio's loading on factor k in month t, and $\bar{\beta}^k$ is the average loading on factor k over the entire time series. We report the results in Panel A of Table 8. We present estimates for δ_r and δ_e from equation (4). A finding that $\delta_r > \delta_e$ indicates the portfolio factor loading is more

[11]Individual stock betas may also change over time since beta for any given month is always estimated using data from the prior 60 months. However, since only one-sixtieth of the estimation period changes from 1 month to the next, this source of time variation is likely dwarfed by variation from changes in the high short interest portfolio's composition.

TABLE 8

Time Series Volatility and Dispersion of Factor Loadings of Highly Shorted Stocks

Panel A of Table 8 presents the results from Sensier and van Dijk (2004) volatility tests as in equation (4) on the time series of average factor loadings for stocks with SIR above the 95th percentile. Panel A presents the average computed volatility during expansions and recessions. The difference between the expansion and recession volatility is computed along with the results from an autocorrelation and heteroscedasticity robust Wald test of the hypothesis that recession volatility will be higher. Panel B presents results from a Newey–West times series regression with one lag testing whether the dispersion of factor loadings among stocks in the highest 5% of short interest declines during recessions. In these tests, the intercept presents the average monthly standard deviation of factor loadings during expansions while the recession variable indicates the recession effect on the standard deviation of factor loadings. In both panels, factor loading is estimated firm by firm using 60 month rolling regressions. Four models are used to estimate factor loadings: CAPM, Carhart 4-factor, Carhart 4-factor augmented with the Pastor and Stambaugh liquidity factor, and the Fama–French 5-factor. Only the incremental factors for each model are shown. *p*-values are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	CAPM	4-Factor			4-Factor + PS Liq	5-Factor	
	Beta	SMB	HML	UMD	Liq	RMW	CMA
	1	2	3	4	5	6	7
Panel A. Volatility of the Time Series							
EXPANSION	0.129	0.176	0.219	0.144	0.125	0.244	0.282
RECESSION	0.170	0.221	0.304	0.283	0.105	0.246	0.311
DIFFERENCE	0.041*	0.045*	0.085***	0.139***	−0.02	0.002	0.029
Wald test *p*-value	(0.064)	(0.087)	(0.004)	(0.000)	(0.934)	(0.479)	(0.209)
Panel B. Dispersion							
RECESSION (β)	−0.100***	−0.017	−0.153***	−0.157***	−0.066**	−0.048	−0.345***
	(0.004)	(0.586)	(0.005)	(0.000)	(0.012)	(0.390)	(0.000)
INTERCEPT (α)	0.762***	1.165***	1.362***	0.872***	0.911***	2.051***	2.263***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

volatile in recessions than expansions. The final line in the table contains p-values for this test.

The estimates in the first column pertain to CAPM Beta (k = RMRF). Consistent with our predictions, the estimate for δ_r exceeds that for δ_e, and the difference is statistically significant at the 10% level (p-value = 0.06). Thus, the CAPM Beta for the portfolio of high short interest stocks is more volatile across recession months than it is across expansion months. The next block contains results for the incremental factors of the 4-factor model (SMB, HML, and UMD).[12] Similar to our findings for CAPM Beta, the three estimates for δ_r all exceed the respective estimates for δ_e, and the differences are all highly statistically significant, which indicates loadings on each of these three factors also are more volatile in recessions. The third block contains tests for the loading on the Pastor and Stambaugh (2003) liquidity factor, while the final block contains tests for the two incremental factors from the Fama and French (2015) 5-factor model, RMW and CMA. None of these remaining loadings have different volatilities in recessions and expansions.

B. Cross-Stock Dispersion in Factor Loadings

If short sellers collect aggregate signals, then at any given time, highly shorted stocks should have similar factor exposure to one another as short sellers move in and out of stocks with similar factor loadings based on the aggregate signals they

[12]The betas used in the CAPM analysis are estimated using a 1-factor CAPM model. The factor loadings for the 4-factor model are estimated using the Carhart (1997) 4-factor model. The Pastor and Stambaugh (2003) liquidity factor loadings are estimated using a 4-factor plus liquidity model. The 5-factor loadings are estimated using the Fama and French (2015) 5-factor model.

receive. Thus our second prediction is that this similarity will be more salient in recessions. In other words, factor loadings should be less disperse amongst high short interest stocks in recessions than in expansions. Once again, our portfolio framework from Section III.A facilitates a test since we estimate loadings stock-by-stock each month. For each stock i in the high short interest portfolio during calendar month t, we take its estimated loading on factor k ($b_{i,t}^{k}$). We the compute DISP_t^k as the standard deviation of $b_{i,t}^{k}$ across high short interest stocks in month t. Finally, we regress the time series of DISP_t^k on a constant and the recession indicator.

The first column of Panel B of Table 8 contains the results for the dispersion of CAPM Beta $\left(\mathrm{DISP}_t^{Beta}\right)$. The coefficient estimate for the recession dummy is -0.10 and is statistically significant. Comparing this magnitude to the estimated intercept of 0.76 indicates the dispersion of CAPM Beta amongst highly shorted stocks is about 13% lower in recessions than in expansions, which is consistent with our prediction. The next block contains results based on the incremental three factors of the 4-factor model (SMB, HML, and UMD). Like the result for CAPM beta, the dispersion in all three loadings falls in recessions, and the difference is statistically significant for two of the three. The third block contains tests based on Pastor and Stambaugh (2003) liquidity factor loading, and the final block has those for the two incremental Fama and French (2015) loadings. Each of these three dispersions falls in recessions, and two of the three differences are statistically significant.

C. Market Timing Tests

The evidence from the prior two sections suggests short sellers behave in a manner that gives more credence to aggregate signals during recessions than during expansions. But to what end? Whether this behavior results in successful market timing, particularly during recessions, is a separate and potentially more interesting question that drives our third prediction. We proceed within the framework offered by Jiang et al. (2007) in their mutual fund market timing study. They estimate the relation between the beta of a mutual fund's *holdings portfolio* and future market returns according to

$$\widehat{\beta}_t = \alpha + \gamma r_{m,t+1} + \eta_t, \tag{5}$$

where $\widehat{\beta}_t$ is the fund's portfolio beta in month t estimated using the betas of its component stocks. Since portfolio betas are based only on long positions, a positive value for γ indicates successful market timing (i.e., the fund is shifting into higher beta stocks prior to positive market returns and lower beta stocks prior to negative market returns). Jiang et al. report that, on average, actively managed domestic equity funds have timing ability.

We conduct an analogous market timing test using the portfolio of high short interest stocks. Similar to Jiang et al., we estimate a baseline market timing model as

$$\tilde{\beta}_t k = \alpha + \gamma_k F_{k,t+1:t+j} + \eta_t, \tag{6}$$

where $\tilde{\beta}_t k$ is a variant of the high short interest portfolio's factor-k loading. The independent variable is the realized return of factor k over the subsequent $j = 1$ or

3 months. To ease interpretations across factors and reduce measurement error, we standardize the original loading series to have 0 mean and unit standard deviation, and we smooth the series by taking its 3-month moving average. Thus, the value of $\tilde{\beta}_t k$ is the moving average of the standardized loading series over the months $t-2$ through t. Since the factor loadings are estimated with error, our specifying $\tilde{\beta}_t k$ as the dependent variable mitigates concerns over resulting spurious influences on our standard errors.

Once again, we devote much of our analysis to the time series of CAPM Beta (i.e., factor k is the average log CRSP value-weighted return over the given horizon) for the high short interest portfolio. Since our portfolio represents short positions, a negative estimate for γ_k would indicate successful market timing.[13] The unconditional estimate of γ (reported in Table 9) is -0.020 for future 1-month market returns (first column) and -0.042 for future 3-month market returns (fifth column). Both are statistically significant. While not our main emphasis, these results are of independent

TABLE 9

Market Timing During Expansions and Recessions

The dependent variable is $\widehat{\beta}^{BETA}_t$ defined as the standardized 3-month moving average of the average CAPM beta of stocks with SIR above the 95th percentile in month t. The primary dependent variable is the future t+1 or t+1 to t+3 average log return on the CRSP value weighted index. The recession indicator equals 1 if month t is a recession month and 0 otherwise. Columns 1 through 4 (5 through 8) present the analysis for 1 (3)month market returns. Columns 3, 4, 7, and 8 include the Welch and Goyal (2008) variables. Columns 1 and 5 present the unconditional market timing tests while the remaining columns present the market timing tests conditional on the business cycle. Columns 4 and 8 include Rapach, Ringgenberg, and Zhou's (2016) short interest index (SII) as a control variable. Values presented in the conditional analysis indicate the sum of coefficients indicating the total expansion or recession relation between $\widehat{\beta}^{CAPM}_t$ or SII and future market returns. p-values for the market return variable are computed using 1-tailed tests of the hypothesis that the sum of coefficients indicating either the expansion or recession relation between $\widehat{\beta}^{CAPM}_t$ and future market returns <0, or that the difference between the expansion and recession relation between $\widehat{\beta}^{CAPM}_t$ and future market returns will also be <0. All other p-values are 2-tailed p values. Newey-West p-values with one or three lags for 1- and 3-month regressions respectively are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	1-Month				3-Month			
	1	2	3	4	5	6	7	8
MARKET_RETURN	−0.0202*				−0.0422*			
	(0.07)				(0.069)			
EXPANSION_ MARKET_RETURN		0.00133	−0.00304	−0.00303		0.00881	0.00106	−0.0000439
(γ)		(0.556)	(0.653)	(0.327)		(0.651)	(0.945)	(0.499)
RECESSION_ MARKET_RETURN		−0.065**	−0.0698***	−0.069***		−0.115***	−0.1519***	−0.173***
($\gamma+\gamma_r$)		(0.014)	(0.000)	(0.001)		(0.002)	(0.000)	(0.000)
DIFFERENCE		−0.0665**	−0.0668***	−0.0662***		−0.124***	−0.153***	−0.173***
(γ_r)		(0.017)	(0.002)	(0.002)		(0.003)	(0.000)	(0.000)
SII				−0.0321				−0.0268
				(0.300)				(0.375)
SII × REC				0.0466				−0.195
				(0.764)				(0.136)
REC		0.963***	0.550**	0.559**		0.979***	0.509**	0.546***
		(0.000)	(0.013)	(0.012)		(0.000)	(0.011)	(0.005)
INTERCEPT	0.0225	−0.119**	−0.411	−0.420	0.0333	−0.123**	−0.257	0.201
	(0.705)	(0.020)	(0.749)	(0.740)	(0.593)	(0.023)	(0.835)	(0.865)
N	526	526	526	526	526	526	526	526
R^2	0.009	0.137	0.600	0.601	0.015	0.150	0.632	0.638
W-G Vars	No	No	Yes	Yes	No	No	Yes	Yes

[13]We use log returns in these tests for consistency with Rapach et al. (2016). Doing so allows us to more easily compare our analysis to theirs which is done in columns 4 and 8 of Table 9.

interest given the large market-timing literature that focuses mostly on mutual funds; the significantly negative coefficients indicate that short sellers, in aggregate, tend to tilt their positions toward higher beta stocks prior to lower market returns.

Turning to our primary focus, Table 9 presents estimates from an augmented version of equation (6) containing a recession indicator and its interaction with the factor-k realization:

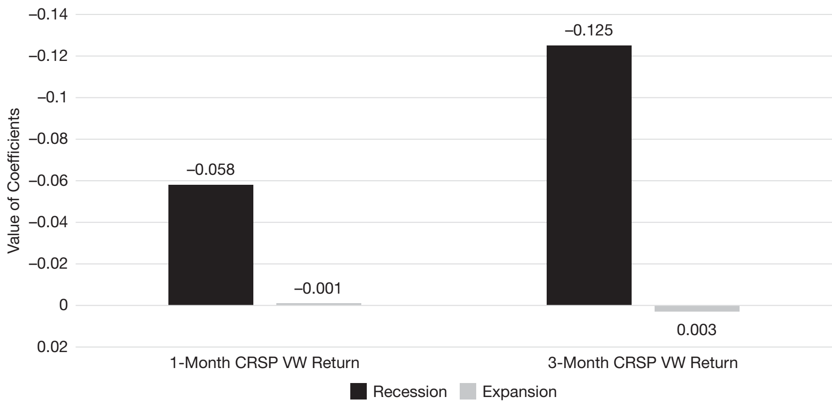
$$(7) \qquad \tilde{\beta}_t k = \alpha + \alpha_r \mathrm{REC}_t + \gamma_k F_{k,t+1:t+j} + \gamma_{rk} \mathrm{REC}_t \times F_{k,t+1:t+j} + \eta_t.$$

We note the recession indicator has the same time subscript as the beta, which corresponds to the time in which short sellers choose their factor exposure.[14] Do short sellers' shift their CAPM betas to predict future market returns more effectively during recessions than during expansions? The second column suggests they do. The market timing coefficient for 1 month ahead market returns in is −0.065 and highly statistically significant in recessions, but a statistically insignificant −0.001 in expansions. The coefficients for 3-month ahead market returns in the sixth column tell a similar story. In recessions, the market timing coefficient is −0.115, again statistically significant, while the coefficient during expansions is statistically 0. Figure 3 presents the main results from Table 9 graphically illustrating the virtual disappearance of the relation between $\tilde{\beta}_t^{\mathrm{BETA}}$ and future market returns during expansions.

FIGURE 3

Relation Between $\widehat{\beta}^{\mathrm{CAPM}}_t$ and Aggregate Stock Returns During Recessions and Expansions

Figure 3 presents a graphical description of the coefficients indicating the relation between $\widehat{\beta}^{\mathrm{CAPM}}_t$ and future returns on the CRSP value-weighted index from equation (7). The black shaded bars on the left present the value of the sum of coefficients $\gamma + \gamma_r$ indicating the magnitude of the relation between $\widehat{\beta}^{\mathrm{CAPM}}_t$ and future market returns during NBER recession months. The gray shaded bars on the right present the value of the coefficient γ from equation (7) which indicates the relation between $\widehat{\beta}^{\mathrm{CAPM}}_t$ and future returns during expansion periods.



[14]To match the time period of the beta, the recession indicator used in the regressions is a 3-month rolling average of the recession indicator time series.

An interpretational comment is warranted. That short sellers better time the market in recessions than during expansions is not a statement about average betas during recessions versus expansions. Rather, market timing refers to the relation between portfolio beta and future market returns. It is this relation, as captured by our estimate of $(\gamma+\gamma_r)$, that changes with the business cycle. So, the beta tilt of the high short interest portfolio better anticipates future market returns during recessions than during expansions.

Perhaps the recession indicator simply captures business cycle variables' ability to explain future stock market returns. To consider this alternative, we include the 14 predictors of market returns identified in Welch and Goyal (2008): log dividend-price ratio, log dividend yield, log earnings-price ratio, log dividend-payout ratio, excess stock return volatility, book-to-mark ratio, net equity expansion, 3-month T-bill rate, long-term government bond yield, long-term government bond return, term spread, default yield spread, default return spread, and inflation.[15] Importantly, when these variables are included in the regressions displayed in the third and seventh columns, the market timing coefficients for recessions are similar or stronger in magnitude than before and those for expansions remain insignificant.

In related work, Rapach et al. (2016) show that a short interest index (SII) based on the average short interest across all stocks correctly predicts future aggregate stock market returns, even after controlling for business cycle variables. We should discern whether the market timing results above are empirically distinct from the predictability arising from SII. Figure 4 plots our high short interest portfolio beta series alongside their SII. We observe no obvious relation between the 2 series; statistically, they are actually slightly negatively correlated (Corr ($\tilde{\beta}_t^{\text{CAPM}}$,SII) = −0.17). For a more formal assessment, we include SII and its interaction with the recession indicator in our market timing models. We present the results in columns 4 and 8 of Table 9. Most importantly, the negative market timing coefficient is virtually unchanged.

The finding that the beta of a portfolio of high short interest stocks contains information about future market returns that is mostly orthogonal to that contained in SII is interesting. The differences in the two series' construction offer an interpretation. The beta series, which represents the average *beta* of stocks investors choose to be heavily short, more likely captures intentional market timing efforts than the SII does. The reason is simple. When possessing a negative signal of future market returns, a market timer would short high-beta stocks to lever up the information. This is exactly the behavior we believe our beta series captures. The SII, on the other hand, which represents the average *level* of short interest across stocks, better reflects a systematic component of short interest and its relation to future returns common to all stocks (Rapach et al. (2016)).

Finally, we use the market timing framework underlying Table 9 to analyze factor timing more generally. Recall that Table 8 offers mixed evidence that short sellers tilt portfolios to make bets on factors other than RMRF. To the extent such factor bets occur, whether they pay off is an empirical question. Table 10

[15]Data for the 14 variables studied in Welch and Goyal (2008) are available from Amit Goyal's webpage at http://www.hec.unil.ch/agoyal/.

FIGURE 4

$\widehat{\beta}_t^{\text{CAPM}}$ and SII From 1974 to 2017

Figure 4 presents the monthly $\widehat{\beta}_t^{\text{CAPM}}$ as well as the short interest index (SII) as developed by Rapach et al. (2016). The solid line is the $\widehat{\beta}_t^{\text{CAPM}}$ while the dotted line is the SII. NBER recession bars are in gray.

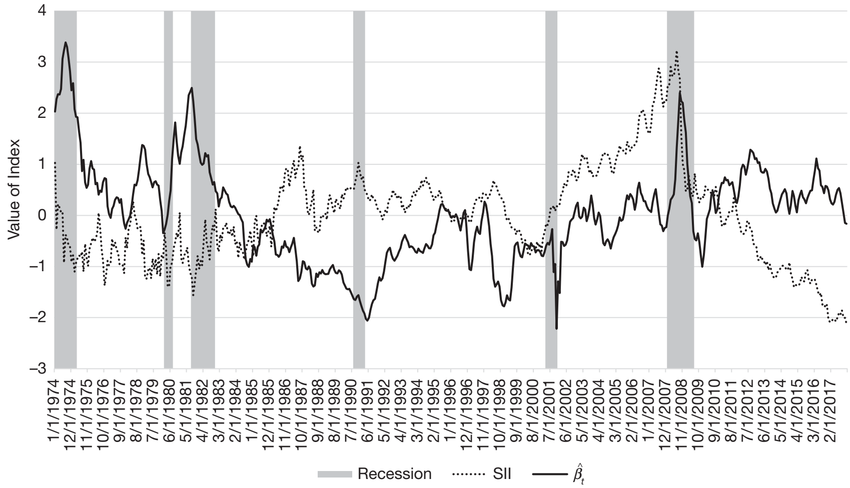


TABLE 10

Factor Timing During Expansions and Recessions

Table 10 presents results for factor timing tests for the SMB, HML, UMD, LIQ, RMW, and CMA factors. Only the incremental factors for each model are shown. Panel A presents the market timing tests unconditional on the state of the economy. In all regressions, the dependent variable is an index defined as the standardized 3-month moving average of the average factor loading for stocks with SIR above the 95th percentile. The variable FUTURE_FACTOR is the $t+1$ to $t+3$ average realization of the given factor. Recessions are defined using NBER recession months. Panel B presents the results of timing tests that are conditional on the state of the economy. The values presented indicate the sum of coefficients indicating the expansion and recession relations between the factor index and the future factor or the difference between the expansion and recession values. All *p*-values are computed using 1-tailed tests of the hypothesis that the coefficient for the variable FUTURE_FACTOR < 0 or that the DIFFERENCE < 0, Newey–West *p*-values with three lags are presented in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

	4-Factor			4-Factor + PS Liq	5-Factor	
	SMB	HML	UMD	Liq	RMW	CMA
	1	2	3	4	5	6
Panel A. Unconditional Factor Timing						
FUTURE_FACTOR	0.007	−0.041	0.036	−0.065**	0.107	0.091
	(0.596)	(0.144)	(0.952)	(0.011)	(0.999)	(0.958)
INTERCEPT	−0.008	0.014	−0.027	0.009	−0.029	−0.038
	(0.922)	(0.875)	(0.748)	(0.911)	(0.716)	(0.642)
N	521	521	521	521	521	521
R^2	0.000	0.006	0.009	0.02	0.029	0.014
Panel B. Conditional Factor Timing						
EXPANSION	0.024	−0.015	0.001	−0.098***	0.100	0.063
	(0.787)	(0.352)	(0.517)	(0.002)	(0.998)	(0.865)
RECESSION	−0.213*	−0.108*	0.109	0.004	0.076	0.163
	(0.064)	(0.087)	(0.999)	(0.545)	(0.819)	(0.923)
DIFFERENCE	−0.237*	−0.094	0.108	0.102	−0.024	0.100
	(0.05)	(0.147)	(0.992)	(0.981)	(0.396)	(0.785)
N	521	521	521	521	521	521
R^2	0.03	0.041	0.107	0.058	0.088	0.034

summarizes timing results for these other factors. The first row contains unconditional timing coefficients. Overall, those results are unremarkable. With the exception of the Pastor and Stambaugh (2003) liquidity factor, there is no unconditional evidence that short sellers successfully time the other factors. The second and third rows contain coefficients estimated for recessions and expansions separately. Here, evidence of successful conditional factor timing is weak as well. Of the incremental factors considered, only the timing coefficient for SMB significantly differs in recessions compared to expansions. Thus while Table 8 indicates short sellers may attempt to time some factors other than the overall market, Table 10 offers far weaker evidence that other such efforts are successful.

V. Wealth Paths

We conclude our analysis with a simple thought experiment that illustrates the value of firm-specific and aggregate signals embedded in short interest. Consider a \$1 investment in each of the following 4 strategies beginning in 1974:

Strategy 1: Buy-and-hold S&P 500. This strategy invests \$1 in the S&P 500 in Jan. 1974 and holds the portfolio from that point forward.

Strategy 2: Stock-picking. This strategy purchases an equal-weighted portfolio of stocks with short interest below the 5th percentile and shorts an equal-weighted portfolio of stocks with short interest above the 95th percentile rebalancing each month.

Strategy 3: Market-timing. This strategy takes a short position in the S&P 500 in month $t+1$ when the standardized CAPM beta ($\tilde{\beta}_t$) of highly shorted stocks (from Section IV.C) exceeds 0.5 in month t and a long position otherwise.

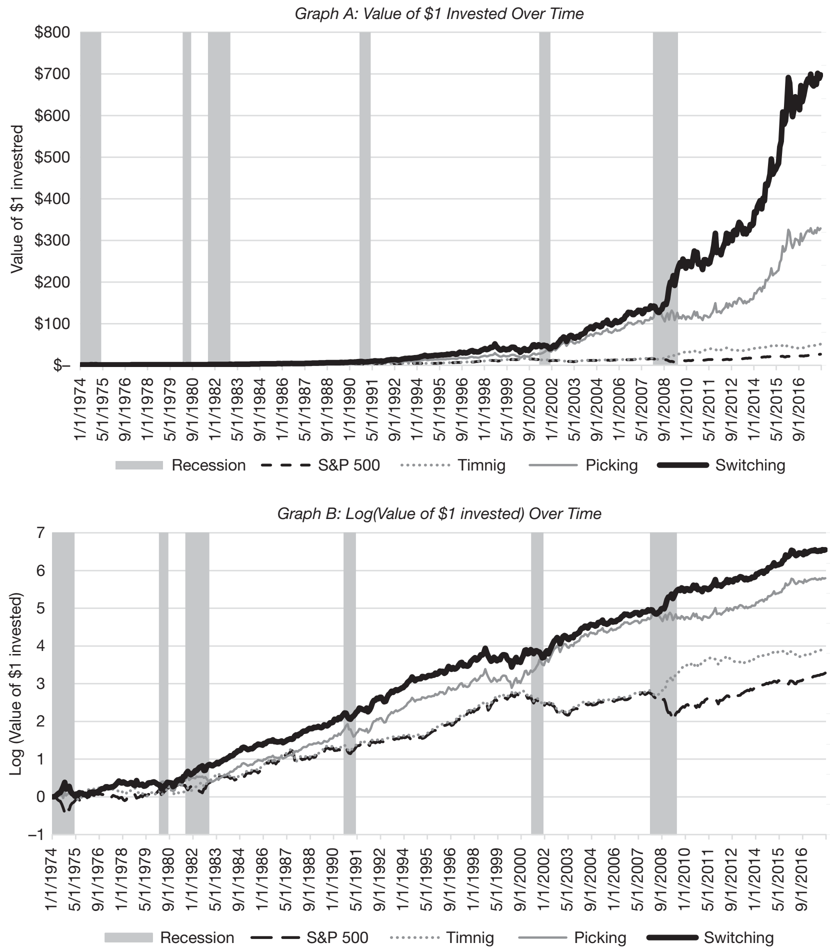
Strategy 4: Simple switching. This strategy switches between Strategy 2 during NBER expansion months and Strategy 3 during NBER recession months.

Figure 5 presents the wealth paths for each strategy from 1974 through 2017. The performance of Strategy 1 serves as a base case for a passively managed stock portfolio. The fact that both Strategies 2 and 3 generate more wealth than the base case suggests that, unconditionally, there is investment value ex post in the firm-specific and aggregate signals embedded in the high short interest stock portfolio. Turning to the individual strategies, we observe that Strategy 2, the stock-picking strategy, clearly generated more wealth than the market timing strategy. This makes sense; our analysis earlier in the paper indicates stronger stock-picking in expansions and better market timing in recessions. Since there are far more expansion months in the data, Strategy 2 should generate more wealth unconditionally. Finally, Strategy 4, the switching strategy, illustrates the key message of our paper. Because it takes on a stock-picking strategy in expansions and a market-timing strategy in recessions – the time periods when each strategy is most successful – this final strategy generates substantially more wealth than either the stock-picking or

FIGURE 5

Wealth Paths

Figure 5 plots the value of 1 dollar invested in Jan. 1974 based on 1 of 4 strategies: the black dashed line indicates the value of holding the S&P 500, the gray dotted line indicates the value of a market timing strategy based on the beta of highly shorted stocks, the solid gray line indicates the value of a stock-picking strategy that holds a portfolio long lightly shorted stocks and short highly shorted stocks. The solid black line indicates the value of switching between timing and stock picking with NBER recession months. Graph A presents the standard value of the wealth paths while Graph B presents the log value of the wealth paths.



market-timing strategy alone and bolsters the argument that short sellers may be acting optimally by alternating which signals they collect and trade on across the business cycle.[16]

[16]Strategy 4, as depicted in Figure 5, switches between Strategies 2 and 3 in the same month the economy switches between an NBER expansion and recession. The result that Strategy 4 generates a higher wealth path than the other strategies considered does not depend on the month switches occur. In unreported results, we vary the switching months from 1 to 3 months following an economic state change and find qualitatively similar results.

VI. Conclusion

Discovering and trading on private valuation signals provides a social good that affects real outcomes: it may lower firms' cost of capital, it may improve CEO incentives, and it may facilitate useful feedback in managerial decision making. Further, traders who discover and trade on private signals provide an additional source of external monitoring. But up to this point, empirical evidence on the nature of traders' information gathering choices and opportunity sets is scant. Our analysis makes some progress as we argue that information-gathering activities of a broad class of sophisticated investors (short sellers) vary predictably with the business cycle. During expansions, short sellers appear to gather and trade on more firm-specific information while during recessions they uncover information that is more macro in nature. These findings are consistent with theories of information acquisition under attention constraints, endogenous information production, as well as theories of time variation in aggregate overconfidence amongst traders.

While we highlight various activities of short sellers, the economic forces at play may feasibly apply to sophisticated traders in general. This possibility motivates interesting questions. If traders collect fewer firm-specific signals during recessions, then are prices less efficient with respect to firm-specific information during down economic times? Does less acquisition of firm specific information during recessions diminish the role of sophisticated traders as monitors of the firm? Are other corporate governance mechanisms more valuable in recessions? Alternatively, are recessions times that spawn nefarious activities like corporate fraud? We look forward to future research that addresses questions such as these.

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