Crowding Risk and Short Squeezes

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Short sellers face unique risks, such as the risk that too many other short sellers crowd into the same stock. We show that short sellers are compensated for entering the crowded trades. The difference between the average returns on portfolios sorted by high versus low short crowdedness is economically sizeable (15% of risk-adjusted return per annum), and the variation in the realized portfolio returns is distinct from other traditional risk factors. Further, short sellers' exposure to crowdedness is often significant and helps explain short squeezes. Our findings offer novel cross-sectional evidence of crowded short risk among short sellers and their pricing implications.

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"Global hedge funds using algorithms to trade stocks endured one of their worst days of the year on Thursday, a Goldman Sachs note on Friday showed, a sign that a sharp rally in shares on hopes that global rate hikes are over caught some off guard.

Systematic fund managers, particularly those which had short bets on highly traded stock names, got caught trying to get out of crowded trades and found themselves stuck in losing positions, Goldman Sachs said."

Reuters, November 4, 2023.

Hedge funds caught in crowded trades suffered in Thursday's stock rally -Goldman Sachs.

"AI is being used in so many ways today and the extent to which AI is being used for trading purposes has been growing tremendously. Policymakers and regulators are concerned about what the implications might be on capital markets. Will everybody try to exit the door or get in at the same time."

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I. Introduction

Arbitrageurs play a critical role in the capital markets. An arbitrageur identifying overpriced security must first borrow it in the securities lending market, post cash or securities collateral, and pay lending fees. In addition, an arbitrageur faces a risk of security recall, regulatory changes, and the risk that too many arbitrageurs are simultaneously entering the same security position. Illiquidity in a crowded position is a significant concern for an arbitrageur, as it may lead to a short squeeze and result in substantial losses. Recognizing the importance of this issue, Goldman Sachs has developed a proprietary measure to assess crowdedness in the hedge funds' long side of the portfolios.[1] While there has been much academic research in finance on arbitrageurs and their impact on asset prices[2], the risk of arbitrageur's *crowdedness in the short position* has not, to our knowledge, received much formal research attention.

[1] For more detail, see https://www.gsam.com/content/dam/gsam/pdfs/us/en/ETF/Goldman-Sachs-Hedge-Fund-VIP-Index-Methodology.pdf?sa=n&rd=n

[2] See D'Avolio (2002) for evidence on the role of loan recalls in lending supply (D'Avolio, 2002), Engelberg, Reed, Ringgenberg (2018) for change in loan fees, Kolasinksi, Reed, and Ringgenberg (2013) and Chague et al. (2017) for search costs, Gargano, Garagno, Sotes-Paladino, and Verwijmeren (2019) for margin constraints, Duan, Hu, and McLean (2010) for arbitrage risk.

In this paper, we examine the risk of crowding risk in a short position. Specifically, we show that stocks sold short associated with high-crowding have lower future returns and experience short squeezes.

Studying the crowdedness in the short position is relevant from academic and regulatory perspectives. First, the existing literature focuses on the crowding in the long positions (Brown, Howard and Lundblad, 2022; Barroso, Edelen, and Karehnke, 2017), overlap in hedge fund long equity portfolios (Sias, Turtle, and Zykaj, 2016), crowded trades and bubbles (Kinlaw, Kritzman and Turkingston, 2019), market crowdedness (Obizhaeva and Wang, 2019), style crowdedness in currency trades (Pojarliev and Levich, 2011), crowdedness at the strategy level (Polk and Lou, 2019). None of these studies, however, investigate arbitrageurs' crowdedness in the short position at the security level. Second, the implications of crowding into the short position are important for capital market regulators. The crowded trade may create a short squeeze risk if many traders exit a similar position simultaneously.[3] If the price suddenly jumps, short sellers may be forced to buy back shares at a higher price to meet margin requirements or prevent further losses. This short covering can drive the price even higher, triggering more short sellers to buy back shares and cover their positions. Short sellers' implicitly levered positions can trigger a short squeeze if there is insufficient liquidity.

Crowding among short sellers could have significant asset pricing implications. Why would arbitrageurs crowd into the levered short position? A high crowding among short sellers could relate to the severity of stock overpricing. A short seller, however, who receives negative information about a firm's fundamentals does not necessarily know how many other short sellers receive the same information. The notion that crowded trades might impact price efficiency originates from Stein (2009). He proposes a model of overcrowding where arbitrageurs stand

[3] Short sellers positioning for MicroStrategy to decline have accumulated paper losses of about $3.3 billion so far in 2024 amid the stock's more than 170% gain, according to data from S3 Partners LLC. That's pushed mark-to-market losses over the last 12 months to more than $4.3 billion. These stocks are both more crowded and much more squeezable than the average US stock. "MicroStrategy Burns Shorts Sellers as Shares Rally With Bitcoin", Bloomberg, March 14, 2024.

ready to correct mispricing, yet they do not know how many other arbitrageurs might be pursuing the same trading strategy. If an unexpectedly large number of arbitrageurs enter the same position, the trade can become overcrowded. The mispricing is not common knowledge among arbitrageurs. All arbitrageurs know of mispricing, and all arbitrageurs understand that the price is too high or too low. However, it is never the case that all arbitrageurs know that everybody knows that everybody knows. The idea that price movements can originate from uncoordinated trading among short sellers is obvious, but it has not yet been investigated directly due to limited data.

Guided by this intuition, we investigate the asset pricing implications of crowding in the short position and arbitrageurs' returns. This paper focuses on short sellers representing good candidates to study the arbitrageurs' crowding. Specifically, we investigate how crowded short positions predict future returns in approximately 4000 U.S. stocks held by short sellers from 2015 to 2019. One major challenge in empirically studying arbitrageurs' crowding has been the lack of data. Since short positions are part of arbitrage trades, several studies track the short side of arbitrage trading by examining short selling at the firm level.[4] Existing short-interest data, however, does not provide the level of crowding in the short position this analysis requires. Using short interest as a proxy of crowding is problematic because the quantity of shorting represents the intersection of supply and demand. Demand for shorting should respond to both the cost and benefit of shorting stocks so that stocks that are very costly to short will have a low short interest. Stocks that are impossible to short will have an infinite shorting cost, yet the level of short interest is zero (Jones and Lamont, 2002). The other issue is that short interest does not tell us how liquid the stock is. If a short seller takes a short position in a crowded stock, he/she needs to know how many days of trading volume are required to cover a short position. Otherwise, the short seller might incorrectly believe there will be more counterparties to provide liquidity when they need to unwind their position. It is also critical to consider the liquidity in the stock loan market. If the loan fees are

[4] Short-sale studies find that short sellers, on average, are informed traders who can predict lower future stock returns (e.g., Asquith, Pathak, and Ritter (2005), Boehmer, Jones, and Zhang (2008), Diether, Lee, and Werner (2009); Hanson and Sunderam (2014)).

high, it will be difficult to cover the short position. A unique feature of our dataset is that it offers a crowded score measure, which captures a crowdedness in the short position. We obtain a measure of crowded short position from a financial technology start-up, S3 Partners.[5] They calculate the crowded score (hereafter *CROWDED SHORT)* using a multi-factor model. The model incorporates the total dollar amount of a short position in a company's stock, short interest as a true percentage of a company's tradeable float, liquidity in the stock market loan measured by increasing loan fees (hard-to-borrow signals), and trading capacity measured by average daily volume. Based on this measure, we attempt to understand better the information content of arbitrageur crowding in the short term. To our knowledge, this is the first measure to capture crowdedness in the short position. It provides substantial value compared to high short-interest stocks, as it is a stronger return predictor. It presents a more complete view of the effect of arbitrage activity on the short side of the market on the returns on stocks by capturing both supply and demand in the equity loan market. This measure is available in real-time (at the start of every trading day) via the Bloomberg terminal.

Our analysis provides several sets of results. First, we use the *CROWDED SHORT* measure to examine whether arbitrageurs are compensated for crowding into the short position. If the equity loan market is constrained, taking a *CROWDED SHORT* position in a stock potentially subjects a short seller to idiosyncratic risk that cannot be diversified away. Thus, *CROWDED SHORT* positions may require a risk premium. We find that it is. We show that our *CROWDED SHORT* proxy is related to future returns: a long-short portfolio formed based on *CROWDED SHORT* earns a 1.28% monthly (15.36% if annualized) four-factor alpha. However, sustained crowdedness in the short position does not occur simply because a company has a high level of SHORT INTEREST. This result holds strongly in double-sorted portfolios that first condition on SHORT INTEREST and then *CROWDED SHORT*. This return predictability holds, controlling for other

[5] S3 Partners is an analytics company with over $3 trillion in assets under advisement on their treasury management platform. Most of S3 Partners' clients are institutional buy and sell side, with some individual retail investors. See S3Partners website here: https://www.s3partners.com/

return predictors. Our results indicate that *CROWDED SHORT* is a more robust return predictor than SHORT INTEREST. The predictive ability of SHORT INTEREST disappears after *CROWDED SHORT* enters the regression model and does not regain its significance after controlling for other firm characteristics. Importantly, the return predictability does not reverse in the long run, suggesting that short sellers crowd into short positions based on value-relevant information. Taken together, the evidence suggests that the *CROWDED SHORT* measure captures the ability of short sellers to, on average, collectively identify stocks with higher risk-adjusted returns.

Second, to better understand how results hold up throughout the cross-section, we also examine sorts on firm size (market capitalization) if the relationship between *CROWDED SHORT* and returns is concentrated in small or large firms. The *CROWDED SHORT* return predictability also holds for small and large market capitalization stocks. Return predictability is generally stronger for small and highly crowded stocks. However, we also find that large and highly crowded stocks earn positive long-short portfolio risk-adjusted returns, albeit the profitability is halved of what the small stock earns. This result aligns with Diamond and Verrecchia's (1987) arguments that the gains from shorting constrained stocks must be sizable enough to induce the short sellers to correct the mispricing reflected in those stocks. Taken together, our size sort results indicate that short sellers are compensated for the risk they take by crowding into the short position.

Third, we provide evidence of a strong relationship between crowdedness in the short position and the firm's information environment. We find a strong negative association between *CROWDED SHORT* and a proxy for differences in beliefs such as stock TURNOVER. We find *CROWDED SHORT* positions associated with high SHORT INTEREST, UTILIZATION, and a low SUPPLY of lendable shares. Hence, shorting fees increase for the stock lending market to clear the equilibrium. Our result suggests that short sellers' crowding into the short position is significantly related to the constrained conditions in the equity lending market.

Fourth, we differentiate our results from other mechanisms limiting arbitrage activity. We document that our results cannot be explained by Miller's (1977) hypothesis that stocks with tight short-sale constraints are more overpriced. Our results hold strongly for stocks with high lending fees, low lending supply, and high variance of lending fees.

Fifth, we find that the *CROWDED SHORT* position predicts short squeezes. Implicitly levered short positions and the risk of share loan recalls coupled with share-lending constraints may force short sellers to exit crowded positions prematurely, triggering exit frictions. Forced exit out of a crowded short position may lead to a rapid increase in share price primarily due to the excessive covering of short positions. This situation occurs because a stock lender recalls his stock to settle a sale, and the short seller cannot replace his stock loan due to the limited loan supply. Hence, short sellers rush to cover their position by buying shares at a higher price in the open market to meet margin requirements or to avoid losses. This article shows that controlling for short-sale constraints, increased *CROWDED SHORT* in month *t* leads to a short squeeze in month *t+1*. Unlike CROWDED SHORT, short interest is negatively related to short squeezes. This result is consistent with Blau (2017), who finds that short interest is negatively related to return skewness (another short squeeze proxy). We also find that institutional short sellers tend to crowd into the short position, not retail. Institutional short sellers' crowding into the short position occasionally generates significant losses due to the small likelihood of short squeezes. Therefore, awareness of a crowded short position is crucial because short sellers may try to exit their position simultaneously and in the same direction. The mass withdrawal from the crowded short position can create liquidity problems as all short sellers rush to exit a "burning house."

Fifth, we find that crowding in short positions significantly affects stock price efficiency. The CROWDED SHORT is negatively correlated with stock price efficiency measures. This suggests that a stock's price efficiency improves when short sellers concentrate their positions. We also find, however, that CROWDED SHORTS that are subject to short squeezed reduce price efficiency. The interaction variable *CROWDED SHORT*SHORT SQUEEZES* is positive, economically, and statistically significant.

Finally, we document that the profitability of the CROWDED SHORT trading strategy varies with economic states. We consider seven simple market timing trading strategies. Each trading strategy is based on tilting portfolio weights toward (away) from a strategy conditional on TED spread, Sentiment, Bloomberg Economic Surprise, or a combination of several variables. We find that the best-performing market timing trading strategy utilizes trading signals from *Sentiment* and *Bloomberg Economic Surprise*: when Sentiment and Bloomberg Economic Surprize increase (decrease) in month *t*, the portfolio weights sidestep (tilting) away (towards) from the *CROWDED SHORT* trading strategy. This strategy yields a 16.7% monthly average alpha with a sharp (information) ratio of 1.64 (53.58).

Our paper makes several contributions. First, to the best of our knowledge, our paper is the first to test a measure of arbitrageurs' crowding in the short term based on lending market data to examine the asset pricing implications directly within a broad sample of U.S. equities. Our paper provides novel evidence that arbitrageurs face the risk of overcrowded trades and are compensated for being in these trades. Specifically, we show that CROWDED SHORT positions are associated with lower future returns. We also show that this effect is pronounced for trades with a long-expected holing horizon. In addition, we show that arbitrageurs who enter CROWDED SHORT positions suffer occasional crashes. The exit from a crowded trade can destabilize if the equity lending market is constrained or there is insufficient liquidity on the other side of the trade. Second, we contribute to the literature on short selling. Recent literature identifies risks that short sellers face while correcting mispricing in financial markets. These risks, for example, include fee-volatility risk (Engelberg, Reed, and Ringgenberg, 2018) and synchronization risk (Abreu and Brunnermeier, 2002, 2003). While extensive empirical evidence supports the relevance of fee-volatility risk and synchronization risk, the impact of crowding in the short position risk has not received much attention. The effect of crowding in the shirt position risk on the cross-section has remained unexplored because of the lack of a stock-level proxy for crowding in the short position. We test a monthly measure of CROWDED SHORT measure to directly examine the asset pricing implications of crowding in the short position within a large cross-section of stocks.

II. Hypotheses Development

The academic literature identifies various constraints on arbitrage, including transaction expenses, the impact of noise traders, and systematic factors like funding liquidity and overall market volatility. An important additional risk has been ignored in the literature. It arises from the arbitrageur's uncertainty about how many other arbitrageurs will enter the same short position. We term this risk a *crowding risk*. In contrast to noise trader risk, crowding risk does not primarily stem from the activity of other noise traders but from uncertainty about how much arbitrage capital is invested in a short position. Noise trader risk is characterized by the potential for prices to move significantly away from their fundamental value. On the other hand, crowding risk refers to the uncertainty of finding counterparties to take the opposite position when exiting a short position. If there's uncertainty about how crowded the short position is, prices may move further away from their fundamental values.

Our main goal is to relate the degree of short sellers' crowding at the stock level to the arbitrage risk and is motivated by the theoretical work of Stein (2009). In particular, Stein (2009) emphasizes that "an important consideration for each arbitrageur is that he cannot know in real-time exactly how many others are using the same model and taking the same position." If an unusually high number of traders take on the same short position, covering the short position can become progressively more difficult. The pressure on short sellers to cover their positions because of unexpected sharp price increases or difficulty in borrowing the security the seller short may result in a short squeeze. Several existing papers support the idea that crowding risk affects arbitrage activities. Khandani and Lo (2007 and 2011) empirically examine the Quant Crisis of August 2007. They find that many quant funds used similar strategies based on common market factors, leading to crowding. Since many funds held similar positions, they were forced to sell simultaneously when the market declined, causing a sharp price drop. According to Pedersen (2009), crowding combined with leverage can generate "liquidity spirals." Stein (2009) identifies two key factors—crowding and leverage—that complicate the impact of sophisticated investors on market efficiency. He argues that the main issue with crowding is that no arbitrageur knows how much trading capital has already been deployed by others. Pojarliev and Levich (2011) examine the crowdedness of trading style in currency strategies. They find that currency managers have significant exposure to several popular strategies. Marks and Shen (2019) explore the relationship between crowding and liquidity. They find that correlated trading among investors can impact both the liquidity and risk of the securities they trade. Brown et al. (2019) measure security-level crowdedness using hedge fund equity holdings from SEC 13F filings. They define crowdedness as the ratio of hedge funds' total positions in a stock to its average daily trading volume. Their findings show that stocks with higher crowdedness tend to experience more severe drawdowns during market downturns. Benzaguen et al. (2020) propose crowding measures based on trade imbalances and provide evidence that momentum strategies have become more crowded in recent years.

We use these results to generate several testable predictions regarding the impact of crowding risk. First, consistent with models of limits to arbitrage (e.g., Shleifer and Vishny (1997)), we hypothesize that stocks with higher arbitrage risk, in this crowding, exhibit greater mispricing. Second, we argue that short sellers, fearing short squeeze, require compensation to hold a CROWDED SHORT position. We empirically test these predictions in the first and second hypotheses:

Hypothesis 1. Short sellers require compensation for entering the CROWDED SHORT position, and therefore, crowding is negatively associated with expected stock returns.

Hypothesis 2. Crowding in the short position positively relates to short squeeze risk for hard-to-borrow stocks.

Hypotheses 1 and 2 guide our empirical analysis in the remainder of the paper.

III. Data

A. Equity Lending Data

We obtain equity lending data from S3 Partners between January 2015 and December 2020. S3 Partners collects transaction-level lending data from lending agents, third-party lenders, beneficial owners, and borrowing data from prime brokers and asset managers. Unlike other securities lending data vendors, S3 Partners captures every trade detail directly through the S3'treasury management platform.[6] S3 Partners aggregates transaction-level data at the daily level for each security. The S3 dataset covers 66,627 equity and fixed-income securities domiciled in over 111 countries and includes data on inactive securities. Gargano (2020) also uses S3 partners lending data.

We employ a proprietary crowding measure supplied by S3 Partners to gauge the crowding in the short position. This measure of crowding indicates the crowdedness in the short position at the stock level. It is calculated using a multi-factor model and includes the following information: the magnitude of shorting, borrowing capacity, and financing rate for a day/stock. The *crowded* score comprises a multi-factor model with a numeric rating from 0 (lowest) to 100 (highest). The score gives the user a normalized way to consider the crowdedness in the short position at the security level comparatively. This measure aims to capture stocks with short sellers ending up on the same trade side.

B. Auxiliary Data Sources

We gather prices, returns, and shares outstanding from the Centre for Research in Security Prices (CRSP) for all common stocks traded on NYSE, Amex, and Nasdaq between January 2015 and

[6] S3 Partners' treasury management platform can be accessed to investors via a subscription on the Bloomberg terminal.

December 2020. We collect book values of equity from COMPUSTAT. We obtain the number of analysts covering stock and calculate the dispersion in stock analysts' forecasts from the I/B/E/S database. We restrict our samples to stocks priced above $1 to mitigate the concern about highly illiquid stocks. Our final sample contains approximately 4,000 stocks.

C. Summary Statistics

Table 1 presents summary statistics for the equity lending market (Panel A), firm fundamental characteristics (Panel B), and pairwise correlations (Panel C). We calculate the time-series averages of the monthly cross-sectional summary statistics for each variable.

[INSERT TABLE 1]

If the short sellers knew how many other short sellers would rush into the same stock, we would expect the initiations of their positions to be low relative to the liquidity in the equity lending market; consequently, the crowded score would be close to zero. The summary statistics in Panel A, however, indicate that for the typical stock in our sample, *CrowdedScore* is above zero (its mean and median are, respectively, 30 and 25).

For the typical firm, approximately 23% of shares outstanding are available to be borrowed[7] and around 10% are on loan at any given point in time. The median LOAN FEE is only 0.31% per annum, while the mean is 2.77%, indicating positive skewness[8]. The mean SHORT INTEREST is 5.25%.

Panel B of Table 1 presents summary statistics for the stock's fundamental characteristics. The mean MARKET CAPITALIZATION for the firms in our sample is $7.66 billion, and the median MARKET CAPITALIZATION is $0.82 billion. The average (median) monthly stock return is 0.02% (0.27%). We also display summary statistics for the different proxies of the

[7] D'Avolio (2002) reports the same shares' supply is available to borrow.

[8] D'Avolio (2002) finds that 91% of the shares lent out the LOAN FEE is less than 1% per annum. Only 9% of shares have LOAN FEEs above 1% per annum. These stocks with high lending fees have a mean LOAN FEE of 4.3% per annum. Fewer than 1% of shares on loan become extremely expensive to borrow, exhibiting LOAN FEEs of 35%-50%.

information environment surrounding a firm that we examine in Section 6: BID-ASK spread, TURNOVER, and control variables used in the analysis.

Panel D reports the correlation matrix for the main variables in our subsequent analysis. The correlation between CROWDED SHORT and SHORT INTEREST is high at 0.82 but far from perfectly correlated since liquidity in the stock loan market and trading capacity varies across stocks. Indeed, these two variables capture different information, which we will exploit in our asset pricing tests in the subsequent sections. The CROWDED SHORT is positively correlated with LOAN FEE (0.21) and UTILIZATION (0.68) but negatively with LOAN SUPPLY (-0.46).

Figure 1 plots the CROWDED SHORT measure. The figure shows that crowdedness in the short position holds relatively constant over time despite a slight decline in the later period of the sample. The CROWDED SHORT measure is 32 at the beginning of our sample period and then declines steadily to around 25. There were two drops in the crowdedness on the short side: the first occurred from October 2016 – December 2016; the second occurred from February 2020 – April 2020. The drop in crowdedness results from the FED funds rate cut, which occurred in October 2016 and February 2020 to spur economic growth.[9] Unlike the CROWDED SHORT position, the SHORT INTEREST remained the same over our sample period, hovering around 5% of shares outstanding. It indicates that crowded score and SHORT INTEREST contain different information. Despite the observed time trends in a CROWDED SHORT position and SHORT INTEREST, we will stick to the focus of this paper, which is an investigation of the cross-sectional differences in short crowdedness at each point in time.

[INSERT FIGURE 1]

[9] (October 2016: 2% to 1.75%: February 2020: 1% to 0.25%)

Figure 2 displays an instance of the data for Tilray Brand Inc. as of September 19, 2018.[10] In a Jan. 21, 2021, article on CNBC.com[11] Brendan Kennedy, CEO of Canadian marijuana producer Tilray, said "I've had a little PTSD over the last couple of days" while watching the trading in GameStop. Kennedy said, "I remember getting five different calls from Nasdaq in a single day about our stock being halted because the short sellers were being squeezed so badly. " I think the short sellers lost something like $600 million on that particular day, Sept. 19, 2018, which actually pales in comparison to what I have been reading about GameStop. "As *long* investors drove the share price up, short sellers increased their positions. The high CROWDED SHORT before September 19, 2018, indicated that many short sellers had taken positions in Tilray, signaling a potential short squeeze. On September 19, 2018, the share price surged from $154 to $214, forcing short sellers to cover their positions. The next day, the price dropped sharply from $214 to $176. In section VII, we assess the strength of the cross-sectional relationship between CROWDED SHORT and short squeezes.

[INSERT FIGURE 2]

IV. Empirical Results

A. The Determinants of Crowded Position

We start by examining what factors play a role in predicting the crowdedness in the short position. Fundamentally, the short sellers' crowding can reflect the degree to which they agree on a stock's overvaluation. To assess and quantify it, we regress CROWDED SHORT on a set of proxies for fundamental drivers of crowding, simultaneously controlling for non-fundamental sources of crowding while selling short. Specifically, we run the following regression:

$$CROWDED\ SHORT_{i,t+1} = \alpha_i + \tau_t + \beta' x_{i,t} + \epsilon_{i,t,} \tag{1}$$

[10] In July 2018, Tilray Brand Inc shares hit an intraday low of around $20 before they rocketed higher. The stock reached an intraday high of $300 per share in September of that year. Short sellers lost $600 million on that particular day, Sept. 19, 2018, due to the short squeeze. https://www.cnbc.com/2021/01/27/tilray-ceo-brendan-kennedy-issues-a-warning-to-gamestop-amc-bosses.html

[11] https://www.cnbc.com/2021/01/27/tilray-ceo-brendan-kennedy-issues-a-warning-to-gamestop-amc-bosses.html

where *CROWDED SHORT i, t* denotes the level of crowdedness in the short position in stock i on month t, αi and τt are stock- and time-fixed effects respectively, and xi,t represents the set of covariates, which includes TURNOVER, the average turnover over the previous month; MARKET CAP, the market value of equity; ANALYST DISPERTION, the ratio between the standard deviation and the average of the quarter-ahead EPS forecasts; SHORT INTEREST, the total quantity of shares that were loaned out as a percentage of shares outstanding; LOAN SUPPLY, total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding; LOAN FEE, the cost of borrowing a share in % per annum; UTILIZATION, the quantity of shares loaned out as a percentage of shares available to be borrowed; OPEN INTEREST, the (log) of the call and put open interest; VOLATILITY, the natural log of return volatility (calculated as the standard deviation of daily stock returns each month); BOOK-TO-MARKET is a ratio of book-to-market value; Return, the stock return expressed in percentage per month; BID-ASK , the daily bid-ask spread as percentage of mid-price averaged over a month in %; PROFITABILITY, the ratio of operating income before depreciation to total assets, LEVERAGE, the ratio of total debt to total market value of assets; VAR (LOAN FEE), the variance of the borrowing fees; RET i,t-6 to t , the stock returns cumulated over the previous six month; RET i,t-12 to t-7 , the stock return cumulated over the previous six months excluding the first six month. Short selling arises mainly because long and short investors disagree about the stocks' valuation. Why would short sellers enter short positions en masse? One explanation is that short sellers have fundamental reasons to agree about the stock's degree of overvaluation.[12]

Of course, there are non-fundamental reasons why short sellers might trade a financial asset, which has nothing to do with beliefs about future price changes. These include liquidity trading, portfolio rebalancing, trading to minimize taxes, and hedging. However, these motives are

[12] Boehmer et al. (2020) empirically examined the sources of short sellers' informational advantage. They found that significant source of short sellers' return predictability comes from fundamental events.

unlikely to explain much of the crowding we observe. Most crowding is likely driven by short sellers' beliefs about the asset's future price – specifically, by agreeing among short sellers about what this future price will be. If short sellers have the same beliefs about a stock's valuation, then *CROWDED SHORT* should be negatively related to disagreement about the stock's future payoff and positively to the stock's overvaluation. Our proxies for differences in beliefs are stock turnover (TURNOVER) and dispersion in analysts' forecast (ANALYST DISPERTION). According to theoretical models developed by Shalen (1993), Harris and Raviv (1993), and Kandel and Pearson (1995), there is a positive relation between belief dispersion and stock TURNOVER when traders interpret common information differently. [13] We also use a dispersion in forecasts across stock analysts as a proxy for belief dispersion, as in Diether et al. (2002). Earlier research demonstrated that larger firms typically have access to more information (e.g., Chae 2005, Zhang 2006). Following this research, our proxy for information asymmetry is firm size (MARKET CAP).

The results are shown in Table 2. The results broadly support the validity of CROWDED SHORT as a proxy for information-driven crowding. First, CROWDED SHORT is strongly negatively associated with TURNOVER (a proxy for differences in beliefs) across all regression models. The CROWDED SHORT is also negatively correlates with ANALYST DISPERSION, albeit insignificantly. Second, CROWDED SHORT is higher for large market capitalization stocks, highlighting a strong and positive with the degree of information asymmetry surrounding the stock. They are, however, unaware of how many other short sellers trade based on the same information set.

[INSERT TABLE 3]

We also note that crowding into the short position tightens the equity lending market. Across all regression models, *CROWDED SHORT* is associated with increased SHORT INTEREST, loan UTILIZATION, and decreased LOAN SUPPLY. This result indicates that most crowded stocks

[13] See for example Hong and Stein (2007) for theoretical motivation of trading volume as a proxy of investors' disagreement.

generally experience an increase in shorting demand, cost of borrowing, and, as a result, contraction of the supply of shares available to borrow. These findings align with Cohen et al. (2007), who suggest that increased shorting demand captures informed trading while shorting supply contraction indicates the tightening of short-sale constraints. An adverse price movement and a constrained equity lending market can lead to a short squeeze. We explore it further in the section VII.

B. Crowded Shorts and Future Returns

In equilibrium, short sellers should be compensated for the risks they face (e.g., Shleifer and Vishny (1997)). If short sellers are concerned about entering a crowded position, they should be compensated for holding this position: a CROWDED SHORT position should predict lower future returns.

In this section, we consider the relationship between *CROWDED SHORT* and 1-month-ahead stock returns to assess the existence of a short crowdedness premium. Our study, which includes univariate portfolio sorts, bivariate portfolio sorts, and panel regressions, shows that the crowding risk premium cannot be explained by other risk factors and stock characteristics that predict future returns.

To examine whether short sellers are compensated for entering the crowded positions, we first examine univariate portfolio sorts. Each month, we sort stocks into quintile portfolios based on *CROWDED SHORT*. The quintile 1 portfolio contains stocks with the lowest *CRWODED SHORT*, and the quintile 5 portfolio comprises stocks with the highest *CROWDED SHORT*. We then evaluate the variation across portfolios in average returns the following month. These portfolios are equal-weighted and rebalanced monthly. We regress the returns of these portfolios on the 4 Fama-French-Carhart factors and use Newey and West's (1987) standard errors to correct for autocorrelation, with a number of lags equal to the length of the holding period.

To preview the relationship between CROWDED SHORT and future returns in our sample, in Figure 3 we plot the mean portfolio returns across 5 CROWDED SHORT portfolios. shows a strong relation between crowded short score and future returns. Stocks in the low crowded quintile earn monthly returns of 0.49% per month while stocks in the high crowded quintile earn monthly returns of -0.42% per month. Thus, a long-short portfolio formed by buying stocks with high crowded short positions and shorting stocks with low crowded short positions earns -0.9% per month. Panels A and B of Table 3 present the resulting alphas of the monthly portfolios, respectively, corresponding to each CROWDED SHORT group. The results confirm the negative relation between CROWDED SHORT and future alpha portfolio returns. Panel A evidences a strong decreasing pattern moving from the first (Q1) to the fifth (Q5) portfolio. While the low-CROWDED SHORT portfolio generates monthly alphas of -0.29 % in Panel A, the high-CROWDED SHORT portfolios generate -1.57% per month (both significant at the 1% level). As a result, the hedge portfolios long in low-CROWDED SHORT stocks and short in high-CRWODED SHORT stocks generate statistically and economically significant alphas of 1.28% per month (15.36% per annum).

[INSERT FIGURE 3]

[INSERT TABLE 3]

To control for other cross-sectional effects, Table 3 also presents conditional double portfolio sorts. Each month, we first allocate stocks into two groups based on the different firm and stock characteristics. These include SHORT INTEREST and MARKET CAPITALIZATION to verify that CROWDED SHORT is not driven by size effect (Fama and French, 1992) and the well-documented predictive power of short interest (Reed, 2003). Within these groups, we further allocate stocks into five portfolios (from low to high) conditional on CROWDED SHORT. We then compute the alphas for the hedge portfolio long in low-CROWDED SHORT and short in low-CROWDED SHORT stocks for each group of the first sorting variable. Panels A and B present the results for the portfolio analyses. The results add strong support for Hypothesis 1. The negative relation between CROWDED SHORT and returns is pervasive across short interest and size groups, indicating that the effect of short sellers' crowding on returns is not subsumed by other well-known cross-sectional determinants. The effect is stronger among small caps, consistent with our above observation that CROWDED SHORT tends to be larger among firms with higher capitalization, as well as among stocks with high short interest. Within these categories, the monthly alphas on the long-short CROWDED SHORT portfolios (0.81% for big and 2.07% small stocks, 0.35% and 1.05% for low- and high short interest stocks.

The CROWDED SHORT generates negative alphas also among lightly shorted stocks. Conditioning on low levels of short interest, alpha is 0.35% per month in column (Panel A, Table 4) (significant at the1% level). This suggests, as expected from crowding risk limiting arbitrage, that relation between CROWDED SHORT and returns is unrelated to the superior ability of short sellers—as reflected by heavy short selling—to identify overpricing.

To test if short sellers are compensated for entering crowded trades after controlling for other covariates, we use follow Diether et al. (2008) and run monthly panel regressions. Specifically, we run monthly return regressions of the form:

$$RET_{i,t+1} = \alpha + \beta_1 * CROWDED\ SHORT_{i,t} + \theta' x_{i,t} + \epsilon_{i,t+1}, \quad (2)$$

where $RET_{i,t+1}$ is the future return of stock *i* over one month, $CROWDED\ SHORT_{i,t}$ is our short sellers' crowdedness measure for stock *i* at time *t*, and $x_{i,t}$ is a vector of control variables, as described below. Our set of controls follows from previous studies and include *LOAN SUPPLY*, the total number of shares owned by institutions with lending programs; *SHORT INTEREST,* the total quantity of shares that were loaned out as a percentage of shares outstanding; *UTILIZATION*, the quantity of shares loaned out as a percentage of shares available to be borrowed; *LOAN FEE* is the cost of borrowing a share in bps per annum; *TURNOVER*, the natural log of trading volume as a percentage of shares outstanding; *BID-ASK Spread*, the natural log of the (as a fraction of the closing mid-price); *IDIO VOL* is the log of idiosyncratic volatility from a Fama and French (1993) three-factor regression; *MARKET CAP*., the natural log market capitalization, *MARKET-TO-BOOK*, the natural log of market-to-book ratio; *RET t-2 to t-7* , the stock return cumulated over the previous six months excluding the first month; *RET, t-13 to t-8* the stock return cumulated over the previous six months excluding the first seven month.

[INSERT TABLE 4]

If short sellers are compensated for crowding into the short position, the sign of β_1 in Equation 2 should be negative, consistent with more crowding leading to lower future returns because of crowding risk. In line with this hypothesis, Table 4 illustrates that *CROWDED SHORT* appears with a negative and significant (at the 1% level) coefficient across all specifications, with values ranging from a minimum of -0.016 (column 1) to a maximum of -0.035 (column 6). These coefficients imply that, holding other determinants constant, the increase in *CROWDED SHORT* in month *t* leads to stock returns of between -1.6% and -3.5% in the following month. As expected, and in line with previous literature, SHORT INTEREST is a bearish signal as a stand-alone predictor in the specification 2. After controlling for SHORT INTEREST (specification 3), the coefficient on SHORT INTEREST becomes statistically insignificant after controlling for *CROWDED SHORT*. As a result, we can conclude that short sellers' crowdedness has a significant impact on predicting future returns above SHORT INTEREST. The SHORT INTEREST does not regain its statistical significance after controlling for equity lending conditions and other firm characteristics (specification 6). The results suggest *CROWDED SHORT* is a robust predictor of future returns in the cross-section, with economic relevance beyond SHORT INTEREST predictions.

In sum, our results in this section confirm the role of crowding risk among short sellers as a distinctive and economically relevant driver of overpricing in the cross-section of stock returns.

V. Long-Run Performance of Crowded Shorts

We show in the previous sections that short sellers' crowdedness predicts future returns over a short horizon of one month. This section examines potential reversal patterns in shorts' crowdedness predictive power. If short-sellers have long-term value-relevant information about firm fundamentals, their crowding into the short positions should predict returns over a long horizon and is unlikely to be followed by return reversals. The negative predictive power of shorts crowdedness around fundamental events, however, is likely to be transitory if it is based on short-term opportunistic trading behavior with little fundamental information.

We implement the reversal test in three steps. Since the reversal pattern can depend on firm size, we first divide our sample firms into two size groups based on previous quarter-end market capitalization. This allows the reversal pattern to vary by firm size. Second, within each size group, we separate firms into quintiles, with the first (fifth) quintile containing the most (least) crowded 20% of firms. We hold the five portfolios for three, six, nine, and twelve months after their formation and compute holding period returns for each quintile. If shorts that rush into the position have predictive power for future returns, the difference between the most and the least crowded portfolio quintiles should be negative. If the CROWDED SHORTs do not have accurate information content, we expect to observe a quick and significant reversal of the return difference back to zero after a few months. In contrast, if shorts contain information about firm fundamentals, the return effect should be permanent, and we should not see a reversal pattern.

We report the corresponding results in Table 5. With the return horizon extended to twelve months, we present results based on risk-adjusted returns, computed as raw returns adjusted by the Fama-French-Carhart (1997) four-factor model. We adjust standard errors using the Newey and West (1987) methodology to correct for autocorrelation, with the number of lags equal to the length of the holding period.

[INSERT TABLE 6]

In Panel A of Table 5, the cumulative three-month alpha to a strategy that buys (sells) low (high) *CROWDED SHORT* measure is 4.01% and is statistically significant. The above strategy generates a 7.95% cumulative alpha when we extend the horizon to nine months. This cumulative return increases to 10.85% if measured over the next 12 months. Therefore, we do not find any evidence of strategy return reversal.

In Panel B, we investigate the performance of the *CROWDED SHORT* strategy in the small market capitalization stocks. We first sort firms into two portfolios (by median) using market capitalization in month t and then sort small market capitalization stocks into quintiles using the *CROWDED SHORT* measure in month *t*. We then report the cumulative alphas of this strategy with horizon [x,y] months after the portfolio formation. The return difference for the small firms over t+1 to t+3 is 7.86% per month with a standard error of 0.0074, which indicates that going long stocks with low *CROWDED SHORT* and going short stocks with high *CROWDED SHORT* earns statistically significant alphas. When we extend the horizon to twelve months, the above long-short strategy alphas decline slightly but do not reverse.

Panel C Table 5 reports the same statistics for large market capitalization firms. The cumulative returns measure over the t+1 to t+3 horizon is 1.46% with a standard error of 0.0046 and increases to 4.02% when the time horizon is extended to 12 months. Again, we do not observe any evidence of a reversal. However, compared with the smaller firms, the return difference is smaller in magnitude, indicating that the predictive power of CROWDED SHORT is stronger and more persistent for smaller firms than for large ones. Overall, there is no statistical evidence of a share price reversal in returns up to twelve months.

To summarize, our examination of return patterns after the trades of short sellers finds no evidence of significant reversals. Especially for small- and large firms, crowding into the short position appears to be mainly motivated by firm fundamental information rather than short-term temporary mispricing.

VI. Alternative Explanations. Short-Selling Constraints

It is generally accepted that short-sale constraints affect the efficiency of security prices (Miller, 1977). Duffie, Garleanu, and Pedersen (2002) develop a model in which search costs and bargaining over loan fees generate endogenous short-selling constraints and affect asset prices. In our case, the lending supply of shares could be viewed as a proxy for the cost of searching. Bai, Chang, and Wang (2006) show that short-sale constraints can lower asset prices and make them more volatile. This happens because short-sale constraints have a significant impact on informed investors, which lowers the informative value of prices. In principle, the CROWDED SHORT could respond to short-selling constraints unrelated to crowding risk.

To show this is the case, in Table 6, we repeat the double-sorted portfolio analysis of Table 3 using either LOAN SUPPLY, LOAN FEE, and VAR (LOAN FEE) as the first conditioning variable. Each of these variables has been shown by prior research (see Geczy et al. (2002), Saffi and Sigurdsson (2011)) to capture the severity of the short-selling constraints in a stock. If our findings purely reflected Miller's Hypothesis, CROWDED SHORT-sorted portfolios should generate negative returns only on stocks with low LOAN SUPPLY, high LOAN FEES and high VARIANCE of LOAN FEES. On the contrary, CROWDED SHORT generates statistically significant risk-adjusted spreads on monthly portfolios (Table 6) of between 0.43% and 1.14% per month on the stocks with the lowest shorting fees, lowest supply of lendable shares and lowest loan fee variance. Spreads on monthly portfolios are economically and statistically significant for all constraint measures.

VII. Crowded Shorts and Short Squeezes

In the previous section, we found that a CROWDED SHORT position is associated with increased share-lending constraints, such as low LOAN SUPPLY and increased share-lending fees. Implicitly levered short positions and the risk of share loan recalls coupled with share-lending constraints may force short sellers to exit crowded positions prematurely, triggering exit frictions. Forced exit out of a CROWDED SHORT position may lead to a rapid increase in share price primarily due to the excessive covering of short positions. This situation occurs because a stock lender recalls his stock to settle a sale, and the short seller cannot replace his stock loan due to the limited LOAN SUPPLY. Hence, short sellers rush to cover their position by buying shares at a higher price in the open market to meet margin requirements or to avoid losses. The rapid price increase, known as a short squeeze, may lead to positive return skewness. If there is a small probability that short sellers are forced to exit crowded position, *CROWDED SHORT* should predict higher positive skewness in stock returns. We use "all lenders squeeze," as defined by Schultz (2023), to gauge the risk of *short squeezes*. This measure identifies a short squeeze event as one where the shares available to lend are fewer than the shares on loan the previous day. We calculate the percentage of days a short squeeze occurs for stock i in month t. To test this prediction, we run a regression of future *short squeeze* on *CROWDED SHORT* and a set of control variables, including

$$SHORT\ SQUEEZE_{\ i,t+1} = \alpha_i + \tau_t + \beta_1 \times CROWDED\ SHORT_{i,t} + \theta' x_{i,t} + \epsilon_{i,t,} \qquad (4)$$

where α_i and τ_t are respectively stock- and time-fixed effects, $CROWDED\ SHORT_{i,t}$ is our CROWDED SHORT measure for stock i at time t, and $x_{i,t}$ is a vector of control variables, as described below.

[INSERT TABLE 7]

The results in Table 7 support our prediction. *CROWDED SHORT predicts* short squeezes in all regression specifications.

The portfolio analysis of the *CROWDED SHORT* strategy in section IV indicates that short sellers are compensated for the risk of holding CROWDED SHORT positions and earning abnormal returns, on average. Thus, they might want to maximize exposure to CROWDED SHORT positions.

Following the *CROWDED SHORT* strategy, however, can occasionally generate significant losses. Therefore, awareness of a CROWDED SHORT position is crucial because arbitrageurs may try to exit their position simultaneously and in the same direction. The mass withdrawal from the CROWDED SHORT position can create liquidity problems as all short sellers rush to exit a "burning house".

VIII. Crowdedness: Retail versus Institutional Short Sellers?

Not all short sellers have information, abilities, and constraints alike. Analysing the heterogeneity can deliver insights into the nature of short seller's crowding and their roles in the stock market. According to a study conducted by Boehmer, Jones, and Zhang (2008), most short sales are executed by institutions, accounting for approximately 75% of the total, while individuals make up less than 2% of the short sales market. As a group, retail investors may face high lending fees and entrance restrictions when short-selling. Therefore, it is likely that the arbitrageurs (institutional short sellers) could crowd into the short position.

To further explore who contributes most to the predictability of returns to CROWDED SHORT positions, we examine how the trading patterns of retail and institutional short sellers affect crowding.

To test this prediction, we run a regression of *CROWDED SHORT on retail and institutional short selling* and a set of control variables, including

$$CROWDED\ SHORT_{i,t+1} = \alpha_i + \tau_t + \beta_1 \times RETAIL\ SHORT_{i,t} + \beta_2 \times INST\ SHORT_{i,t} + \theta' x_{i,t} + \epsilon_{i,t,} \quad (4)$$

where α_i and τ_t are respectively stock- and time-fixed effects, $RETAIL\ SHORT_{i,t}$ is retail investors' shorting flow, expressed as a percentage of shares outstanding, $INST\ SHORT_{i,t}$

institutional investors' shorting flow, expressed as a percentage of shares outstanding, and $x_{i,t}$ is a vector of control variables, as described below.

[INSERT TABLE 8]

The results are reported in Table 7. The key finding is that institutional short selling is a powerful predictor of the CROWDED SHORT position. The *Inst Short* coefficient is 0.939 (t-stat 2.04). As predicted, institutional short sellers engage in crowding.

IX. Crowded Shorts and Price Efficiency

In the preceding sections, we show that short sellers crowd into the short positions. We next investigate the broader implications of crowding risk. If crowding risk is a limit to arbitrage, it may also decrease price efficiency. We use our proxy for crowding risk to examine whether higher crowding risk lowers price efficiency. We begin by calculating the price efficiency measures proposed by Hou and Moskowitz (2005). We run a regression of the daily returns of stock *i* on the current market return, as well as the returns for the previous four weeks. The coefficients on the lagged market returns indicate the degree of price delay. If the return on stock *i* immediately reflects all available information, the lagged returns will show limited explanatory power. Specifically, for each stock *i* and month *t*, we estimate the regression:

$$RET_{i,t} = \alpha + \beta_1^{i,y} \times r_{m,t} + \left(\sum_{j=1}^{4} \delta_j^{i,y} \, r_{m,t-j} \right) + \epsilon_{i,t}$$

where $RET_{i,t}$ is the return on stock *i* in week t and $r_{m,t}$ is the market return from CRSP in week *t*. We then calculate the measure of price delay, labelled D1 as follows:

$$D1_{i,y} = 1 - \frac{R^2_{[\delta_1=\delta_2=\delta_3=\delta_4=0]}}{R^2}$$

where the denominator is unconstrained R^2, and the numerator is the R^2 from a regression in which the coefficients on all lagged market returns are constrained to equal zero. Next, we test whether our proxy for crowding risk is linked to greater price delay, indicating lower price efficiency. Using the D1 delay measure, we run the following regression:

$$PRICE\ DELAY_{i,t} = \alpha_i + \tau_t + \beta_1 \times CROWDED\ SHORT_{i,t} + \theta' x_{i,t} + \epsilon_{i,t,} \quad (5)$$

where α_i and τ_t are respectively stock- and time-fixed effects, $CrowdedShort_{i,t}$ is our CROWDED SHORT measure for stock *i* at time *t*, and $x_{i,t}$ is a vector of control variables, as described below. future short sale constraints is associated with decreased price efficiency.

[INSERT TABLE 9]

The results are reported in Table 9. We find crowding in the short position is associated with increased price efficiency. In all models, the negative and statistically significant coefficient on *CROWDED SHORT* indicates that higher crowding into the short position is associated with a significantly larger price delay for the measure calculated in equation (5). Next, we re-run all regression models, introducing an interaction variable *SHORT SQUEEZE*CROWDED SHORT.* The coefficient is positive, economically, and statistically significant across models 5-8. This result suggests that *CROWDED SHORT* positions that experience temporary short squeezes reduce the speed of the flow of information into prices.

X. Economic State Variables and Dynamic Weighting of Crowded Short Portfolio

Several studies found that short sellers' stock-picking behavior may vary conditionally with the business conditions. According to Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) the most significant advantage of gathering firm-specific signals occurs during economic expansions as these periods generally correspond with decreased overall market volatility and reduced risk. They argue that if short sellers have limited information-processing capacity, they would behave more like stock pickers during economic expansions and market timers during recessions. Veldkamp (2005) posits that the production of information rises during expansions due to the real investment facilitating the generation of cost-effective signals. Furthermore, in Van Nieuwerburgh and Veldkamp's (2006) model, the accuracy of information signals is heightened during expansions. Dixon and Kelly (2022) find that short positions reflect new firm-specific information in expansions and aggregate information in recessions.

Theories of overconfidence suggest that during economic expansions, short-sellers may display superior stock-picking abilities compared to recessions. According to Gervais and Odean (2001), successful traders tend to become overconfident and learn about their capabilities. They contend that collective overconfidence will vary with stock price levels because the typical trader has a long exposure. Thus, during economic expansions characterized by generally rising stock prices, short sellers may have a greater opportunity to take advantage of their overconfident trading competitors.

Studies of market-wide sentiment conclude that investor sentiment affects stock prices. For example, Stambaugh, Jianfeng, and Yuan (2011) explore the role of investor sentiment in a broad set of anomalies in cross-sectional stock returns. They find that the short leg of each strategy is more profitable following high sentiment. This is consistent with the notion that the overpricing is stronger following high sentiment periods. Changes in investor sentiment, however, might not be fully countered by shoer sellers due to noise trader risk (Shleifer and Summers, 1990).

Whether short sellers gather different types of information during different economic states is ultimately an empirical question. We examine this formally by investigating how the mean return of a *CROWDED SHORT* portfolio is linked to the variation in the economic state variables. To relate *CROWDED SHORT* trading to various state variables that predict the strategy's profits, we run time-series regressions of returns to the *CROWDED SHORT* trading strategy on these market state variables. We include the following conditioning variables: the difference between the interest rates on interbank loans and short-term U.S. government debt,"T-bills", (TED), Wugler's (2006) sentiment index (Sentiment), and the degree to which street economists either under- or overestimate those top-tier indicators posted on Bloomberg economic calendar (Bloomberg Economic Surprise).

We conduct the following market timing test using the portfolio of *CROWDED SHORT* stocks.

$$\text{Ret}_{CROWDED\ SHORT,\ t} = \alpha_0 + \beta_1 \times R_{m,t-1} + \beta_2 \times TED_{t-1} + \beta_3 \times Sentiment_{t-1} + \beta_4 \times Bloomberg\ Economic\ Surprize_{t-1} + \varepsilon_t, \quad (5)$$

where $\text{Ret}_{CROWDED\ SHORT,\ t}$ is monthly returns of the long-short CROWDED SHORT trading strategy; *Rm* is the value-weighted index of all firms in CRSP; *TED spread* denotes the difference between the interest rates on interbank loans and short-term U.S. government debt ("T-bills"); *Sentiment* is Baker and Wugler's (2006) sentiment index. *Bloomberg Economic Surprize* is an index calculated as the % difference between the actual economic data release and the median of analysts' forecasts for that release, smoothed with a six-month decay. Each data release is weighted annually within its sector and the overall index.

[INSERT TABLE 10]

The regression results are reported in Table 10. The results show that profits from the *CROWDED SHORT* trading strategy are strongly related to economic state variables. It relates negatively to *TED Spread, Sentiment, and Bloomberg Economic Surprise*. All three economic state variables for 1 month-ahead strategy returns are statistically significant. The widening in *TED spread* in month t leads to a reduction of the *CROWDED SHORT* profitability in month t+1. This result indicates that shocks to asset liquidity and, as a result, the liquidity of the margin loan market hurt the profitability of the *CROWDED SHORT* trading strategy. We also find that when the *Sentiment* is high in month *t,* the profitability of the *CROWDED SHORT* strategy falls in month *t+1.* These results could imply that short sellers who crowd into the short position might be deterred by the risk in arbitrage (Shleifer and Vishny, 1997). Short sellers crowd into the short position in the belief that its price is too high can be correct in that the price eventually falls, but they face the risk that the price will go up before it goes down. Such a price move, requiring additional capital, can force the short seller to liquidate at a loss. Short sellers could also avoid crowding due to the increased attention from noise traders as in De Long, Shleifer, Summers, and Waldmann (1990). *CROWDED SHORT's* profitability also suffers following the increase in the percentage difference between the forecast and actual economic data release. The coefficient of Bloomberg Economic Surprize is -0.0045 with a standard error of 0.0024. This result indicates that stocks with a high dispersion of opinion and binding short-sale constraints may experience price increases that are not justified by fundamentals (Miller 1977).

The evidence from the prior section suggests that the TED spread, Sentiment index, and Bloomberg economic surprise predict the profitability of the *CROWDED SHORT* trading strategy. But to what end? Whether this prediction results in successful market timing is a separate and potentially more interesting question. In our case, we use economic state variables as timing signals to increase or decrease portfolio weights of the *CROWDED SHORT* trading strategy (buy least crowded stocks and sell short most crowded stocks). Using the insight from the economic states and CROWDED SHORT analysis, we design a trading strategy that dynamically adjusts the weights on the *CROWDED SHORT* trading strategy. Specifically, to generate a trading signal, we use three indices jointly: *TED* spread, which denotes the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"); Baker and Wugler’s (2006) *Sentiment* index; and *Bloomberg Economic Surprize* index (*BES*) which tracks the degree to which published economic data differ from forecasts. We combine these three indices to construct the portfolio weights as follows. First, we define a combined index, V_t that represents the economic state on month *t* such that;

$$V_t = \frac{1}{3}TED_t + \frac{1}{3}Sentiment_t + \frac{1}{3}BES_t \tag{5}$$

We then define monthly standardized V_t:

$$Z_t = \frac{V_t - \bar{V}_t}{\sigma_V} \tag{6}$$

Assuming the state of the economy to behave normally distributed with a mean, μ_v and standard deviation, σ_v, we transform Z_t into a weight measure such that;

$$W_t = 2 * (1 - F[Z_t]) \tag{7}$$

where *F* is the cumulative normal distribution parameterized by μ_v and σ_v. Thus, a greater (lower) value of W_t indicates tilting (sidestep) the portfolio towards (away from) the trading strategy in month *t+1*. In other words, W_t allows us to move in and out of a financial market based on economic state variables.

[INSERT TABLE 11]

Panel A Table 11 presents a comparison of the performance of the various *CROWDED SHORT* trading strategies. Next to each strategy, we report excess returns, standard deviations, risk-adjusted returns, and sharp and information ratios. The CROWDED SHORT (benchmark) trading strategy earns 11.16 % annual alpha (with a sharp information ratio of 0.96 and 38.81 correspondingly) when we do not use any signals to trade. When, however, we use trading signals to tilt dynamic portfolio weights, the performance of the *CROWDED SHORT* trading strategy gradually improves. For example, using *Sentiment* to increase (decrease) investment alpha to the CROWDED SHORT trading strategy to 16.41% per annum (with sharp and information ratio of 1.62 and 50.40 correspondingly). The dynamic *CROWDED SHORT* strategy performs best when it utilizes trading signals from *Sentiment* and *Bloomberg Economic Surprise*: when Sentiment and Bloomberg Economic Surprize increase (decrease) in month *t*, the portfolio weights sidestep (tilting) away (towards) from the *CROWDED SHORT* trading strategy. This strategy yields a 16.7% monthly average alpha with a sharp (information) ratio of 1.64 (53.58).

Overall, Tables 10 and 11 indicate that the timing of economic state variables can increase the profitability of the *CROWDED SHORT* trading strategy. The implementation of the CROWDED SHORT trading strategy, which involves adjusting the weights of the signals used in the approach, generates significantly more profitable strategies.

XI. Conclusion

We show that the crowdedness in a short position is an important component of short seller returns. Using a novel measure of *CROWDED SHORT* at the security level, we examine the determinants of short crowdedness and its impact on asset prices. While crowdedness has declined slightly over time, it exhibits significant cross-sectional variation. The portfolio strategy that buys (sells short) low (high) *CROWDED SHORT* stocks is associated with sizable variation in average returns after controlling for common risk factors. Yes, CROWDED SHORT positions also experience occasional short squeezes. Exiting CROWDED SHORT positions can sometimes hurt short sellers' returns and destabilize the market.

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Table 1
Summary Statistics

Variables	mean	sd	p1	p25	p50	p75	p95
Panel A: Lending Market Characteristics							
CROWDED SHORT	30	20	2	15	25	40	73
SHORT INTEREST, %	5.25	6.54	0.03	1.37	3.00	6.80	17.22
LOAN SUPPLY, %	23.19	9.49	2.55	17.88	24.12	27.98	40.89
LOAN FEE, %	2.77	10.59	0.31	0.31	0.31	0.52	12.19
UTILIZATION, %	10.50	17.03	0.04	1.20	3.82	10.90	53.50
Panel B: Firm Characteristics							
RETURN, %	0.18	13.33	-37.36	-5.46	0.34	6.05	19
BID-ASK SPREAD, %	0.47	0.76	0.01	0.04	0.11	0.48	2.31
IDIO VOL	0.38	0.26	0.09	0.21	0.31	0.48	0.87
TURNOVER, %	2.75	72.52	0.02	0.32	0.62	1.07	2.95
MARKET CAP ($B)	8.88	38.82	0.01	0.21	0.97	4	34.95
BOOK-TO-MARKET	0.61	0.70	0.02	0.24	0.46	0.80	1.51

Panel C: Correlation Matrix

	CROWDED SHORT	SHORT INTEREST	LOAN SUPPLY	LOAN FEE	UTILIZATION	Return	BID-ASK Spread	IDIO VOL	TURNOVER	MARKET CAP	BOOK-TO-MARKET
CROWDED SHORT	1.00										
SHORT INTEREST	0.82	1.00									
LOAN SUPPLY	-0.46	-0.37	1.00								
LOAN FEE	0.21	0.09	-0.02	1.00							
UTILIZATION	0.68	0.57	-0.25	0.40	1.00						
RETURN	-0.02	-0.03	0.01	-0.03	-0.03	1.00					
BID-ASK SPREAD	-0.20	-0.23	-0.07	0.00	-0.09	-0.04	1.00				
IDIO VOL	0.21	0.27	0.05	0.27	0.31	-0.07	-0.11	1.00			
TURNOVER	0.15	0.13	0.03	0.25	0.16	0.04	0.01	0.22	1.00		
MARKET CAP	-0.02	-0.10	0.03	-0.05	-0.11	0.01	-0.13	-0.07	-0.02	1.00	
BOOK-TO-MARKET	-0.13	-0.08	-0.01	0.04	-0.06	-0.05	0.23	0.09	0.07	-0.08	1.00

This table presents summary statistics for the main variables in our analysis. For each variable, we first compute monthly cross-sectional summary statistics and report the time-series mean of each statistic. The sample combines equity lending data from S3 Partners with data from CRSP and Compustat. The sample contains approximately 4000 U.S. equities from January 2015 through December 2020. Panel A displays the mean, standard deviation, and the 1st, 25th, 75th, and 95th percentiles of selected equity lending variables. *CROWDED SHORT* is a proprietary measure calculated by S3 Partners. *SHORT INTEREST* is the total quantity of shares loaned out as a percentage of outstanding shares. *LOAN SUPPLY* represents the total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding. *LOAN FEE* is the cost of borrowing a share in % per annum. *UTILIZATION* is the quantity of shares loaned out as a percentage of shares available to be borrowed. Panel B displays firm characteristics. *RETURN* is the stock return expressed in percentage per month. *BID-ASK SPREAD* is the daily BID-ASK spread as a percentage of mid-price averaged over a month in %; *IDIO VOL* is the log of idiosyncratic volatility from a Fama and French (1993) three-factor regression. *TURNOVER* is the total number of shares sold on a day as a percentage of shares outstanding; *MARKET CAP* is the market value of equity in dollar billions. *BOOK-TO-MARKET* is a ratio of BOOK-TO-MARKET value. Panel C presents the correlation matrix. We first compute cross-sectional correlations each month and then report the time-series mean.

Figure 1. Time-series of CROWDED SHORT and SHORT INTEREST. This figure shows monthly averages of CROWDED SHORT score and SHORT INTEREST between January 15 and December 2020.

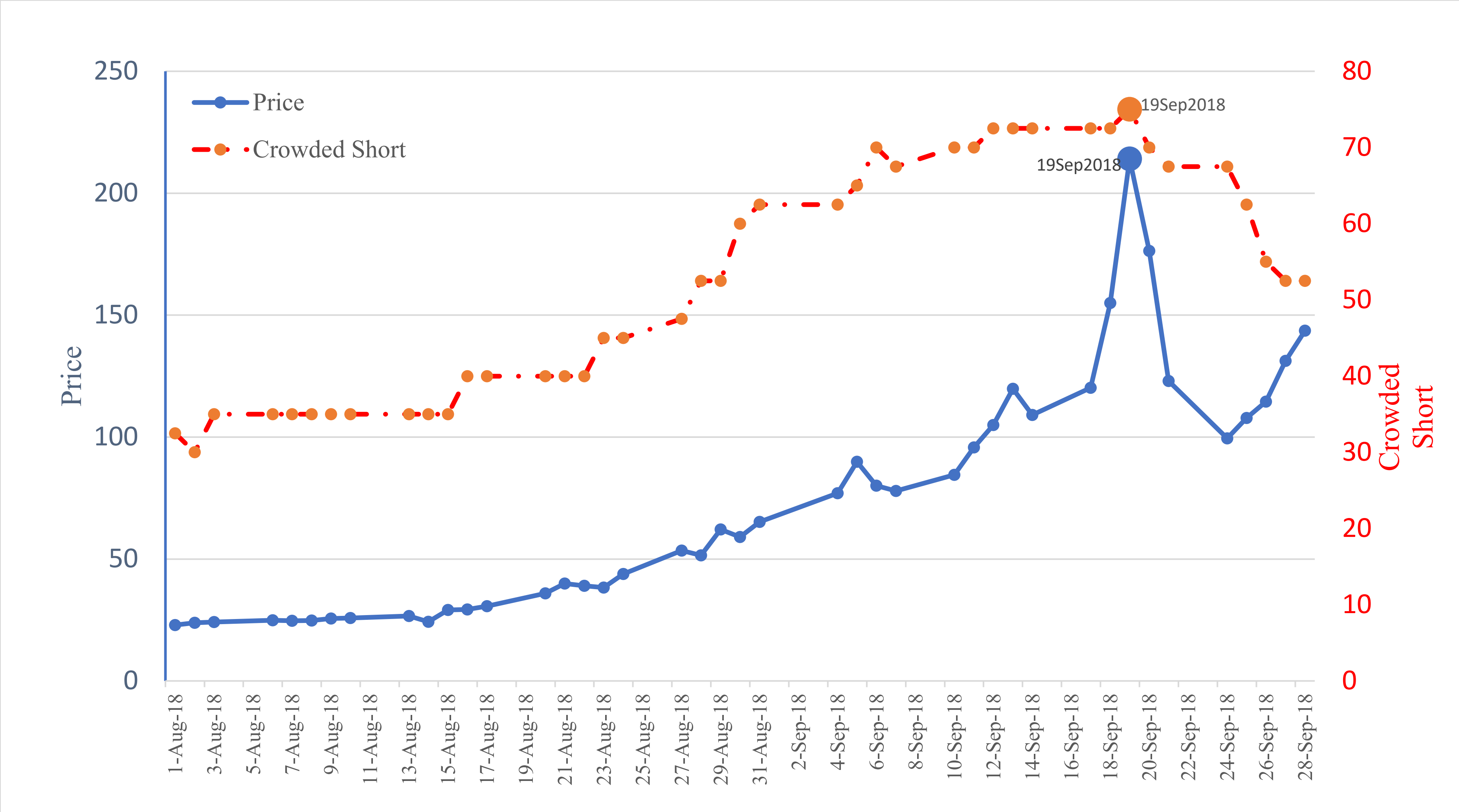

Figure 2. Tilray Short Squeeze. This figure displays the time series of the evolution of Tilray's Brand Inc Price (blue solid line, left *y*-axis) and *CROWDED SHORT* (red dashed line, right *y*-axis) from 1st August 2018 to 28th September 2018.

Table 2 Forecasting Model of Future Crowding

Explanatory Variable	*CROWDED SHORT, t+1*		
	1	2	3
TURNOVER	-1.018	-1.336	-1.337
	[-7.18]	[-6.80]	[-6.28]
MARKET CAP	0.016	0.019	0.022
	[7.16]	[6.24]	[6.70]
ANALYST DISPERSION	-0.000	-0.000	-0.000
	[-0.23]	[-1.06]	[-1.22]
SHORT INTEREST	2.971	3.001	3.039
	[32.70]	[28.76]	[28.00]
LOAN SUPPLY	-0.203	-0.226	-0.209
	[-7.70]	[-7.20]	[-6.40]
LOAN FEE	-0.023	-0.047	-0.047
	[-0.94]	[-1.31]	[-1.16]
UTILIZATION	0.081	0.075	0.069
	[5.56]	[4.48]	[3.94]
OPEN INTEREST	-0.005	-0.004	-0.004
	[-7.86]	[-5.40]	[-5.28]
VOLATILITY		-0.013	-0.014
		[-7.74]	[-7.67]
BOOK-TO-MARKET		-0.001	-0.002
		[-0.60]	[-0.95]
BID-ASK		0.010	0.010
		[5.02]	[5.04]
PROFITABILITY		-0.069	-0.064
		[-3.59]	[-3.34]
LEVERAGE		0.011	0.013
		[1.34]	[1.59]
VAR (LOAN FEE)		-0.000	-0.000
		[-0.20]	[-0.54]
RET $_{t\text{-}6\ to\ t}$			-0.008
			[-3.38]
RET $_{t\text{-}12\ to\ t\text{-}7}$			-0.007
			[-3.09]
Adj. R^2	0.920	0.922	0.923
No. of obs.	119,066	103,074	102,656

This table reports coefficient estimates and associated standard errors (in parentheses) of the following panel regression $CROWDED\ SHORT_{i,t} = \alpha_i + \tau_t + \beta' x_{i,t} + \varepsilon_{i,t}$, where $CROWDED\ SHORT_{i,t}$ denotes the level of crowdedness in the short position in stock i on month t, α_i and τ_t are stock- and time-fixed effects respectively, and $x_{i,t}$ represents the set of covariates, which includes *TURNOVER,* the average turnover over the previous month; *MARKET CAP,* the market value of equity; *ANALYST DISPERTION*, the ratio between the standard deviation and the average of the quarter-ahead EPS forecasts; *SHORT INTEREST,* the total quantity of shares that were loaned out as a percentage of shares outstanding; *LOAN SUPPLY*, total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding;

LOAN FEE, the cost of borrowing a share in % per annum; *UTILIZATION,* the quantity of shares loaned out as a percentage of shares available to be borrowed; *OPEN INTEREST*, the (log) of the call and put open interest; *VOLATILITY*, the natural log of return volatility (calculated as the standard deviation of daily stock returns each month); *BOOK-TO-MARKET* is a ratio of book-to-market value; *Return*, the stock return expressed in percentage per month; *BID-ASK* , the daily bid-ask spread as percentage of mid-price averaged over a month in %; *PROFITABILITY*, the ratio of operating income before depreciation to total assets, *LEVERAGE*, the ratio of total debt to total market value of assets; *VAR (LOAN FEE),* the variance of the borrowing fees*;* $RET_{i,t\text{-}6\ to\ t}$, the stock returns cumulated over the previous six month; $RET_{i,t\text{-}12\ to\ t\text{-}7}$, the stock return cumulated over the previous six months excluding the first six month. t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. Adj.R^2 is the adjusted R-square, and No. of obs. is the number of observations.

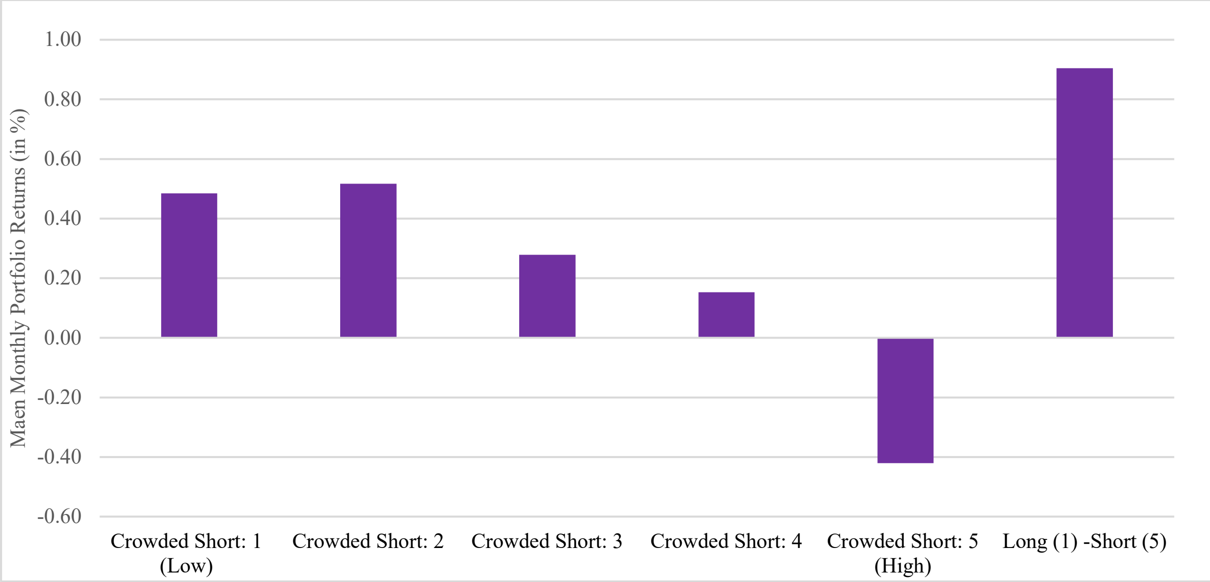

Figure 3. Portfolio Returns from conditioning on *CrowdedShort* Score. Panel A displays mean monthly percentage returns for portfolios and Panel B plots the cumulative return to long-short portfolios calculated over the period January 2015 through December 2020. Each month, portfolios are formed by sorting into quintiles using the previous month's CROWDED SHORT score and these portfolios are held for one month. At the far right of Panel A, we display returns from a long-short portfolio that takes a long position in the low CROWDED SHORT portfolio (quintile 1) and a short position in the high CROWDED SHORT portfolio (quintile 5). In Panel B, we plot the cumulative returns to a long-short portfolio that buys stocks in the lowest quintile of CROWDED SHORT and shorts stocks in the highest quintile of CROWDED SHORT position.

Table 3

Monthly Portfolio Four-Factor Alphas from Conditioning on Crowded Short Position

Panel A: CROWDED SHORT and SHORT INTEREST

Portfolio	CROWDED SHORT 1	CROWDED SHORT 2	CROWDED SHORT 3	CROWDED SHORT 4	CROWDED SHORT 5	Long (1) - Short (5)
All Firms	-0.29	-0.35	-0.61	-0.97	-1.57	1.28
	[-2.18]	[-3.10]	[-6.00]	[-7.72]	[-8.50]	[6.73]
Short Interest:						
1 (Low)	-0.08	-0.38	-0.31	-0.38	-0.43	0.35
	[-0.44]	[-2.95]	[-2.54]	[-3.16]	[-3.48]	[2.08]
2 (High)	-0.74	-0.84	-1.06	-1.28	-1.79	1.05
	[-4.41]	[-6.87]	[-6.68]	[-8.08]	[-7.49]	[4.71]

Panel B: CROWDED SHORT and FIRM SIZE

Portfolio	CROWDED SHORT 1	CROWDED SHORT 2	CROWDED SHORT 3	CROWDED SHORT 4	CROWDED SHORT 5	Long (1) - Short (5)
Size:						
1 (Low)	-0.15	-0.38	-0.78	-1.46	-2.22	2.07
	[-0.76]	[-2.67]	[-3.90]	[-6.38]	[-7.58]	[7.27]
2 (High)	-0.26	-0.35	-0.37	-0.57	-1.07	0.81
	[-1.92]	[-2.42]	[-4.40]	[-5.76]	[-6.14]	[3.93]

This table presents monthly Fama-French-Carhart 4 factor alphas (in percent) calculated from January 2015 through December 2020. In Panel A, we examine equal-weighted portfolios formed by first sorting into two portfolios using the previous month's SHORT INTEREST and then sorting into quintiles using the previous month's CROWDED SHORT score. In Panel B, we examine equal-weighted portfolios formed by first sorting into two portfolios using the previous month's MARKET CAPITALIZATION and then sorting into quintiles using the previous month's CROWDED SHORT score. All portfolios are held for one month. The last column in each panel, Long (1) – Short (5), shows returns on a long-short portfolio that takes a long position in the low CROWDED SHORT portfolio (quintile 1) and a short position in the high CROWDED SHORT portfolio (quintile 5). The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate on the excess market return (MKT), size (SMB), BOOK-TO-MARKET (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard errors using Newey and West's (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period.

Table 4

Crowded Short and Future Returns

Explanatory Variable	*RET, t+1*					
	1	2	3	4	5	6
CROWDED SHORT	-0.016		-0.018	-0.018	-0.017	-0.035
	[-9.68]		[-3.44]	[-2.91]	[-2.80]	[-4.49]
SHORT INTEREST		-0.038	-0.015	-0.019	-0.031	-0.038
		[-7.94]	[-0.86]	[-0.80]	[-1.32]	[-1.69]
BOOK-TO-MARKET				0.007	0.007	0.005
				[2.09]	[2.00]	[1.62]
MARKET CAP				-0.035	-0.039	-0.044
				[-8.17]	[-7.43]	[-7.67]
RET $_{t\text{-}6\ to\ t}$				-0.007	-0.007	-0.005
				[-0.98]	[-0.98]	[-0.67]
RET $_{t\text{-}12\ to\ t\text{-}7}$				-0.007	-0.007	-0.006
				[-1.07]	[-1.09]	[-0.85]
BID-ASK					-0.009	-0.006
					[-2.07]	[-1.56]
IDIO VOL					0.012	0.010
					[1.83]	[1.54]
TURNOVER					-0.001	-0.001
					[-2.44]	[-2.68]
SUPPLY						-0.137
						[-4.25]
LOAN FEE						-0.026
						[-2.36]
UTILIZATION						-0.016
						[-2.06]
Adj. R^2	0.211	0.190	0.223	0.246	0.246	0.248
No. of obs.	176,519	176,519	176,519	161,890	159,238	157,375

This table reports Fama and MacBeth (1973) estimates and associated *t*-statistics (in parentheses) from the daily regression $RET_{i,t+1} = \alpha + \beta\ CROWDED\ SHORT_{i,t} + \theta' x_{i,t} + \varepsilon_{i,t+1}$, where $RET_{i,t+1}$ is future return of stock *i* in month *t+1*, $CROWDED\ SHORT_{i,t}$ denotes the level of crowdedness in the short position in stock i on month *t*, and $x_{i,t}$ is a vector of control variables. Our set of controls includes: *SHORT INTEREST*, the total quantity of shares that were loaned out as a percentage of shares outstanding; *BOOK-TO-MARKET* is a ratio of *BOOK-TO-MARKET* value; *MARKET CAP*, the market value of equity; $RET_{i,t\text{-}6\ to\ t}$, the stock returns cumulated over the previous six months; $RET_{i,t\text{-}12\ to\ t\text{-}7}$, the stock return cumulated over the previous six months excluding the first six month; ; *BID-ASK* spread, the daily BID-ASK spread as percentage of mid-price averaged over a month in %; *IDIO VOL*, the log of idiosyncratic volatility from a Fama and French (1993) three-factor regression; *TURNOVER*, the total number of shares sold on a day as a percentage of shares outstanding; *SUPPLY*, the total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding; *LOAN FEE*, the cost of borrowing a share in % per annum; *UTILIZATION*, the number of shares loaned out as a percentage of shares are available to be borrowed; t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. Adj.R^2 is the adjusted R-square, and No. of obs. is the number of observations.

Table 5

Long-Run Performance of CROWDED SHORT Portfolios

Panel A: All Firms	Holding period						
	t+1 to t+3	*t+1 to t+6*	*t+1 to t+9*	*t+1 to t+12*	*t+4 to t+6*	*t+7 to t+9*	*t+10 to t+12*
CROWDED SHORT 1	-1.27	-2.00	-3.61	-4.66	-1.41	-1.58	-1.57
	[-3.53]	[-3.77]	[-6.44]	[-4.91]	[-4.27]	[-5.27]	[-4.62]
CROWDED SHORT 5	-5.28	-9.95	-14.46	-18.63	-5.34	-5.59	-5.35
	[-11.21]	[-13.63]	[-19.54]	[-16.20]	[-10.47]	[-10.35]	[-9.22]
Long (1) - Short (5)	4.01	4.01	7.95	10.85	13.97	3.94	4.01
	[7.86]	[7.86]	[10.19]	[15.96]	[11.18]	[7.88]	[8.18]
Panel B: Small Firms							
CROWDED SHORT 1	-1.73	-3.21	-5.25	-8.63	-1.87	-1.99	-1.60
	[-3.33]	[3.96]	[-5.96]	[-6.64]	[-4.80]	[-6.42]	[-4.57]
CROWDED SHORT 5	-9.59	-17.62	-25.22	-31.32	-9.49	-9.79	-9.21
	[-12.14]	[-15.46]	[-17.64]	[-19.10]	[-10.78]	[-11.38]	[-11.66]
Long (1) - Short (5)	7.86	14.41	19.96	22.70	7.62	7.80	7.61
	[10.62]	[11.81]	[11.95]	[9.38]	[9.41]	[9.63]	[10.87]
Panel C: Large Firms							
CROWDED SHORT 1	-0.58	-0.91	-1.78	-2.19	-0.61	-0.84	-1.04
	[-1.68]	[-1.23]	[-2.41]	[-1.63]	[-1.61]	[-2.10]	[-2.54]
CROWDED SHORT 5	-2.05	-3.71	-5.27	-6.20	-1.84	-2.06	-2.00
	[-5.26]	[-6.18]	[-6.43]	[-6.39]	[4.82]	[5.72]	[-5.13]
Long (1) - Short (5)	1.46	2.81	3.49	4.02	1.23	1.22	0.96
	[3.17]	[3.35]	[4.50]	[3.41]	[2.62]	[2.71]	[2.29]

This table presents the average monthly returns for portfolios calculated from January 2015 through December 2020. In Panel A, we examine equal-weighted portfolios formed by sorting firms by *CROWDED SHORT* measure in month *t*. Quintile 1 contains stocks with low crowding, and Quintiles 5 contains stocks with high crowding. In Panel B, we investigate equal-weighted portfolios formed by first sorting firms into two portfolios (by median) using market capitalization in month *t* and then sorting small market capitalization stocks into quantiles using the *CROWDED SHORT* measure in month *t*. In Panel C, we investigate equal-weighted portfolios formed by first sorting firms into two portfolios (by median) using market capitalization in month t and then sorting large market capitalization stocks into quantiles using the *CROWDED SHORT* measure in month *t*. The calendar month *t* return of each portfolio with horizon [*x*,*y*] months after formation is the cumulative of month *t* portfolio returns. The Long (1) – Short (5) shows returns on a long-short portfolio that takes a long position in the low *CROWDED SHORT* portfolio (quintile 1) and a short position in the high *CROWDED SHORT* portfolio (quintile 5). The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate on the excess market return (MKT), size (SMB), BOOK-TO-MARKET (HML), and momentum (MOM) factors. We report the time-series mean of the parameter estimates and adjusted standard errors using Newey and West's (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period. Coefficients marked with ***, **, and * are significant at the 1%, 5%, and 10% levels.

Table 6

Crowded Short and Short-Selling Constraints

Portfolio	CROWDED SHORT 1	CROWDED SHORT 1	CROWDED SHORT 1	CROWDED SHORT 1	CROWDED SHORT 1	Long (1) - Short (5)
Loan Supply:						
1 (Low)	-0.47	-0.78	-1.04	-1.06	-1.61	1.14
	[-3.27]	[-6.27]	[-5.74]	[-7.61]	[-7.34]	[4.69]
2 (High)	-0.12	-0.32	-0.52	-0.33	-1.39	1.27
	[-0.65]	[-2.27]	[-3.00]	[-3.30]	[-4.73]	[4.36]
Loan Fee:						
1 (Low)	-0.33	-0.26	-0.43	-0.59	-0.75	0.43
	[-2.57]	[-2.08]	[-4.81]	[-6.56]	[-5.26]	[2.37]
2 (High)	-0.25	-0.48	-1.56	-2.18	-2.36	2.11
	[-0.96]	[-2.02]	[-4.83]	[-7.22]	[-7.68]	[6.37]
Var (Loan Fee):						
1 (Low)	-0.31	-0.33	-0.51	-0.69	-0.83	0.52
	[-2.31]	[-2.59]	[-5.48]	[-5.77]	[-5.07]	[2.71]
2 (High)	-0.22	-0.28	-0.71	-1.57	-2.16	1.94
	[-1.25]	[-2.27]	[-3.90]	[-6.24]	[-8.18]	[7.27]
Idio Vol:						
1 (Low)	-0.18	-0.12	-0.37	-0.41	-0.66	0.48
	[-1.38]	[-1.03]	[-3.53]	[-4.23]	[-4.72]	[2.72]
2 (High)	-0.42	-0.79	-0.95	-1.58	-2.15	1.73
	[-2.35]	[-4.08]	[-5.64]	[-7.01]	[-8.23]	[7.33]

This table presents monthly Fama-French-Carhart 4 factor alphas (in percent) calculated from January 2015 through December 2020. Results refer to portfolios formed by first sorting on the level of one of the variables in the first column into two portfolios, then sorting CROWDED SHORT into quintiles. SUPPLY is the quantity of shares available to be borrowed expressed as a percentage of shares outstanding; FEE is the borrowing fee; VAR (LOAN) FEE is the variance of the borrowing fees over the previous month; IDIO VOL is the idiosyncratic volatility over the previous month; The reported alphas are the intercept from regressing portfolio returns in excess of the risk-free rate on the excess market return (MKT), size (SMB), BOOK-TO-MARKET (HML), and momentum (MOM) factors. t-statistics are based on adjusted standard errors using Newey and West's (1987) methodology to correct for autocorrelation, with a number of lags equal to the length of the holding period.

Table 7

Crowded Short and Short Squeeze

Explanatory Variable	*SHORT SQUEEZE i, t+1*			
	1	2	3	4
CROWDED SHORT	0.162	0.036	0.067	0.054
	[8.72]	[2.38]	[4.45]	[3.40]
SHORT INTEREST	-0.575	-0.609	-0.647	-0.576
	[-7.57]	[-11.08]	[-8.97]	[-6.65]
LOAN FEE		0.004	0.002	-0.026
		[0.19]	[0.10]	[-1.14]
UTILIZATION		0.012	0.037	0.029
		[0.96]	[2.92]	[2.46]
SUPPLY		-0.577	-0.356	-0.325
		[-13.90]	[-7.98]	[-7.22]
RET t-2 to t-7			0.006	0.004
			[2.03]	[1.69]
RET t-8 to t-13			0.004	0.003
			[1.68]	[1.38]
BOOK-TO-MARKET			0.005	0.003
			[1.42]	[1.03]
MARKET CAP			-0.003	-0.002
			[-0.91]	[-0.47]
BID-ASK			-0.012	-0.010
			[-4.49]	[-4.00]
IDIO VOL			0.011	0.009
			[2.26]	[2.07]
TURNOVER			-0.003	-0.028
			[-11.93]	[-4.84]
PROFITABILITY			0.069	0.054
			[1.79]	[1.55]
LEVERAGE			0.006	0.002
			[0.49]	[0.19]
TAIL FEE				0.001
				[2.49]
TAIL UTILIZATION				0.000
				[0.90]
VAR (LOAN FEE)				0.002
				[1.34]
Adj. R^2	0.431	0.453	0.428	0.421
No. of obs.	173,222	171,001	141,673	135.766

This table reports coefficient estimates and associated standard errors (in parentheses) of the following panel regression *SHORT SQUEEZE i, t+1* =αi + τt + β’xi,t + εi,t, where SHORT SQUEEZE i, t+1 is a percentage of days in a month when the shares available to lend are less than the shares on loan the previous day in stock i on month t+1, αi and τt are stock- and time-fixed effects respectively, and xi,t represents the set of covariates, which includes *SHORT INTEREST*, the total quantity of shares that were loaned out as a percentage of shares outstanding; *LOAN SUPPLY*, total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding;

LOAN FEE, the cost of borrowing a share in % per annum; *UTILIZATION*, the quantity of shares loaned out as a percentage of shares available to be borrowed; *BID-ASK* spread, the daily bid-ask spread as percentage of mid-price averaged over a month in %; *IDIO VOL*, the log of idiosyncratic volatility from a Fama and French (1993) three-factor regression; *TURNOVER*, the total number of shares sold on a day as a percentage of shares outstanding; MARKET CAP, the market value of equity; *BOOK-TO-MARKET* is a ratio of book-to-market value; *RET i,t-1* , the stock returns cumulated over the previous month; *RET i,t-2 to t-7* , the stock return cumulated over the previous six months excluding the first month. t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. Adj.R^2 is the adjusted R-square, and No. of obs. is the number of observations.

Table 8

Institutional and Retail Short Sellers' Crowding

Explanatory Variable	*CROWDED SHORT, t+1*							
	1	2	3	4	5	6	7	8
RTL SHORT	-1.203	-0.740	-5.882	-8.603				
	[-2.25]	[-0.32]	[-2.47]	[-3.45]				
INST SHORT					0.939	5.791	8.199	9.793
					[2.04]	[3.40]	[3.99]	[4.58]
TURNOVER	0.135	-0.287	0.022	0.059	-0.036	-1.291	-1.660	-2.082
	[3.09]	[-2.12]	[0.16]	[0.37]	[-1.17]	[-3.93]	[-4.08]	[-4.97]
MARKET CAP	-0.038	-0.020	-0.028	-0.027	-0.038	-0.020	-0.029	-0.028
	[-8.52]	[-4.85]	[-5.19]	[-4.43]	[-8.54]	[-4.91]	[-5.35]	[-4.56]
ANALYST DISP	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	[0.19]	[0.47]	[0.54]	[0.50]	[0.19]	[0.50]	[0.59]	[0.56]
LOAN SUPPLY	-1.218	-0.888	-0.961	-0.981	-1.215	-0.879	-0.949	-0.968
	[-26.62]	[-19.18]	[-18.15]	[-17.87]	[-26.70]	[-19.17]	[-17.97]	[-17.64]
LOAN FEE	0.255	-0.034	0.075	0.082	0.252	-0.042	0.059	0.065
	[6.73]	[-0.97]	[2.39]	[2.46]	[6.81]	[-1.20]	[1.83]	[1.84]
UTILIZATION		0.569	0.568	0.566		0.567	0.566	0.563
		[29.62]	[25.64]	[24.87]		[29.27]	[25.22]	[24.32]
OPEN INTEREST		0.003	0.003	0.002		0.003	0.003	0.003
		[2.46]	[2.42]	[2.21]		[2.79]	[2.92]	[2.90]
VOLATILITY			-0.016	-0.016			-0.015	-0.013
			[-9.96]	[-9.41]			[-7.78]	[-6.88]
BOOK-TO-MARKET			-0.016	-0.016			-0.016	-0.016
			[-3.49]	[-3.51]			[-3.48]	[-3.51]
BID-ASK			-0.000	-0.000			-0.004	-0.004
			[-0.11]	[-0.03]			[-1.03]	[-1.20]
PROFITABILITY			0.001	-0.005			0.003	-0.003
			[0.02]	[-0.15]			[0.09]	[-0.08]
LEVERAGE			0.038	0.040			0.037	0.039
			[2.37]	[2.45]			[2.28]	[2.34]
VAR (FEE)			-0.006	-0.006			-0.006	-0.006
			[-3.97]	[-3.81]			[-3.50]	[-3.35]
RET t-6 to t				-0.001				-0.002
				[-0.33]				[-0.51]
RET t-12 to t-7				0.001				0.001
				[0.37]				[0.37]
Adj. R^2	0.774	0.836	0.842	0.843	0.774	0.836	0.843	0.844
No. of obs.	135,489	117,212	102,941	102,523	135,489	117,212	102,941	102,523

This table reports coefficient estimates and associated standard errors (in parentheses) of the following panel regression $CROWDED\ SHORT_{i,\ t} = \alpha_i + \tau_t + \beta' x_{i,t} + \varepsilon_{i,t}$, where $CROWDED\ SHORT_{i,\ t}$ denotes the level of crowdedness in the short position in stock i on month t, α_i and τ_t are stock- and time-fixed effects respectively, and $x_{i,t}$ represents the set of covariates, which includes *TURNOVER,* the average turnover over the previous month; *MARKET CAP,* the market value of equity; *ANALYST DISPERTION*, the ratio between the standard deviation and the average of the quarter-ahead EPS forecasts; *LOAN SUPPLY*, total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding; *LOAN FEE,* the cost of borrowing a share in % per annum; *UTILIZATION,* the quantity of shares loaned out as a percentage of shares available to be borrowed; *OPEN INTEREST*, the (log) of the call and put open interest; *VOLATILITY*, the natural log of return volatility (calculated as the standard deviation of daily stock returns each month);

BOOK-TO-MARKET is a ratio of book-to-market value; *Return*, the stock return expressed in percentage per month; *BID-ASK* , the daily bid-ask spread as percentage of mid-price averaged over a month in %; *PROFITABILITY*, the ratio of operating income before depreciation to total assets, *LEVERAGE*, the ratio of total debt to total market value of assets; *VAR (LOAN FEE),* the variance of the borrowing fees; $RET_{i,t\text{-}6\ to\ t}$, the stock returns cumulated over the previous six month; $RET_{i,t\text{-}12\ to\ t\text{-}7}$, the stock return cumulated over the previous six months excluding the first six month. t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. Adj.R^2 is the adjusted R-square, and No. of obs. is the number of observations.

Table 9

Crowded Short and Price Efficiency

Explanatory Variable	Dependent Variable: Price Delay (D1), t							
	1	2	3	4	5	6	7	8
CROWDED SHORT	-0.057	-0.075	-0.060	-0.066	-0.230	-0.293	-0.220	-0.184
	[-3.15]	[-3.49]	[-2.85]	[-2.78]	[-4.59]	[-5.80]	[-3.90]	[-2.67]
SHORT INTEREST	0.165	0.155	0.140	0.154	0.176	0.182	0.171	0.174
	[3.59]	[3.52]	[3.26]	[2.75]	[3.72]	[4.00]	[3.77]	[2.85]
LOAN FEE		0.054	0.050	0.061		0.057	0.052	0.063
		[4.45]	[4.12]	[4.75]		[4.68]	[4.34]	[5.00]
UTILIZATION		0.104	0.084	0.062		0.102	0.083	0.062
		[6.30]	[5.57]	[3.90]		[6.22]	[5.49]	[3.86]
SUPPLY		0.157	0.132	0.030		0.141	0.131	0.029
		[3.54]	[3.04]	[0.63]		[3.23]	[3.05]	[0.62]
RET t-6 to t			-0.017	0.012			-0.017	0.012
			[-1.46]	[1.04]			[-1.43]	[1.04]
RET t-12 to t-7			-0.028	-0.002			-0.028	-0.001
			[-3.73]	[-0.18]			[-3.68]	[-0.18]
BOOK-TO-MARKET				0.009				0.009
				[2.50]				[2.43]
MARKET CAP				-0.037				-0.036
				[-3.96]				[-3.93]
BID-ASK				0.009				0.009
				[1.52]				[1.49]
IDIO VOL				0.023				0.023
				[2.14]				[2.16]
TURNOVER				0.001				0.001
				[4.51]				[4.20]
SHORT SQUEEZE					-0.109	-0.114	-0.066	-0.050
					[-5.87]	[-5.95]	[-3.10]	[-2.10]

SHORT SQUEEZE*CROWDED SHORT					0.178	0.216	0.157	0.116
					[3.95]	[4.72]	[3.05]	[1.87]
Adj. R^2	0.352	0.353	0.355	0.358	0.353	0.353	0.355	0.358
No. of obs.	176,571	174,351	170,936	157,408	176,571	174,351	170,936	157,408

This table reports coefficient estimates and associated standard errors (in parentheses) of the following panel regression (D1) i, t+1 =αi + τt + β'xi,t + εi,t, where Short Squeeze i, t+1 is a percentage of days in a month when the shares available to lend are less than the shares on loan the previous day in stock i on month t+1, αi and τt are stock- and time-fixed effects respectively, and xi,t represents the set of covariates, which includes SHORT INTEREST, the total quantity of shares that were loaned out as a percentage of shares outstanding; LOAN SUPPLY, total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding; LOAN FEE, the cost of borrowing a share in % per annum; UTILIZATION, the quantity of shares loaned out as a percentage of shares available to be borrowed; Return, the stock return expressed in percentage per month; BID-ASK Spread, the daily BID-ASK spread as percentage of mid-price averaged over a month in %; IDIO VOL, the log of idiosyncratic volatility from a Fama and French (1993) three-factor regression; TURNOVER, the total number of shares sold on a day as a percentage of shares outstanding; MARKET CAP, the market value of equity; BOOK-TO-MARKET is a ratio of BOOK-TO-MARKET value; RET i,t-6 to t , the stock returns cumulated over the previous six month; RET i,t-2 to t-7 , the stock return cumulated over the previous six months excluding the first month. t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. SHORT SQUEEZE i, t is a percentage of days in a month when the shares available to lend are less than the shares on loan the previous day in stock i on month t. Adj.R^2 is the adjusted R-square, and No. of obs. is the number of observations.

Table 10

Crowding and Economic State Variables

Explanatory Variable	Dependent Variable: Monthly returns of the long-short Crowded Short strategy RET$_{CROWDED\ SHORT,\ t}$				
	1	2	3	4	5
Rm, t-1	-0.35	-0.33	-0.31	-0.28	-0.23
	[-0.71]	[0.81]	[0.78]	[0.60]	[0.85]
TED SPREAD, t-1		-0.0086			-0.98
		[1.43]			[2.51]
SENTIMENT, t-1			-0.0089		-0.010
			[2.02]		[3.25]
BLOOMBERG ECONOMIC SURPRIZE, t-1				-0.58	-0.45
				[2.00]	[1.88]
Constant	0.95	1.07	0.95	0.93	1.08
	[2.71]	[3.45]	[2.88]	[2.74]	[3.89]

This table reports coefficient estimates and associated standard errors (in parentheses) for a set of time series regression based on the following regression specification:

$$RET_{CROWDED\ SHORT,\ t} = \alpha_0 + \beta_1 \times R_{m,t-1} + \beta_2 \times TED_{t-1} + \beta_3 \times Sentiment_{t-1} + \beta_4 \times Bloomberg\ Economic\ Surprize_{t-1} + \varepsilon_t,$$

where RET$_{CROWDED\ SHORT,\ t}$ is monthly returns of the long-short CROWDED SHORT trading strategy; *Rm* is the value-weighted index of all firms in CRSP; *TED spread* denotes the difference between the interest rates on interbank loans and on short-term U.S. government debt ("T-bills"); *SENTIMENT* is Baker and Wugler's (2006) sentiment index. *BLOOMBERG ECONOMIC SURPRIZE* is an index calculated as the % difference between the actual economic data release and the median of analysts' forecasts for that release, smoothed with a six-month decay. Each of the data releases is given an annual weight within its sector and the overall index. Regressors are standardized to have 0 mean and unit standard deviation. t-statistics, reported in brackets, are based on standard errors clustered in the stock and time dimensions. Adj.R2 is the adjusted R-square, and No. of obs. is the number of observations.

Table 12

Dynamic Weighting of CROWDED SHORT Trading Strategy

Timing	Excess Return, %	Std dev, %	Alpha, %	SRatio	IR, %
Panel A: Market timing					
η (TED)	8.78	8.59	9.29	1.02	30.93
η (Sentiment)	14.7	9.1	16.41	1.62	50.40
η (Bloomberg Economic Surprize)	12.78	9.22	14.83	1.39	47.71
η (Sentiment-Bloomberg Economic Surprise)	14.98	9.12	16.7	1.64	53.58
η (TED-Sentiment-Bloomberg Economic Surprise)	14.52	8.79	15.68	1.65	51.49
η (TED-Sentiment)	12.62	8.63	16.33	1.46	46.22
η (TED-Bloomberg Economic Surprise)	12.99	8.58	13.84	1.51	51.92
Panel B: Benchmark					
CROWDED SHORT	8.25	8.56	11.16	0.96	38.81

This table reports the economic value of timing *CROWDED SHORT* trading strategy. The timing strategy η (*TED*) buys (sells) the least (most) CROWDED SHORT if the propensity of *TED* spread is low(high). Similarly, η (Sentiment) depicts the timing strategy corresponding to Wugler's (2006) *Sentiment* index, and η (Bloomberg Economic Surprise) is based on the degree to which Street economists either under- or overestimate those top-tier indicators posted on Bloomberg ECO. The remaining timing strategies follow different TED, Sentiment, and Bloomberg Economic Surprise combinations. For each strategy, we report the average return (*Avg RET*), standard deviation (*Std dev*), Alpha (Fama-French-Carhart risk-adjusted returns), Sharpe ratio (*SRatio*), and Information Ratio (*IR*). The returns are annualized and in percentage.