In Search of Shares: Inelastic Ownership as a Constraint to Short Covering

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Abstract:

Heavily-shorted firms with inelastic ownership (including passive, insider, and long-term ownership) experience higher announcement returns and greater subsequent reversals after positive earnings surprises. The higher returns are the result of higher volume and greater price impact of short covering. Our inferences are robust to alternative samples around large changes in inelastic ownership, a two-stage approach using residual ownership, and an exogenous short-covering trigger caused by macro funding shocks. We highlight a significant constraint faced by short-sellers when closing out short positions. This contrasts to the prior work examining short-selling constraints when initiating and maintaining short positions.

Keywords: short-selling constraints, securities lending, short covering, passive investing, ownership structure, earnings announcements, short squeezes

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1. Introduction

Ownership structure can affect security pricing through the supply of shares available to purchase. We study this issue by examining the effect of ownership structure on short covering by short-sellers. A round-trip of short-sale transaction involves three steps: opening (or initiating) the short position by borrowing shares and selling them, maintaining the position by paying the borrowing fee, and closing (or covering) the position by purchasing shares and returning them to the lender. There is extensive research examining constraints that limit the first two steps of short selling thereby acting as limits to arbitrage. This includes outright short-selling bans (e.g., Beber and Pagano 2013), uptick rules (e.g., Diether, Lee, and Wemer 2009), and limited lendable supply (e.g., Prado, Saffi, and Sturgess 2016) that make it difficult to open a position, and high and volatile lending fees as well as mark-to-market collateral requirement (Engelberg, Reed, and Ringgenberg 2018) that make it difficult to maintain a position. The constraints in the covering leg has received less attention potentially because the buying of shares to cover positions is considered frictionless and easy. In this paper, we identify a key constraint faced by short-sellers in this third step. In particular, we focus on the impact of reduced availability of shares caused by inelastic ownership (i.e., less sensitive to price movements, such as passive ownership) on the ability of short-sellers to cover their positions. While we focus on shares purchases driven by short-sellers in this paper, our results speak to purchases made by long buyers as well.

The ownership structure has a significant impact on the shares traded on the market. For example, index funds and ETFs are unlikely to trade shares based on price movements or mispricing, but rather based on index reconstitution and flows into and out of the funds. Similarly, insiders could be locked-in or unwilling to trade due to insider-trading concerns. In addition, long-term investors could be unwilling to respond to short-term price changes and sell their positions (e.g., Berkshire Hathaway). Providers of index products recognize the limiting effect of ownership on shares that are locked-in and not easily available to trade by using float-weights instead of overall market capitalization (e.g., S&P Dow Jones Indices 2021).

The short covering constraint caused by lack of available shares to purchase can be very costly to short-sellers. Practitioners have long recognized the idea that short-sellers might need to cover their positions quickly due to an unexpectedly large increase in stock prices, particularly when accompanied by expensive loans, margin calls, buy-in risk, and risk management protocols (Engelberg et al. 2018). This rush to cover positions could trigger a cycle of additional price increases and further covering, resulting in what is commonly known as a short squeeze (SEC 2015). Allen, Haas, Nowak, and Tengulov (2021) discuss how short covering pressures cause Volkswagen (VW) to briefly become the most valuable company in the world in 2008 as below:

> *[The undisclosed holding by banks who were hedging Porsche's derivative contracts] implied that the free-float of VW's shares was decreased significantly. Therefore, it became increasingly difficult for short-sellers to acquire VW shares to cover their short positions when the share price started rising after Porsche's press release. This in turn exerted increasing price pressure on VW's stock and resulted in more than EUR 20 billion losses for investors that had entered into these short- sell trades.* — *Allen et al. (2021)*

As in both the Volkswagen and most recently the GameStop cases, short-sellers can suffer huge losses when a limited availability of stocks for purchase is paired with high demand from short-sellers to cover their positions.[1] This limited supply of shares to purchase when short-sellers are trying to cover their positions can result in a more severe feedback loop effect in which buying

[1] Gamestop (GME) in January 2021 is another example of short squeeze. It was triggered by concerted buying of a large group of retail investors connected on the WallStreetBets online forum. The stock had short interest of 140% in mid-January and the forum urged members to buy and hold shares in GME even in the face of risks and losses. The idea was to reduce the supply of shares available for short-sellers to buy thereby squeezing them. Further, the firm also has concentrated insider and passive ownership.

demand from short-sellers raises the target firm's stock price even higher, thereby forcing short-sellers to cover even more positions.

We focus on quasi-indexer and dedicated ownership as defined in Bushee (1998) as well as insider ownership, primarily because these three easily-identifiable groups are least likely to sell their shares. We create an index of the availability of shares to be purchased, *P-Score*, as 100% *minus* the percentage of shares outstanding owned by these three types of owners. A higher *P-Score* indicates that more ownership is in the hands of owners who are willing to sell their holdings (i.e., it is easier to purchase shares to cover short positions). During our sample period, we see a slight decrease of *P-Score* from 53.8% in January 2006 to 51.9% in December 2019, consistent with the rise of index funds, ETFs, and passive investing. The cross-sectional variation is considerable – the inter-quartile range is 40% (from 32% to 72%). Consistent with prior work showing that passive ownership increases securities lending (Palia and Sokolinski 2019), we find that *P-Score* is highly negatively correlated with the lendable supply.

To get the sharpest evidence of short covering constraint, we need two conditions to generate strong short-covering demand: high existing short interest and a trigger event of good news surprise. Existing high short interest reflects a situation where there is potential pent-up demand to cover and demonstrates that initiating and maintaining short positions is not a constraint (i.e., there is demand for shorting and availability of lendable shares). The news event provides the catalyst that triggers the rush to cover short positions (i.e., opens the covering floodgates). We use "good news" earnings announcements to provide such an event as in Lasser, Wang, and Zhang (2010) and Hong, Kubik, and Fishman (2012). Together, the high short interest and the good news earnings announcement can cause short-sellers to rush to cover, thereby hurting returns. We focus on how the supply constraint driven by inelastic ownership affects returns around events that trigger purchase demand (i.e., positive earnings news). Specifically, as our main hypothesis we expect earnings announcement returns for firms with high short interest and positive earnings surprise to be higher when their stock ownership is more inelastic.

While our research design is similar to that in Lasser et al. (2010) and particularly in Hong et al. (2012), it is important to note that our paper examines the broad issue of supply constraints on security pricing. These papers focus on the demand side of short covering by examining the effect of high short interest on earnings announcement returns. Our paper focuses on the supply constraint caused by ownership structure and its effect on short-sellers. While we use the machinery in these papers, we also look at another setting of macro funding shocks as in Richardson, Saffi, and Sigurdsson (2017).

Consistent with Hong et al. (2012), using returns from day -1 to day 5, we show that prices of highly shorted firms are incrementally more sensitive to positive earnings shocks compared with prices of stocks with low short interest, a pattern attributed to the price pressure from covering the short positions. More importantly, we find that these results are primarily driven by firms with more inelastic ownership (i.e., low *P-Score*) and the between-subsample difference is significant based on multiple methods. Our inference is robust to several alternative windows.

If the price run up observed for highly-shorted firms with low *P-Score* is attributable to the buying pressure driven by demand for short covering combined with a lack of available shares to purchase, then the shock should be temporary and followed by a reversal once the demand for short covering has faded. Consistent with this prediction, we find that highly-shorted firms experience lower returns in a subsequent window (day 6 to 10) after the positive earnings announcements. More importantly, this pattern again only exists for firms with low *P-Score* and the between-subsample difference is significant. Again, the inference is robust to several alternative windows. Taken together, these results suggest that inelastic ownership constrains short-sellers' ability to cover their positions.

We delve deeper into the adverse returns experienced by short-sellers by examining two distinct but interrelated channels: (1) each unit of short covering leads to bigger price responses due to limited supply of shares (i.e., the price impact channel), and (2) the price impact triggers a reinforcing cycle causing more overall short covering (i.e., the volume channel). As expected, we find that returns around earnings announcements are significantly more sensitive to short covering for low *P-Score* firms than for high *P-Score* firms after positive earnings news. Further, we find that the greater price impact also leads to more short covering for heavily-shorted firms with low *P-Score* after positive earnings shocks.

We employ three different approaches to sharpen the inferences and to alleviate potential endogeneity concerns. First, we conduct change analyses based on large quarter-over-quarter decreases and increases in *P-Score* (i.e., more than 10 percentage points change in *P-Score*). This approach essentially uses the firm as its own control. We find that after large decreases (increases) in *P-Score*, earnings announcement returns become more (less) responsive to the buying pressure caused by short covering, and the reversals in the subsequent week become stronger (weaker). These symmetric return patterns around both increases and decreases in *P-Score* provide additional support on the role of inelastic ownership in limiting arbitrage. Second, we conduct a two-stage approach to explicitly remove (1) the impact of size (Nagel 2005) and (2) any time-invariant factors in determining *P-Score*. Using the residuals of regressing logit transformation of *P-Score* on the logged market cap and the logged market cap squared after controlling for the firm fixed effects, we find that all our main inferences remain the same. Finally, we use the market-wide funding shocks used in Richardson et al. (2017) as a quasi-experiment to observe the impact of *P-*

Score when there is an exogenous demand of short covering. Richardson et al. (2017) find that aggregate negative shocks force short-sellers to unwind their exposures and lead to trading losses. We build on their study and find that the losses are greater for portfolios with lower *P-Score* than with higher *P-Score*, providing additional confirmation of our main results based on earnings announcements.

We conduct three additional analyses. First, we broaden our analysis to examine the overall relation between *P-Score* and the profitability of short-sale transactions (not just around earnings announcements or market-wide funding shocks). Using a calendar-time approach based on Desai, Ramesh, Thiagarajan, and Balachandran (2002), we find that heavily shorted firms with low *P-Score* have much less negative future abnormal returns than their counterparts with high *P-Score*. These results suggest that high inelastic ownership, while making it easier for short-sellers to enter short positions (e.g., Prado et al. 2016), actually makes it harder for them to close their positions, therefore reducing their profits. Second, we discuss the differences between *P-Score* and *Days-to-Cover* (*DTC*), a commonly used metric of evaluating short-squeeze risk, and show that our results hold after controlling for *DTC*. Third, we emphasize that firms with lower *P-Score* are more liquid, suggesting that illiquidity is unlikely the driver of higher returns to short covering demand.

Our paper primarily contributes to the short-selling literature. Existing research studies short-selling constraints in the first two stages of the short-selling ecosystem – initiating and maintaining short positions. In contrast, this paper focuses on the constraint in the final stage: the covering of short positions. To the best of our knowledge, we are among the first to carry out a large-sample analyses on short covering constraints.[2] Other work examining short covering

[2] There are a few studies focusing on specific cases of Volkswagen (Godfrey 2016 and Allen et al. 2021), and market corners (Allen, Litov, and Mei 2006). Those authors also highlight that the lack of shares supply, usually due to explicit market manipulations, could cause rapid price increases when short sellers rush to close out their positions.

primarily focus on the reasons for short covering and the return implications. Specifically, Hong et al. (2012) and Lasser et al. (2010) examine earnings announcement returns and find that the returns of firms with high short interest become excessively sensitive to positive shocks due to short covering. Richardson et al. (2017) show that aggregate short-selling hedge returns reverse around market-wide negative shocks, which cause a reduction in overall short leverage and available capital. In these papers, short interest and the earnings announcements or aggregate funding shocks create short covering demand. In addition, Blocher and Ringgenberg (2019) find that increases in stock prices or loan fees are significant factors that drive short-sellers to cover their short positions. Boehmer, Duong, and Huszár (2018) find a positive reaction to short covering in Japanese market that only partially reverses, indicating information contents in the covering. Hong et al. (2016) examine the effect of crowded trades on short-selling profitability.

Our paper also identifies a dark side of inelastic ownership as a short covering constraint. This contributes to the literature that has documented various benefits of buy-and-hold ownership, such as reducing managerial myopia and improving governance (e.g., Bushee 1998; Zhou 2001). Relatedly, the case for passive ownership is particularly interesting, because existing work shows that it helps short-sellers by increasing the supply of lendable shares and relaxing short-selling constraints (e.g., Prodo et al. 2016). While this continues to be true, we show that it hurts short-sellers by limiting their ability to close out short positions, and as a result reduces the profitability of these positions due to price impact of the short covering. This finding adds to the literature on the dark side of passive investing instruments such as ETFs (Israeli, Lee and Sridharan, 2017).

Finally, our paper also contributes to the vast literature that examines returns around earnings announcements, including studies on earnings response coefficients (ERCs) (e.g., Collins and Kothari 1989; Ghosh, Gu, and Jain 2005) and earnings announcement premium (e.g., Ball and

Kothari 1991; Savor and Wilson 2016). The paper is related to Johnson and So (2018) who find that earnings announcement return is related to asymmetric cost of trading before earnings announcements. The asymmetric cost is attributable to price protection behavior on the part of intermediaries. This causes a predictable upward bias in pre-announcement returns that subsequently reverses. In a similar vein, our paper identifies potential correlated omitted variables that confound earnings announcements returns. In our setting, the response to an earnings announcement is affected by the level of short interest and its interaction with the nature of ownership, causing an asymmetric effect on announcement returns and subsequent reversals. As a result, researchers should account for the impact of short covering and its interaction with ownership structure when examining earnings announcement returns and ERCs.[3]

2. Constructing *P-Score* and Descriptive Statistics

2.1 Constructing *P-Score*

We construct an index to measure the proportion of shares that are easily available for investors to buy. We consider three groups of inelastic shareholders who are usually *not* ready to sell their shares to meet increasing demand: insiders, quasi-indexers, and dedicated institutional investors as classified by Bushee (1998) and Bushee and Noe (2000).

It is a common practice to exclude insider ownership to calculate "free float" in popular financial press such as Yahoo! Finance. We use the insider transaction disclosures on Form 3/4/5, compiled by WRDS Insiders Data, to infer insider ownership at the end of each month. Important to us, Form 3/4/5 reports the number of shares held by the trading insider *after* each trade. As a result, we can infer each insider's shareholding at each month-end from the most recent disclosure

[3] This paper is also related to the literature on the supply elasticity of equities. For example, Bagwell (1992) concludes that the supply curve is upward sloping based on the positive relation between the repurchase size and the premium.

in the previous three years prior to the month-end.[4] Then we aggregate all insiders' shareholdings for the same firm-month and divide by total shares outstanding to calculate the percentage of insider ownership (*Insider%*).

Bushee (1998) and Bushee and Noe (2000) classify all 13F filers into three groups based on prior investment behaviors. "Transient" institutions are characterized as having high levels of portfolio turnover and diversification, reflecting the short-term focus of those investors. "Dedicated" institutions are characterized as taking large stakes in firms and having low portfolio turnover, and "quasi-indexers" are characterized as having low portfolio turnover and highly diversified holdings. Dedicated investors and quasi-indexers share the same feature of low portfolio turnover, although for different reasons, making their shares inelastic and less available to potential buyers such as short-sellers who try to cover their positions. We use the permanent classification provided on Professor Brian Bushee's website to classify institutions. We mostly rely on Thomson Reuter Institutional (13F) Holdings databases for institutional holding, and supplement it with the WRDS 13F holding databases from 2013Q2 due to the potential data incompleteness of Thomson Reuters (WRDS 2017). Then we aggregate the shareholdings of all institutions of the same type together. As the 13F database is at the firm-quarter level, we use the last available reported number at or prior to the month-end as the shareholding for each month. We then calculate *P-Score* as 100% minus the ownership percentages of insiders, quasi indexers, and dedicated investors.[5] As examples, Amazon and Microsoft have *P-Scores* of 0.481 and 0.453,

[4] There is a trade-off for using longer or shorter period of insider trading transactions. If we use longer period, we are less likely to miss any insiders who do not trade frequently; however, we are more likely to misclassify those former-insiders as current insiders. We use Form 3/4/5 filed in the three years prior to the month-end in our analyses. Results are quantitatively similar if we use two or five years. We also exclude the first 12 months of all IPO firms as we might not have sufficient insider trading records. The inferences are unchanged if we exclude the first 24 or 36 months of all IPO firms.

[5] Shorting potentially creates another group of owners, because someone needs to buy those shares sold short by the short-sellers. This group could act has a potential pool of sellers when the short-sellers try to cover their positions. However, those investors do not change the fact that short-sellers are in a more disadvantaged position when the

respectively, at the end of 2019. This indicates that 48.1% (45.3%) of Amazon (Microsoft) stock is held by owners who may be more willing to sell their shares.

2.2 Summary statistics

Figure 1 plots the means of monthly *P-Score*, and the three components excluded in the calculation in our sample period from January 2006 to December 2019, requiring non-missing for any of those variables. We can see that the four lines are relatively stable, with *P-Score* (solid red line) ranging from 48.7% in late 2007 to 57.5% in early 2011. Quasi-indexer ownership (long dash black line) ranges from 29.9% in early 2011 to 37.3% in middle 2016, while dedicated ownership (short dash green line) remains around 3%, and insider ownership (dash dot blue line) stays around 11% during our sample period.

Next, we use the daily data at the equity loan market from Markit to calculate (a) daily short interest as the shares on loan scaled by total shares outstanding (*SIR*), (b) daily lendable supply as shares available for lending scaled by total shares outstanding (*LendSupply*), and (c) daily utilization rate as shares on the loan scaled by total shares available for lending (*Utilize*). We also collect the "daily cost of borrowing score" provided by Markit (*DCBS*).[6] We then take the monthly average of all these daily variables for each stock and create firm-month variables *SIR*, *LendSupply*, *Utilize*, and *DCBS*, respectively.

We also collect a few key firm characteristics from CRSP and I/B/E/S. Specifically, we measure *Log MktCap* as the log of market cap at the month end, *AnaCov* as the number of analysts providing any forecasts in the year, *Illiquidity* as the monthly average of Amihud (2002) illiquidity

ownership is more inelastic, because in such case those investors would have higher bargaining power when short-sellers are forced to buy from them. Nevertheless, we also address this possibility empirically by treating the short interest as additional shares available to purchase and adjusting our *P-Score* accordingly. We find that our results continue to hold after making this modification to the *P-Score*.

[6] Markit is a comprehensive dataset covering more than USD 16 trillion in global securities from 20,000 institutional funds and over three million intraday transactions. Markit's data are collected from lending desks of more than 100 institutional lenders, who collectively represent the largest pool of loanable equity inventory in the world.

measure, *Turnover* as the monthly average ratio of trading volume scaled by total shares outstanding, and *Volatility* as the monthly standard deviation of daily stock returns.

Table 1 presents sample distribution by year, summary statistics, and correlations of those variables. Overall, there are 716,846 firm-month observations from 2006 to 2019 with non-missing values of all three sets of ownership structure, equity lending, and market trading variables. Panel A shows that the sample is evenly distributed across the 14 years, with the fewest observations in 2011 (44,832) to the most in 2016 (57,057).

Panel B presents the summary statistics. During our sample period, the mean (median) of *P-Score* is 0.510 (0.483), suggesting that roughly half of the outstanding shares are freely available for purchase if there is a demand uptick. However, there is considerable variation – the interquartile range is about 0.40, with the 1st quartile of 0.324 and the 3rd quartile of 0.715. A closer look at the statistics of the three types of ownership in calculating *P-Score* reveals that the main source of variation is quasi-indexer ownership, with an interquartile range of 0.41. Insider ownership also plays a significant role with an interquartile range of 0.11.

The short-selling related variables are consistent with prior work, such as Beneish, Lee, and Nichols (2015). The average *SIR* is 3.4% and the median is 1.3%, which is consistent with their variable of *BOLQ* with the mean and median of 3.4% and 1.6% respectively. The mean (medians) of *LendSupply* is 17.1% (16.6%), *DCBS* 1.92 (1.00), and *Utilize* 24.4% (10.4%), which are all close to the stats of 17.4% (16.6%), 1.64 (1.00), and 21.5% (12%) in Beneish et al. (2015). Other variables are comparable to the statistics reported by Prado et al. (2016).

Table 1 Panel C presents the correlations among the variables in Panel B. By construction, *P-Score* is highly negatively correlated with ownership by insiders, quasi-indexers, and dedicated investors. Further, *P-Score* is highly negatively correlated with lendable shares, consistent with prior research that passive investors have a positive effect on lendable shares (e.g., Prado et al., 2016; Palia and Sokolinski 2019). *P-Score* is also negatively correlated with short interest, market cap, analyst coverage, and trading volume turnover, and positively correlated with lending fees, utilization rate of lending supply, illiquidity, and volatility.

3. *P-Score* and Short Covering after Positive Earnings Surprises

The goal of this paper is to study inelastic ownership as a constraint to short covering by limiting short-sellers' ability to buy-to-cover short positions. Our main analyses are built on Hong et al. (2012), who argue and find that the prices of highly shorted stocks are excessively sensitive to positive shocks compared with stocks with low short interest. We use Hong et al. (2012)'s framework to examine the role of inelastic ownership in the context of positive earnings announcement surprises when short-sellers likely rush to cover their short positions.[7]

3.1 *P-Score* and market reactions after positive earnings surprises

Hong et al. (2012) estimate a pooled regression of cumulative abnormal returns around quarterly earnings announcement dates on a high earnings surprise dummy variable, a dummy variable for whether a stock is highly shorted before the earnings date, and the interaction of the highly shorted dummy and the high earnings surprise dummy. The coefficient for the interaction term then reveals the difference in the sensitivity of the stock price to news between highly shorted stocks and stocks with little short interest. We adopt Hong et al.'s (2012) framework and estimate the following pooled regression, using quarterly earnings announcements from 2006 to 2019:

$$\begin{aligned} CAR_{i,t} = {} & \alpha + \beta_1 HiUE_{i,t} + \beta_2\, HiSIR_{i,t} + \beta_3 HiUE_{i,t} * HiSIR_{i,t} + MKTCAP\ dummies_{i,t} \\ & + P/E\ dummies_{i,t} + DISAGREEMENT\ dummies_{i,t} + CONVDEBT\ dummy_{i,t} \end{aligned} \tag{1}$$

[7] We do not focus on "bad news" earnings surprises because investors who own the shares do not face the same exit pressures as those faced by short-sellers around "good news" earnings surprises. Unlike owners of long positions, short-sellers face unlimited downside risk, margin requirements, leverage, and buy-in risk. As a result, we do not expect to see any effect of inelastic ownership on firms with high short interest around "bad news" announcements as there is no pressure to close short positions. In untabulated analyses we find results consistent with this expectation.

$$+ \text{VOLATILITY dummies}_{i,t} + \text{INDUSTRY dummies}_{i,t} + \text{EXCHANGE dummies}_{i,t}$$
$$+ \text{QUARTER dummies}_{i,t} + \varepsilon_{i,t}$$

CAR is the cumulative abnormal returns from day -1 (i.e., the trading day before the earnings announcement date) to day 5 in main analyses and we examine other windows in robustness tests.[8] Abnormal returns are adjusted by the four-factor characteristic-based portfolio return as in Daniel, Grinblatt, Titman, and Wermers (1997).[9] We replace the earnings announcement date to the next day if the announcement is made after market closes based on the timestamp in IBES. As in Hong et al. (2012), *HiUE* is an indicator equal one if a firm's earnings surprise is in the top tercile of the earnings surprise distribution for stocks in our sample for that quarter and zero otherwise. *HiSIR* is an indicator equal to one if the stock is in the top tercile of the short ratio distribution for stocks in our sample for the quarter of the observation and zero otherwise. The variable of interest is the interaction term of *HiUE* and *HiSIR*, which captures the difference in the sensitivity of the stock price to news between highly shorted stocks and stocks with little short interest. All control variables are defined as in Hong et al. (2012). Specifically, we include the following series of indicators: *MKTCAP dummies* (market cap divided into 25 dummies by quarter), *P/E dummies* (price-to-earnings divided into 25 dummies by quarter and one additional dummy variable for negative earnings stocks), *DISAGREEMENT dummies* (the dispersion in analyst forecasts divided into 25 dummies by quarter), *CONVDEBT dummy* (a dummy for the firm having positive convertible debt), *VOLATILITY dummies* (return volatility of firms in the previous month calculated using daily returns divided into 25 dummies by quarter),

[8] Godfrey (2016) observes that "The stock price reaction to Porsche's news was surprisingly slow. Price discovery evolved over two days." Had Porsche not offered a solution, the squeeze would have continued in future days. The short squeeze of GME lasted more than a week. We use a slightly longer window than Hong et al. (2012) to capture a more complete picture of the short squeeze.

[9] Using raw returns or size-decile adjusted returns leads to quantitatively similar but slightly stronger results.

Fama-French 49 industry fixed effects, stock exchange fixed effects, and quarter fixed effects.[10] We tabulate results based on including stock fixed effects as in Hong et al.'s (2012) main specification, and excluding stock fixed effects would overall lead to slightly stronger results. The standard errors are clustered by stock as in Hong et al. (2012), but the inferences are not sensitive to alternative clustering approaches such as clustering by both stock and quarter.

Table 2 Panel A presents the summary statistics of these variables. *CAR[-1,5]* (* 100) in the overall sample is negative, with a mean of -0.482. The average return continues to be negative in the next one week (*CAR [6,10]* (* 100)), with a mean of -0.300. This is consistent with the average negative mean of -0.001 for *Earnings Surprise*. The mean (median) of the short interest is about 4.3% (2.1%) and its standard deviation is 5.5%. The *P-Score* in this sample tilts slightly towards the lower end, with a mean of 0.436 relative to the mean of 0.510 in the general stock-month level data tabulated in Table 1, this is largely because requiring analyst forecast data excludes those smaller firms with lower passive ownership (and therefore higher *P-Score*). We make use of the daily short interest data provided by Markit and calculate the net short covering as the net decrease in short interest in the window of [-1,5]. We find that the average net covering in this window (*ShortCov[-1, 5]*) is negative with a mean of -0.033%. We also define an indicator variable of *D_ShortCov [-1,5]* equal to one if the short interest level decreases in the window of [-1, 5]. Its mean is 0.489, suggesting that slightly less than half of the observations witness a net short covering.

Table 2 Panel B provides results of the regression in Equation 1. In Column 1, we find a positive coefficient on *HiUE*, a negative coefficient on *HiSIR*, and a positive coefficient on their

[10] We follow Hong et al. (2012) in creating 25 dummies for market cap, P/E ratio, disagreement, and volatility. This approach allows us to better control for the non-linear relationship between those variables and the dependent variables. Nevertheless, untabulated analyses show that our main results are quantitatively similar if we replace those dummies with the raw values of the four variables in the regressions.

interaction term, all highly significant. These results confirm the main finding in Hong et al. (2012) that stock prices are more sensitive to positive earnings news for highly shorted stocks, as short-sellers rush to cover short positions, therefore pushing prices even higher. Our key findings are in Columns 2 and 3, where we split the sample based on *P-Score*. Specifically, we create *P-Score* terciles within quarter and short interest tercile, and define an indicator of *HiPScore* equal to one for the top tercile and zero otherwise, in the same way as we define indicators of *HiUE* and *HiSIR* following Hong et al. (2012).[11] Then we partition the sample into the top tercile of *P-Score* (Column 2) and the remaining two terciles (Column 3). We find that the results in Column 1 are primarily driven by the sample with low *P-Score*. The coefficient of *HiUE* * *HiSIR* is insignificant in Column 2 (Coeff. = 0.254; t = 0.887) and is highly significant and positive in Column 3 (Coeff. = 0.824; t = 4.581). In terms of economic magnitude, highly shorted stocks earn more than 0.8% higher returns in [-1, 5] than less shorted stocks after the positive earnings shocks for firms with relatively low *P-Score*, but their counterparts with high *P-Score* do not earn significantly higher returns in the same window than less shorted stocks after the positive earnings shocks.

We use three approaches to evaluate the differences between the subsamples with high versus low *P-Score*. First, we follow Da, Engelberg, and Gao (2011) and Shroff, Verdi, and Yu (2014) and use bootstrapping method. Specifically, we randomly assign an observation into the top and the bottom two terciles of *P-Score*, and re-estimate the results in Columns 2 and 3 and take the difference in the coefficient of *HiUE* * *HiSIR*. We repeat this procedure for 1,000 times, and get an empirical distribution of this difference. We find that only 30 out of 1,000 random assignments generate a difference in the coefficient of *HiUE* * *HiSIR* between the high versus low

[11] Our results are similar if we focus on only the top and bottom tercile. We sort *P-Score* within short interest terciles to achieve a balanced joint distribution due to their relatively large correlations (i.e., -0.34 in Table 1 Panel C). Our inferences remain unchanged if we sort *P-Score* independently (i.e., only within the quarter), or conditional on earnings surprise terciles, or conditional on both the short interest terciles and earnings surprises terciles.

P-Score subsamples smaller than -0.570 (= 0.254 – 0.824) in our actual subsamples, suggesting a *p*-value of 0.030. Second, in Column 4 we use a triple interaction and test whether the coefficient of *HiUE * HiSIR* differs between Columns 2 and 3 in a pooled regression. The triple interaction term is significant at the 10% levels (Coeff. = -0.578; *t* = -1.786). Third, we run quarterly Fama and MacBeth's (1973) regressions of Column 4. We report in Column 5 the time-series averages of the cross-sectional regression coefficients on all independent variables, and the *t*-statistics are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. We find that the average coefficient of the triple interaction term is significant at the 1% level and is close in magnitude to its counterpart in Column 4 (Coeff. = -0.669; *t* =-2.804). Taken together, those results show that inelastic ownership leads to excessively high prices when short-sellers rush to cover their short positions due to positive earnings shocks.

While we report results based on the window of [-1, 5], our inferences are not sensitive to this research-design choice. In Panel C, we report subsample analyses results using alternative return windows around earnings announcements: [-1, 3], [-1, 4], [-1, 6] and [-1, 7]. We find the same pattern as in Panel B that the coefficient of *HiUE * HiSIR* is insignificant in the high *P-Score* sample, but highly significant at the low *P-Score* sample. Further, the bootstrapping tests show that the difference in *HiUE * HiSIR* is significant at the 10% level for all four alternative windows.

3.2 *P-Score* and return reversals in the subsequent period

Next, we investigate subsequent returns immediately after the earning announcement window. Following Hong et al.'s (2012) reasoning, if the buying pressure of short covering temporarily pushes prices to above fundamental value, we expect to see return reversals in a subsequent period. This effect should be stronger for stocks with low *P-Score* where the original positive returns are stronger. We focus on returns in the next week (i.e., five trading days) to capture this correction. In Table 3, Panel A, we replace *CAR[-1,5]* with *CAR[6,10]* as the dependent variable in Equation 1, and conduct the same analyses as in the Panel B of Table 2.

In Column 1 of Table 3 Panel A, we find a negative coefficient on the interaction term of *HiUE* * *HiSIR* (Coeff. = -0.232; t = -2.868), indicating a reversal in the subsequent period after buying pressure pushes prices up at the earnings announcement as in Hong et al. (2012). When we split the sample into high *P-Score* (Column 2) and low *P-Score* (Column 3), we find that the coefficient of *HiUE* * *HiSIR* turns positive and insignificant in Column 2 (Coeff. = 0.015; t = 0.090), but remains highly significantly negative in Column 3 (Coeff. = -0.362; t = -4.009). As in Panel B of Table 2, we also use three methods to assess the difference between the two subsamples. Specifically, the bootstrapping test indicates that only 20 out of 1,000 random assignments generate a difference in the coefficient of *HiUE* * *HiSIR* between the high versus low *P-Score* subsamples larger than 0.377 (= 0.015 – (-0.362)) in our actual subsamples, suggesting a p-value of 0.020. The triple interaction in Column 4 is significantly positive at the 10% level (Coeff. = 0.322, t = 1.755). Finally, the time-series average coefficient of the triple interaction term in Fama-MacBeth regressions is similar in both magnitude and significance level to its counterpart in Column 4 (Coeff. = 0.327; t = 1.976). The higher returns followed by stronger reversals for highly-shorted firms with low *P-Score* provide strong evidence that their stock prices are pushed to an excessively high level after positive earnings shocks, due to inelastic ownership limiting shares available for short-sellers to buy-to-cover.[12]

[12] As Hong et al. (2012) articulate, the reversals can also help us to rule out alternative explanations based on the informativeness of earnings surprises. One may argue that positive earnings surprises to highly-shorted firms have stronger informational content, and it is possible that this is particularly true for low *P-Score* firms. However, this explanation would predict that the highly shorted firms with low *P-Score* continue to outperform their lightly-shorted counterparts in the subsequent period after the positive earnings announcements.

Echoing Table 2, Panel C, we also show report subsample analyses results using four alternative five-day windows of [4, 8], [5, 9], [7, 11] and [8, 12] to test the reversals. Panel B of Table 3 show the same pattern with Panel C of Table 2 that the coefficient of *HiUE* * *HiSIR* is insignificant in the high *P-Score* sample, but highly significant at the low *P-Score* sample. Further, the bootstrapping tests show that difference in *HiUE* * *HiSIR* between subsamples is significant at the 10% level for [5, 9] and 5% level for [7, 11]. Taken together, those results indicate that our findings are robust to alternative windows.

3.3 Inelastic ownership and market reactions: channels

We argue that there are two distinct but interrelated channels through which inelastic stock ownership leads to higher market reactions in response to positive earnings shocks. First, due to the more limited supply of shares, a given level of short covering demand would increase price impact and push prices higher than otherwise (i.e., the price impact channel). Second, the greater price impact can trigger a reinforcing cycle which in turn forces more short-sellers to cover their positions (i.e., the volume channel). The availability of daily short interest data allows us to directly measure the net short covering as the decrease in short interest and examine whether these two channels influence the overall return performance separately.

Shortage of available shares can increase price impact thereby making the price more responsive to a given level of short covering demand. To formally test this prediction, in Panel A of Table 3, we replace the *HiSIR* in Panel B of Table 2 with *ShortCov[-1,5]* (i.e., the net short covering in the window of [-1, 5]) to directly capture the sensitivity of returns to short covering. We find that firms experiencing higher net short covering after the earnings announcement have incrementally higher returns after positive earnings surprises, as indicated by the significantly positive coefficient on *HiUE* * *ShortCov[-1, 5]* (Coeff. = 0.340; t = 2.821). Importantly, after we split the sample between high *P-Score* (Column 2) and low *P-Score* (Column 3), we find that the coefficient is insignificant in Column 2 (Coeff. = 0.175; *t* = 0.734), but remains highly significantly positive in Column 3 (Coeff. = 0.421; *t* = 3.011). While the difference is insignificant based on all three testing approaches, these results are consistent with the argument that a given level of short covering would push prices higher for low *P-Score* firms as compared with high *P-Score* firms, a pattern which in turn forces more short-sellers to cover their positions.

To test the effect of supply shortage on short-covering demand, we replace *CAR[-1,5]* with *ShortCov [-1,5]* as the dependent variable in Equation 1, and conduct the same analyses as in Table 2, Panel B. Panel B of Table 3 reports the results. In Column 1, we find that higher unexpected earnings and higher existing short interest are associated with decreases in short interest after the earnings announcements. Importantly, we find that the coefficient of the interaction term of *HiUE* * *HiSIR* is positive and highly significant (Coeff. = 0.128; *t* = 9.976), indicating that positive earnings lead to even bigger short covering for highly shorted firms. We split the sample between high *P-Score* (Column 2) and low *P-Score* (Column 3). While we find that the interaction term is significant for both groups, the magnitude is larger for the low *P-Score* group. This is consistent with a feedback loop causing greater short covering in firms with low *P-Score*. The difference is significant at the 5% level based on bootstrapping method and 10% level based on the other two methods.[13] Overall, the two panels in Table 4 combined provide evidence on the two channels through which inelastic ownership in highly shorted firms leads to higher market reactions in response to positive earnings shocks.

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[13] A short-seller who sells-short on day *t* can borrow the shares on *t+3* for delivery to buyers and minimize the borrowing costs, as equity transactions are settled in a *T+3* cycle (*T+2* after September 5, 2017) (Geczy, Musto, and Reed 2002). In this case, the short interest recorded in Markit on day *t* reflects short sales that had been initiated by *t-3*. If we use short interest observed on *t+3* (*t+2* after September 5, 2017) to measure short sale of day *t* when the dependent variable is about the quantity of share shorted (Richardson et al. 2017), all patterns are similar but the between-subsample difference is no longer statistically significant.

4. Robustness Analyses

4.1. Change analyses: evidence from large decreases and increases in *P-Score*

One might argue that the firms with high versus low *P-Score* are inherently different, and some unobservable differences could drive the difference in return responses to the buying pressure caused by short covering. Note such a story would need to explain the systematic reversals in Table 3. In addition, we include various control variables as well as firm and time fixed effects as in Hong et al. (2012) in our analyses, suggesting that any firm- and time-specific factors, and various time-varying firm characteristics are unlikely to be driving our results. While we do not have an alternative explanation in mind that we view as viable, we acknowledge such a possibility. Therefore, we conduct change analyses, focusing on earnings announcements before and after large changes in *P-Score*. While still imperfect, our goal is to hold the firms' fundamentals largely constant while allowing *P-Score* to vary over a short period of time.

We calculate quarter-over-quarter changes in *P-Score* using the ending *P-Score* of each calendar quarter, retaining quarters with a decrease or increase in *P-Score* of at least 10 percentage-points over the prior quarter (e.g., from 40% to 30% or to 50%). We examine how our results differ in the three years (i.e., 12 quarters) prior to the changes versus the three years after those changes. We remove earnings announcements when they are (1) prior to or after one decrease-event *and* one increase-event, or (2) between two decrease-events or two increase-events, because those observations have different pre-post classifications based on different events.[14] Further, we remove earnings announcements made in the event quarters (i.e., witnessing the large decreases or

[14] For example, if firm A has large increases in *P-Score* in QTR 4 and QTR8, we delete the earnings announcements made from QTR 5 to QTR 7 because they are after one increase in QTR 4, but before another increase in QTR 6. If firm B has one large increase in *P-Score* in QTR 10 and one large decrease in QTR 18, we delete the earnings announcements made from QTR 19 to QTR 22, because they are after one increase in QTR 10, but also after one decrease in QTR 18. For the same reason, we also delete earnings announcements made from QTR 6 to QTR 9.

increases in *P-Score* relative to the prior quarters) to avoid misclassification of pre versus post. During our sample period, we identify 3,363 *P-Score* increase events, and 3,446 decrease events. After applying the above filters, we end up with 27,208 earnings announcements in the decrease-event tests, and 34,392 earnings announcements in the increase-event tests.

Table 5 Panel A report results using large decreases in *P*-Score. We focus on the returns of the earnings announcement period (i.e., *CAR[-1, 5]*) in Columns 1 – 3 and the returns of the subsequent period (i.e., *CAR[6, 10]*) in Columns 4 – 6. For both return windows, we first report results in the subsamples of pre- and post-large decreases as well as their bootstrapping *p*-value and then the triple interaction regressions. We find that the coefficient of *HiUE * HiSIR* is insignificant in the pre-decrease period for both return windows in Columns 1 and 4, but significantly positive in Column 2 for *CAR [-1, 5]* and significantly negative in Column 5 for *CAR[6, 10]*. Both bootstrapping method and triple-interaction regressions in Columns 4 and 6 show that the subsample differences for both return windows are statistically significant.

Similarly, Table 5 Panel B report results using large increases in *P*-Score. As in Panel A, we focus on the returns of the earnings announcement period (i.e., *CAR[-1, 5]*) in Columns 1 – 3 and the returns of the subsequent period (i.e., *CAR[6, 10]*) in Columns 4 – 6. Again for both return windows, we first report results in the subsamples of pre- and post-large increases as well as their bootstrapping *p*-value and then the triple interaction regressions. Interestingly, we find that the coefficient of *HiUE * HiSIR* in the pre-increase period is significantly positive in Column 1 for *CAR [-1, 5]*, but significantly negative in Column 4 for *CAR[6, 10]*. By contrast, both coefficients are insignificant in Columns 2 and 5. The difference is insignificant at the conventional level based on both bootstrapping method and triple-interaction regressions in Columns 4 and 6.

Taken together, these results provide evidence to support the interpretation of our main results. While we cannot completely rule out the possibility of alternative explanations, the analyses in Table 5 based on both large decreases and large increases in *P-Score* make it much less likely for an alternative story to explain such symmetric patterns.

4.2 Residual *P-Score* after removing the impacts of size and firm fixed effects

As an alternative way to deal with the potential endogeneity of *P-Score*, we conduct a two-stage approach to explicitly remove (1) the impact of size (Nagel 2005) and (2) any time-invariant factors. Specifically, we build on Nagel (2005) and regress the logit transformation of *P-Score* on the logged market cap and the logged market cap squared, controlling for the firm fixed effects. We then partition the observations into subsamples with top tercile versus bottom two terciles of *P-Score* based on the residuals of this regression. Table 6 Panel A and Panel B replicates the main results reported in Table 2 and Table 3 using *Residual P-Score* rather than the raw *P-Score*.

Overall, we find that the results are similar to those reported in Table 2. Specifically, in Panel A we find that the *HiUE * HiSIR* is highly significantly positive in Column 1, and this is driven by the subsample of low *Residual P-Score* (Column 3), as the interaction is insignificant for the subsample with high *Residual P-Score* (Column 2).[15] The difference between Column 2 and Column 3 is highly significant based on all three methods of bootstrapping, triple interactions in both a pooled regression reported in Column 4, and quarterly Fama-MacBeth regressions as reported in Column 5 with the average coefficients. In Panel B we find that the *HiUE * HiSIR* is highly significantly negative in Column 1, and this is driven by the subsample of low *Residual P-Score* (Column 3), as the interaction is insignificant for the subsample with high *Residual P-Score* (Column 2). However, the difference between Column 2 and Column 3 is insignificant at the

[15] The sample size is slightly smaller than that in Table 2 Panel B because we require non-missing value for the partitioning variable – Residual *P-Score*.

conventional level based on any of the three methods, including bootstrapping, the triple interactions in a pooled regression (Column 4) and the Fama-MacBeth method (Column 5).

4.3 Funding shocks as a quasi-natural experiment and an alternative trigger of short covering demand

We study the inelastic ownership as a constraint to short covering by limiting the supply of available shares when short-sellers try to cover their positions. All analyses so far are based on positive earnings shocks as a trigger for short covering. In this subsection, we adopt another type of trigger event for short covering demand – the funding shocks as used in Richardson et al. (2017), who find that the hedge returns of buying least-shorted stocks and shorting most-shorted stocks become negative following market-wide negative shocks. They build on the fact that levered investors such as short-sellers are forced to de-lever when the funding capital becomes less available due to the heightened market uncertainty.[16] The analyses in this section serve at least three purposes. First, we provide evidence that inelastic ownership acts as a constraint to short covering in a different setting other than earnings surprises. Second, these two events are also different in nature: while positive earnings announcements trigger short covering due to the first moment effects (i.e., good news leads to higher margin requirements), the market uncertainty caused by aggregate negative shocks trigger short covering due to second moment effects (i.e., higher variance leads to higher value-at-risk). Third and most importantly, as the market-wide funding shocks are exogenous to individual firms' ownership structure, this setting also acts as a quasi-experiment for us to observe the impact of *P-Score* when there is an exogenous demand of short covering.[17]

[16] The reduction in funding can be driven by a few reasons that reinforce each other: the brokers would raise margin requirement, and the perceived risk can also lead to redemption of funds, inciting fire sales of securities.
[17] One possible setting to observe exogenous variation in *P-Score* is the Russell indexes reconstitution. We considered this setting but decided that it is not feasible due to the rule change in 2007. It is important to note that most papers

We follow Richardson et al.'s (2017) design and build a daily hedged portfolio of buying stocks in the bottom quintile of short interest and shorting stocks in the top quintile. We first confirm their main results: while this hedge portfolio leads to significantly positive risk-adjusted alpha of about 9 basis points per day, it suffers significant losses after market crashes ($D_{RET(MKT)<2.5\sigma}$, defined as one if the aggregate market return on the previous day is more than 2.5 standard deviations below the mean and zero otherwise, based on a rolling 252-day basis), after the Quant Crisis (D_{QUANT}, defined as one for trading days between August 6 – 8, 2007 and zero otherwise), after the Lehman bankruptcy (D_{LEHMAN}, defined as one for trading days between September 16 – 18, 2008 and zero otherwise), and after large spikes in VIX volatility index ($D_{Large\Delta VIX}$, defined as one if ΔVIX_{t-1}—the percentage change in the VIX volatility index from day t-2 to day t-1—is in the top quarter of the distribution and zero otherwise).[18] Their interpretation is that short-sellers are forced to unwind their short positions after the funding shocks caused by the aggregate negative shocks.

We expect the losses to the hedged portfolio constructed above would be even greater for low *P-Score* firms as the short covering triggered by funding shocks would push prices even higher. Specifically, we sort *P-Score* into quintiles within each daily quintile of short interest, and construct a hedged portfolio based on quintiles of short interest for each *P-Score* quintile. We again confirm that the significant losses after market-wide shocks are evident in each *P-Score* quintile.

using this setting focus on years prior to 2006, when the Russell 1000 simply included the 1,000 largest stocks at the end of the last trading day in May, whereas the Russell 2000 included the next 2,000 largest stocks. While there are controversies on the best practice of implementing a regression discontinuity design (RDD), it was quite common for firms switching indexes (e.g., Appel, Gormley, and Keim 2020; Wei and Young 2020). In 2007, Russell implemented a rule called "banding" to purposefully minimize the number of stocks that switch indexes each year (please refer to Appel, Gormley, and Keim (2019) page 2,730 for more details), making it difficult to use it in our paper.

[18] We use the first four out of eight proxies in Richardson et al. (2017) because they are publicly available. Note Richardson et al. (2017) use the ΔVIX_{t-1}. To highlight the impact of major funding shock events as in three other indicators, we transform ΔVIX_{t-1} into an indicator of $D_{Large\Delta VIX}$ in this analysis. Using ΔVIX_{t-1} leads to directionally the same but statistically weaker results.

To compare the loss differences attributed to *P-Score*, we regress the difference in hedged returns between the bottom and top quintiles of *P-Score* on the five Fama and French (2015) factors as well as the momentum factor (Carhart 1997), and proxies for funding shocks, as in Equation (2):

$$\text{HedgeReturnDiff}_t = \alpha_0 + \alpha_1\, \text{RMRF}_t + \alpha_2\, \text{SMB}_t + \alpha_3\, \text{HML}_t + \alpha_4\, \text{CMA}_t + \alpha_5\, \text{RMW}_t + \alpha_6\, \text{UMD}_t + \sum \alpha_i\, \text{FundingShock}_i + \varepsilon_t \quad (2)$$

where *HedgeReturnDiff* is the daily hedged return in the portfolio of the bottom quintile of *P-Score* minus the daily hedged return in the portfolio of the top quintile of *P-Score*. *RMRF* is the market factor, *SMB* is the size factor, *HML* is the book-to-market factor, *CMA* is the investment factor, *RMW* is the profitability factor, and *UMD* is the momentum factor. As in Richardson et al. (2017), we include three indicators of $D_{RET(MKT)<2.5\sigma}$, D_{QUANT}, and D_{LEHMAN} in one regression and put $D_{Large\Delta VIX}$ in a separate one. We also create *P-Score* quintiles based on both the raw numbers (as used in the main analyses) in Columns 1 – 2 and the residual values (as discussed in the prior subsection) in Columns 3 – 4 of Table 7. We find that D_{QUANT} is significantly negative at the 1% level in both Column 1 and Column 3. $D_{RET(MKT)<2.5\sigma}$ has mixed signs in Columns 1 and 3 but none is significant. D_{LEHMAN} is negative in both columns and significant at the 10% level in Column 3. $D_{Large\Delta VIX}$ is negative in both Columns 2 and 4 and significant at the 5% level in Column 2. Taken together, this alternative and exogenous trigger of short covering supports our prediction that inelastic ownership constrains supply of shares when short-sellers rush to buy-to-cover their positions.

5. Additional Analyses

5.1. *P-Score* and short-sellers' overall returns

While the analyses so far have focused on short horizon returns around an event which is likely to pressure short-sellers into covering their positions, the question is whether this is generalizable to a broader sample of short-sellers' returns. We then follow the calendar-time portfolio approach in Desai et al. (2002) and examine whether firms with high short interest are associated with less negative returns for firms with low *P-Score* than for firms with high *P-Score*.

Specifically, we form equal-weighted portfolios with monthly average of short interest in Markit higher than 10% in the previous month. We then keep each firm in the portfolio for 12 months after it first enters the portfolio. As a result, we have monthly portfolio returns from January 2006 to December 2019. We then regress the monthly portfolio excess returns on the five Fama and French (2015) factors and the momentum factor (Carhart 1997), as in Equation (3):

$$RPRF_t = \alpha_0 + \alpha_1\, RMRF_t + \alpha_2\, SMB_t + \alpha_3\, HML_t + \alpha_4\, CMA_t + \alpha_5\, RMW_t + \alpha_6\, UMD_t + \varepsilon_t \qquad (3)$$

where *RPRF* is the monthly portfolio return for the short interest sample minus the one-month risk-free rate, *RMRF* is the market factor, *SMB* is the size factor, *HML* is the book-to-market factor, *CMA* is the investment factor, *RMW* is the profitability factor, and *UMD* is the momentum factor. All risk factors are the same to those in Equation 2 but measured at the monthly level.

Table 8, Panel A reports the OLS estimate of Equation 3. We first confirm the Desai et al. (2002) results that firms with high short interest do exhibit negative alpha, consistent with the view that short-sellers are sophisticated investors. More importantly, when we split the sample based on whether the *P-Score* is in the top monthly tercile among those highly-shorted stocks, we find that the alpha for stocks with high *P-Score* is more much negative than stocks with low *P-Score* (-210 versus -29 bps).[19] This is consistent with our prediction that the buying pressure caused by short-sellers' covering pushes stock prices higher, thereby eating up their profits. In untabulated robustness analyses, we confirm that our inferences are robust if we focus on those firm-months with average short interest higher than 5% rather than 10%, if we construct calendar-time portfolio

[19] The alphas in this table are all highly significant because we focus on a small sample with very high short interest, which has strong predictive power of future returns as documented in the prior literature (e.g., Richardson et al. 2017).

at the daily level rather at the monthly level, or if we split stocks with low lending fees (i.e., General collateral or GC) and with high lending fees (i.e., on Special) based on *P-Score*.

5.2 *P-Score* and days-to-cover (*DTC*)

Finally, we discuss the relation between *P-Score* and days-to-cover (*DTC*), a metric widely used in practice to gauge the possibility of a short squeeze (Hong et al. 2016). *DTC* is calculated as short interest scaled by shares turnover, respectively representing demand and supply of shares in short covering. We find that *P-Score* is different from *DTC* in several ways. First, ownership structure is a mechanism that could influence both short interest (the numerator of *DTC*) as well as the ability to exit short positions possibly as a result of lower trading volume (the denominator of *DTC*). Indeed, we find that *P-Score* is negatively associated with both short interest and turnover, resulting a rather low correlation with *DTC* (Pearson correlation of -0.05).

More importantly, in untabulated analyses we confirm that our main results hold after explicitly controlling for *DTC*. Specifically, for the earnings announcement tests, when we create *P-Score* terciles within each *DTC* tercile, the difference between low versus high *P-Score* subsamples becomes even stronger. For the calendar-time analyses, when we partition the heavily-shorted sample based on two dimensions – high versus low *P-Score* and high versus low *DTC*, we find that low *P-Score* firms still have much less negative future returns than high *P-Score* firms even conditional on the same level of *DTC*. Taken together, those results show that *P-Score* captures a distinct construct different from *DTC*.

5.3 *P-Score* and Illiquidity

As illustrated in Amihud's (2002) illiquidity measure calculation, the price impact of each trade is higher when the liquidity is lower. As a result, it is possible that the higher earnings announcement returns to short covering demand for firms with lower *P-Score* are driven by illiquidity. We argue that this is unlikely for two reasons. First, Panel C of Table 1 shows that *P-Score* has a strong positive correlation with *Illiquidity* (Coeff. = 0.26), suggesting that firms with lower *P-Score* are actually more liquid. Second, in untabulated analyses we split the sample in Table 2 based on terciles of *Illiquidity*, and we find that the coefficient of *HiUNEX * HiSIR* is significantly more positive for the subsample with lower *Illiquidity* than for the subsample with higher *Illiquidity*. Similarly, we also find that the return reactions to short covering demand is higher for firms with higher (rather than lower) shares turnover (*Turnover*). Taken together, those results suggest that our results are unlikely driven by the liquidity-related reasons.

6. Conclusion

A round-trip short sale transaction involves three steps: opening, maintaining, and finally closing out the short position, each step having its own constraints. However, the prior literature on short-selling constraints primarily focus on the costs and frictions in the first two steps. In this paper, we show that inelastic ownership act as a constraint to short covering by limiting shares available for short-sellers to buy-to-cover their positions.

We find that highly-shorted firms experience higher returns around positive earnings surprises but greater reversals in subsequent periods when ownership is inelastic. Evidence also suggests that these higher returns for highly-shorted firms with inelastic ownership coincide with greater short covering and are more sensitive to short covering after positive earnings shocks. The results are robust to alternative samples using large changes in inelastic ownership, a two-stage approach using residual ownership, and an exogenous trigger of short covering demand caused by macro funding shocks. Generalizing these results to a setting beyond earnings announcements, we find that highly-shorted firms with more inelastic ownership are less profitable to short-sellers.

Taken together, these results provide evidence that inelastic ownership constrains short-sellers' ability to buy-to-cover their positions. As evident in the case of Volkswagen (Allen et al. 2021) and the recent case of GameStop, limited supply of shares is a major contributor to short squeezes, which are considered one of the major risks short-sellers face (Kumar 2015). Our results have implications for short-sellers in that we identify an important factor for them to evaluate potential exit risk of their short positions. The paper also highlights a potential downside to inelastic ownership, whose benefits such as reducing managerial myopia have been well documented in the literature. In particular, our paper points to the interesting impact of passive ownership on short selling: while it makes easier for short-sellers to open short positions by increasing lendable supply, it makes it harder for them to close positions by decreasing purchasable supply. Finally, our findings highlight that short covering and its interaction with ownership structure are potential correlated omitted variables that should be accounted for in studies examining earnings announcement returns.

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Appendix A: Variable definitions

Variable names	Definitions
P-Score	An index of shares available to purchase, measured as 100% – *QIX%* – *DED%* – *Insider%* at each month-end. When used in the earnings announcement setting, it is measured in the month prior to the earnings announcement
Insider%	The proportion of shares owned by all insiders measured at the end of each month. We infer each insider's shareholding at each month-end from the most recent Form 3/4/5 in the past three years prior to the month-end
QIX%	The proportion of shares owned by quasi-indexers as classified by Bushee (1998), measured by the last available reported number at or prior to the month-end
DED%	The proportion of shares owned by dedicated investors as classified by Bushee (1998), measured by the last available reported number at or prior to the month-end
SIR	The monthly average of the ratio of the daily shares on the loan from Markit scaled by total shares outstanding
LendSupply	The monthly average of the ratio of daily shares available for lending from Markit scaled by total shares outstanding
DCBS	The monthly average of "daily cost of borrowing score" created by Markit
Utilize	The monthly average of the ratio of daily shares on the loan scaled by total shares available for lending, both from Markit. Those observations with value higher than one are replaced as one
Log MktCap	The log of market cap at the month end. When used in the earnings announcement setting, it is measured at the month end prior to the earnings announcement
AnaCov	The number of analysts providing any forecasts in the year
Illiquidity	The monthly average of daily Amihud (2002) illiquidity measure, which is calculated as the log of one plus the ratio of absolute daily return (multiplied by 10^6) to its daily dollar volume
Turnover	the monthly average of the ratio of trading volume scaled by total shares outstanding
Volatility	The monthly standard deviation of daily stock returns. When used in the earnings announcement setting, it is measured in the month prior to the earnings announcement

Additional variables used in the main Earnings Announcement tests

CAR[-1,5]	The cumulative abnormal return in the window of [-1, 5], where day 0 is the earnings announcement date. Abnormal returns are adjusted by the DGTW four-factor characteristic-based portfolio returns as in Daniel et al. (1997)
CAR[6,10]	The cumulative abnormal return adjusted by the DGTW portfolio returns in the window of [6, 10], where day 0 is the earnings announcement date
Earnings Surprise	Actual quarterly EPS minus the latest consensus forecasts scaled by the price on the consensus date
Short Interest	Markit daily short interest two trading days prior to the earnings announcement date, i.e., the trading date prior to the start of the CAR window of [-1, 5]
P/E (if nonmissing)	Price-to-earnings ratio defined as the month-end price prior to the earnings announcement scaled by the latest annual diluted EPS excluding extraordinary items (only defined for positive earnings)

Disagreement	Dispersion in analyst forecasts, defined as the difference between the highest and the lowest forecasts, scaled by the price on the consensus date prior to the earnings announcement
Convdebt	The amount of convertible debt (in million dollars) measured at the latest fiscal year end at or prior to the current quarter
HiUE	An indicator equal one if a firm's earnings surprise is in the top tercile of *Earnings Surprise* sorted for stocks in our sample within each quarter, and zero otherwise
HiSIR	An indicator equal to one if the stock is in the top tercile of *Short Interest* sorted for stocks in our sample within each quarter, and zero otherwise
HiPScore	An indicator equal to one if the stock is in the top tercile of *P-Score* sorted for stocks in our sample within each quarter and each short interest tercile, and zero otherwise
ShortCov[-1,5]	Net short covering, calculated as the short interest ratio two trading days prior to the earnings announcement date minus the short interest ratio on the fifth trading day after earnings announcement
D_ShortCov[-1,5]	An indicator of net short covering, equal to one if the short interest ratio on the fifth trading day after earnings announcement is lower than the ratio prior to the earnings announcement date, and zero otherwise

Additional variables used in the robustness analyses

PostDec	An indicator equal to one for earnings announcements made in the 12 quarters after the quarter with more than 10 percentage points *decrease* in *P-Score* over the prior quarter, and zero for earnings announcements made in the 12 quarters before the quarter with such big decrease in *P-Score*
PostInc	An indicator equal to one for earnings announcements made in the 12 quarters after the quarter with more than 10 percentage points *increase* in *P-Score* over the prior quarter, and zero for earnings announcements made in the 12 quarters before the quarter with such big increase in *P-Score*
Residual P-Score	The residual of the following regression: $\text{Log}(\frac{PScore_{i,t}}{1-PScore_{i,t}}) = \beta_0 + \beta_1 \text{ Log MktCap}_{i,t} + \beta_2 (\text{Log MktCap}_{i,t})^2 + \text{Firm}_i + \varepsilon_{i,t}$
$D_{RET(MKT)<2.5\sigma}$	An indicator equal to one if the aggregate market return on the previous day is more than 2.5 standard deviations below the mean and zero otherwise. The standard deviation and mean are based on a rolling 252-day basis
D_{QUANT}	An indicator equal to one for trading days between August 6 – 8, 2007 and zero otherwise
D_{LEHMAN}	An indicator equal to one for trading days between September 16 – 18, 2008 and zero otherwise
ΔVIX_{t-1}	The percentage change in the VIX volatility index from trading day t-2 to day t-1
$D_{Large\Delta VIX}$	An indicator equal to one if ΔVIX_{t-1} is in the top quarter of the distribution, and zero otherwise
HedgeReturnDiff	The daily hedged return in the portfolio of the bottom quintile of *P-Score* minus the daily hedged return in the portfolio of the top quintile of *P-Score*. For a given day, the hedged portfolio is constructed by buying stocks in the bottom quintile of short interest, and shorting stocks in the bottom quintile of short interest.
RMRF	The market factor, obtained from Kenneth French's website. We use the daily versions of this variable and the other five factors listed below for the funding shock tests in Section 4, and the monthly versions of these variable for the short-selling profitability tests in Section 5

SMB	The size factor obtained from Kenneth French's website
HML	The book-to-market factor obtained from Kenneth French's website
CMA	The investment factor obtained from Kenneth French's website
RMW	The profitability factor obtained from Kenneth French's website
UMD	The momentum factor obtained from Kenneth French's website
DTC	The monthly average of the ratio of the daily shares on the loan from Markit scaled by daily trading volume

Table 1: Sample distribution, summary statistics, and correlations

This table reports the sample distribution across years (Panel A), summary statistics (Panel B), and Pearson correlations (Panel C) among ownership structure variables, equity lending variables, and market trading variables. The sample is at the firm-month level. In Panel C, the correlation coefficients in bold and italic are significant at the 0.01 level. All variables are defined in the Appendix A.

Panel A: The sample distribution across years

Year	Freq.	Percent	Cum.
2006	48,497	6.77%	6.77%
2007	50,733	7.08%	13.84%
2008	51,857	7.23%	21.08%
2009	45,345	6.33%	27.40%
2010	50,306	7.02%	34.42%
2011	44,832	6.25%	40.67%
2012	45,435	6.34%	47.01%
2013	47,813	6.67%	53.68%
2014	53,634	7.48%	61.16%
2015	54,689	7.63%	68.79%
2016	57,057	7.96%	76.75%
2017	55,326	7.72%	84.47%
2018	54,936	7.66%	92.13%
2019	56,386	7.87%	100%
Total	716,846	100%	

Panel B: Summary statistics of key variables (*N* = 716,846)

stats	Mean	Median	STD	Min	5^{th}	25^{th}	75^{th}	95^{th}	Max
P-Score	0.510	0.483	0.260	0.000	0.072	0.324	0.715	0.947	1.000
Insider%	0.102	0.022	0.180	0.000	0.000	0.004	0.113	0.504	1.000
QIX%	0.368	0.378	0.234	0.000	0.017	0.152	0.561	0.734	0.940
DED%	0.025	0.000	0.060	0.000	0.000	0.000	0.015	0.143	0.436
SIR	0.034	0.013	0.051	0.000	0.000	0.002	0.044	0.147	0.347
LendSupply	0.171	0.166	0.132	0.000	0.001	0.041	0.278	0.390	0.555
DCBS	1.918	1.000	1.936	1.000	1.000	1.000	1.818	6.700	10.00
Utilize	0.244	0.104	0.306	0.000	0.002	0.026	0.338	1.000	1.000
Log MktCap	3.780	0.561	10.06	0.002	0.023	0.144	2.317	19.63	96.65
AnaCov	7.754	5.000	8.051	0.000	0.000	1.000	11.00	25.00	37.00
Illiquidity	0.142	0.005	0.385	0.000	0.000	0.001	0.052	0.929	4.320
Turnover	8.390	5.390	12.10	0.060	0.562	2.510	10.00	24.70	332.0
Volatility	0.027	0.021	0.027	0.000	0.007	0.013	0.033	0.067	4.079

Panel C: Pearson correlations among key variables

1. P-Score	1	2	3	4	5	6	7	8	9	10	11	12
2. Insider%	***-0.44***											
3. QIX%	***-0.74***	***-0.21***										
4. DED%	***-0.29***	***0.17***	***-0.03***									
5. SIR	***-0.34***	***-0.01***	***0.38***	***0.03***								
6. LendSupply	***-0.58***	***-0.20***	***0.81***	***-0.03***	***0.43***							
7. DCBS	***0.40***	***0.05***	***-0.48***	***-0.05***	***0.00***	***-0.46***						
8. Utilize	***0.07***	***0.05***	***-0.11***	***-0.01***	***0.40***	***-0.05***	***0.40***					
9. Log MktCap	***-0.13***	***-0.12***	***0.24***	***-0.03***	***-0.09***	***0.17***	***-0.16***	***-0.09***				
10. AnaCov	***-0.39***	***-0.11***	***0.53***	***-0.02***	***0.23***	***0.45***	***-0.30***	***-0.04***	***0.56***			
11. Illiquidity	***0.26***	***0.13***	***-0.39***	***-0.03***	***-0.20***	***-0.36***	***0.15***	***-0.08***	***-0.14***	***-0.31***		
12. Turnover	***-0.10***	***-0.04***	***0.15***	***-0.03***	***0.40***	***0.20***	***0.11***	***0.21***	0.00	***0.24***	***-0.18***	
13. Volatility	***0.07***	***0.13***	***-0.18***	***0.02***	***0.11***	***-0.12***	***0.18***	***0.13***	***-0.15***	***-0.11***	***0.30***	***0.37***

Table 2: The buying pressure from short-sellers after positive earnings announcements

This table examines the impact of *P-Score* on how the buying pressure caused by short covering affects returns after good news earnings announcements, following the framework of Hong et al. (2012). Panel A reports the summary statistics of variables used in our main earnings-announcement tests. Panel B tabulates the regression results focusing on the return windows of [-1, 5], with full sample results in Column 1, results of top tercile of *P-Score* in Column 2, results of remaining two terciles of *P-Score* in Column 3, full sample results with triple interactions in Column 4, and quarterly Fama-MacBeth regression results in Column 5. Panel C tabulates the regression results focusing on the alternative return windows of [-1, 3], [-1, 4], [-1, 6], and [-1, 7], with results of top tercile of *P-Score* first, followed by results of remaining two terciles of *P-Score*. In both Panels B and C, we report the bootstrapping *p*-value in testing the difference in *HiUE * HiSIR* between high versus low *P-Score* subsamples based on 1,000 random samples. All variables are defined in Appendix A. *t* statistics in parentheses in Columns 1 – 4 of Panel B are based on standard errors clustered by firm. *t*-statistics in Column 5 of Panel B are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: Summary statistics (N = 164,273)

stats	Mean	Median	STD	Min	5th	25th	75th	95th	Max
*CAR[-1,5] (*100)*	-0.482	-0.274	11.25	-166.9	-17.50	-5.25	4.51	15.62	578.7
*CAR[6,10](*100)*	-0.300	-0.276	6.546	-98.71	-8.377	-2.626	1.998	7.502	651.2
Earnings Surprise	-0.001	0.000	0.018	-0.132	-0.022	-0.001	0.003	0.016	0.057
Short Interest	0.043	0.021	0.055	0.000	0.001	0.006	0.058	0.165	0.362
*Short_Cov[-1,5] (*100)*	-0.033	-0.003	0.831	-5.302	-1.386	-0.244	0.209	1.221	5.450
D_ShortCov[-1,5]	0.489	0.000	0.500	0.000	0.000	0.000	1.000	1.000	1.000
P-Score	0.436	0.417	0.225	0.000	0.039	0.289	0.575	0.849	1.000
MktCap	4.742	0.974	11.09	0.008	0.057	0.285	3.404	24.27	96.65
P/E (if nonmissing)	36.36	20.80	61.52	1.64	7.04	14.37	32.55	109.8	794.6
Disagreement	0.075	0.005	0.562	0.000	0.000	0.002	0.017	0.146	17.96
Volatility	0.024	0.020	0.017	0.005	0.008	0.013	0.029	0.056	0.194
Convdebt (in million)	28.39	0.00	115.00	0.000	0.000	0.000	0.000	200.00	1,150

Panel B: *P-Score* and the buying pressure after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[-1,5](*100)*					
Sample	Full	*HiPScore* = 1	*HiPScore* = 0	Full	Fama-MacBeth
HiUE	5.367***	5.404***	5.360***	5.353***	5.066***
	(58.704)	(33.627)	(50.101)	(50.538)	(19.490)
HiSIR	-0.501***	-0.692***	-0.294***	-0.383***	-0.280**
	(-5.277)	(-3.299)	(-2.755)	(-3.683)	(-2.093)
*HiUE * HiSIR*	0.614***	0.254	0.824***	0.826***	0.754***
	(3.979)	(0.887)	(4.581)	(4.628)	(3.388)
Bootstrapping:		Col (2) = Col (3): p = 0.030			
HiPScore				-0.094	-0.101
				(-0.753)	(-1.176)
*HiUE * HiPScore*				0.033	0.305**
				(0.183)	(2.122)
*HiSIR * HiPScore*				-0.330	-0.412***
				(-1.644)	(-2.848)
*HiUE * HiSIR * HiPScore*				-0.578*	-0.669***
				(-1.786)	(-2.804)
Observations	160,074	51,930	107,441	160,074	159,811
Adjusted R^2	0.082	0.079	0.089	0.082	0.124
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Panel C: *P-Score* and the buying pressure after positive earnings announcements based on different windows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV = 100*	*CAR[-1,3]*		*CAR[-1,4]*		*CAR[-1,6]*		*CAR[-1,7]*	
	HiPScore =	*HiPScore =*	*HiPScore =*	*HiPScore =*	*HiPScore =*	*HiPScore =*	*HiPScore =*	*HiPScore =*
Sample =	1	0	1	0	1	0	1	0
HiUNEX	5.187***	5.265***	5.303***	5.350***	5.428***	5.393***	5.549***	5.462***
	(34.707)	(51.670)	(34.118)	(50.817)	(32.797)	(48.674)	(32.852)	(48.439)
HiSIR	-0.544***	-0.285***	-0.677***	-0.283***	-0.706***	-0.303***	-0.718***	-0.295***
	(-2.910)	(-2.817)	(-3.351)	(-2.715)	(-3.269)	(-2.734)	(-3.240)	(-2.597)
*HiUNEX * HiSIR*	0.412	0.878***	0.331	0.814***	0.210	0.728***	0.144	0.656***
	(1.549)	(5.191)	(1.195)	(4.633)	(0.713)	(3.940)	(0.480)	(3.457)
	Col (1) = Col (2):		Col (3) = Col (4):		Col (5) = Col (6):		Col (7) = Col (8):	
Bootstrapping:	*p* = 0.053		*p* = 0.053		*p* = 0.054		*p* = 0.062	
Observations	51,930	107,441	51,930	107,441	51,923	107,438	51,923	107,436
Adjusted R-squared	0.085	0.093	0.082	0.091	0.077	0.086	0.075	0.085
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: *P-Score* and the reversals in the subsequent period after positive earnings announcements

This table examines the impact of *P-Score* on how the buying pressure caused by short covering affects the reversals in the subsequent period after good news earnings announcements, following the framework of Hong et al. (2012). Panel A tabulates the regression results focusing on the return windows of [6, 10], with full sample results in Column 1, results of top tercile of *P-Score* in Column 2, results of remaining two terciles of *P-Score* in Column 3, full sample results with triple interactions in Column 4, and quarterly Fama-MacBeth regression results in Column 5. Panel B tabulates the regression results focusing on the alternative return windows of [4, 8], [5, 9], [7, 11], and [8, 12], with results of top tercile of *P-Score* first, followed by results of remaining two terciles of *P-Score*. In both panels, we report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between high versus low *P-Score* subsamples based on 1,000 random samples. All variables are defined in Appendix A. *t* statistics in parentheses in Columns 1 – 4 of Panel A are based on standard errors clustered by firm. *t*-statistics in Column 5 of Panel A are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: *P-Score* and the reversals in the subsequent period

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[6,10](*100)*					
Sample	Pooled	*HiPScore* = 1	*HiPScore* = 0	Pooled	Fama-MacBeth
HiUE	0.147***	0.116	0.159***	0.163***	0.138**
	(3.271)	(1.323)	(3.159)	(3.289)	(2.457)
HiSIR	0.021	-0.070	0.086	0.053	0.064
	(0.343)	(-0.548)	(1.234)	(0.790)	(1.584)
*HiUE * HiSIR*	-0.232***	0.015	-0.362***	-0.342***	-0.335***
	(-2.868)	(0.090)	(-4.009)	(-3.806)	(-3.771)
Bootstrapping:		Col (2) = Col (3): *p* = 0.020			
HiPScore				0.076	0.037
				(1.008)	(0.717)
*HiUE * HiPScore*				-0.048	0.011
				(-0.514)	(0.193)
*HiSIR * HiPScore*				-0.112	-0.112
				(-0.901)	(-1.255)
*HiUE * HiSIR * HiPScore*				0.322*	0.327*
				(1.755)	(1.976)
Observations	160,062	51,923	107,438	160,062	159,799
Adjusted R^2	0.021	0.020	0.026	0.021	0.068
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Panel B: *P-Score* and the reversals in the subsequent period based on different windows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV = 100*	*CAR[4,8]*		*CAR[5,9]*		*CAR[7,11]*		*CAR[8,12]*	
Sample =	*HiPScore* = 1	*HiPScore* = 0	*HiPScore* = 1	*HiPScore* = 0	*HiPScore* = 1	*HiPScore* = 0	*HiPScore* = 1	*HiPScore* = 0
HiUNEX	0.441***	0.262***	0.255***	0.162***	0.069	0.165***	0.012	0.096**
	(5.016)	(5.248)	(3.095)	(3.213)	(0.764)	(3.555)	(0.138)	(2.047)
HiSIR	-0.222*	-0.029	-0.111	0.009	-0.076	0.073	-0.054	0.074
	(-1.721)	(-0.505)	(-0.924)	(0.162)	(-0.553)	(1.199)	(-0.392)	(1.227)
*HiUNEX * HiSIR*	-0.207	-0.268***	0.006	-0.256***	0.094	-0.313***	0.001	-0.207**
	(-1.265)	(-3.122)	(0.037)	(-3.055)	(0.567)	(-3.573)	(0.004)	(-2.313)
	Col (1) = Col (2):		Col (3) = Col (4):		Col (5) = Col (6):		Col (7) = Col (8):	
Bootstrapping:	*p* = 0.378		*p* = 0.062		*p* = 0.012		*p* = 0.138	
Observations	51,925	107,440	51,924	107,439	51,923	107,437	51,922	107,436
Adjusted R^2	0.023	0.033	0.022	0.032	0.023	0.034	0.018	0.034
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Inelastic ownership and market reactions after positive earnings announcements: channels

This table examines two channels through which *P-Score* affects returns of highly-shorted stocks after good news earnings announcements. Panel A presents results on the first channel: a given level of short covering would push prices even higher in low *P-Score* firms due to the short supply of shares. We use the same regression framework of Equation 1 but replace *HiSIR* with *ShortCov[-1,5](*100)*. Panel B presents results on the second channel: the price pressure would push short-sellers to cover more positions after positive earnings announcements in low *P-Score* firms. We again use the same regression framework of Equation 1 but replace *CAR* with *ShortCov[-1,5](*100)*. In both panels, we tabulate the regression results with full sample results in Column 1, results of top tercile of *P-Score* in Column 2, results of remaining two terciles of *P-Score* in Column 3, full sample results with triple interactions in Column 4, and quarterly Fama-MacBeth regression results in Column 5. All variables are defined in Appendix A. *t* statistics in parentheses in Columns 1 – 4 are based on standard errors clustered by firm. *t*-statistics in Column 5 are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: The sensitivity of returns to short covering after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[-1,5](*100)*					
Sample	Full	*HiPScore* = 1	*HiPScore* = 0	Full	Fama-MacBeth
HiUE	5.412***	5.336***	5.463***	5.458***	5.149***
	(66.166)	(37.212)	(57.324)	(58.057)	(20.616)
ShortCov[-1,5]	1.450***	1.987***	1.216***	1.222***	1.209***
	(20.573)	(12.017)	(16.914)	(16.992)	(7.405)
*HiUE * ShortCov[-1, 5]*	0.340***	0.175	0.421***	0.412***	0.347**
	(2.821)	(0.734)	(3.011)	(2.942)	(2.075)
Bootstrapping:		Col (2) = Col (3): $p = 0.137$			
HiPScore				-0.210*	-0.203**
				(-1.911)	(-2.142)
*HiUE * HiPScore*				-0.132	0.150
				(-0.836)	(0.970)
*ShortCov[-1, 5] * HiPScore*				0.788***	0.770***
				(4.633)	(7.935)
*HiUE*ShortCov[-1,5]*HiPScore*				-0.323	-0.278
				(-1.218)	(-1.272)
Observations	158,263	51,205	106,357	158,263	158,475
Adjusted R^2	0.095	0.096	0.100	0.096	0.139
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Panel B: The short covering after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)
DV = *ShortCov[-1,5](*100)*					
Sample	Full	*HiPScore* = 1	*HiPScore* = 0	Full	Fama-MacBeth
HiUE	0.062***	0.048***	0.069***	0.068***	0.062***
	(16.411)	(7.710)	(14.178)	(14.461)	(8.737)
HiSIR	0.128***	0.102***	0.150***	0.150***	0.090***
	(15.729)	(6.991)	(14.845)	(15.177)	(4.686)
*HiUE * HiSIR*	0.128***	0.105***	0.149***	0.147***	0.132***
	(9.976)	(4.973)	(9.354)	(9.275)	(8.972)
Bootstrapping:		Col (2) = Col (3): p = 0.047			
HiPScore				0.020***	0.018**
				(2.699)	(2.097)
*HiUE * HiPScore*				-0.020***	-0.022***
				(-2.691)	(-3.126)
*HiSIR * HiPScore*				-0.068***	-0.063***
				(-4.129)	(-3.434)
*HiUE * HiSIR * HiPScore*				-0.050*	-0.049*
				(-1.936)	(-1.909)
Observations	158,263	51,205	106,357	158,263	158,475
Adjusted R^2	0.033	0.046	0.037	0.034	0.072
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Table 5: Large changes in *P-Score* and the buying pressure after positive earnings announcements

This table examines how large decreases (Panel A) and large increases (Panel B) in *P-Score* affects the return patterns due to the buying pressure of short covering after positive earnings announcements. We identify large decrease and large increases in *P-Score* based on whether the quarter-over-quarter change is larger than 10 percentage points (e.g., from 40% to 30% or to 50%). We then compare earnings announcements made in the 12 quarters before and after the large decreases and increases. In both panels, we use *CAR[-1, 5](*100)* as the dependent variables from Columns 1 – 3 to examine the overreactions, and use *CAR[6, 10](*100)* as the dependent variables in Columns 4 – 6 to examine the reversals. In Panel A (B), we report results in the subsample of pre-decrease (increase) in Columns 1 and 4, results in the subsample of post-decrease (increase) in Columns 2 and 5, and results with triple interaction in Columns 3 and 6. We report the bootstrapping *p*-value in testing the difference in *HiUE * HiSIR* between pre- versus post-decrease (increase) subsamples based on 1,000 random samples. All variables are defined in Appendix A. *t* statistics in parentheses are based on standard errors clustered by firm. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: Large decreases in *P-Score* and the buying pressure after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)	(6)
DV =		*CAR[-1, 5]*			*CAR[6, 10]*	
Sample	Pre-Decrease	Post-Decrease	Full	Pre-Decrease	Post-Decrease	Full
HiUE	5.609***	5.632***	5.960***	0.235	0.358**	0.142
	(17.831)	(19.723)	(18.379)	(1.379)	(2.432)	(0.661)
HiSIR	-1.137**	-0.371	-0.847**	-0.399*	0.061	-0.326
	(-2.493)	(-1.007)	(-2.292)	(-1.720)	(0.354)	(-1.522)
*HiUE * HiSIR*	0.218	1.483***	0.042	0.239	-0.838***	0.301
	(0.312)	(3.291)	(0.062)	(0.682)	(-3.644)	(0.887)
Bootstrapping:	Col (1) = Col (2): *p* = 0.057			Col (4) = Col (5): *p* = 0.010		
PostDec			-0.076			-0.119
			(-0.328)			(-0.936)
*HiUE * PostDec*			-0.479			0.159
			(-1.184)			(0.647)
*HiSIR * PostDec*			-0.153			0.521*
			(-0.356)			(1.949)
*HiUE * HiSIR * PostDec*			1.588**			-1.218***
			(1.969)			(-2.877)
Observations	9,957	16,930	27,208	9,957	16,930	27,208
Adjusted R^2	0.161	0.096	0.095	0.032	0.031	0.028
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Large increases in *P-Score* and the buying pressure after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)	(6)
DV =		*CAR[-1, 5]*			*CAR[6, 10]*	
Sample	Pre-Increase	Post-Increase	Full	Pre-Increase	Post-Increase	Full
HiUE	6.175***	5.266***	6.210***	0.206	-0.015	0.211
	(23.774)	(18.380)	(24.801)	(1.468)	(-0.094)	(1.562)
HiSIR	-0.229	0.211	-0.417	-0.287*	0.114	-0.262*
	(-0.628)	(0.548)	(-1.393)	(-1.659)	(0.521)	(-1.723)
*HiUE * HiSIR*	0.776*	0.497	0.706*	-0.572**	-0.378	-0.521**
	(1.750)	(0.938)	(1.682)	(-2.574)	(-1.159)	(-2.424)
Bootstrapping:	Col (1) = Col (2): *p* = 0.355			Col (4) = Col (5): *p* = 0.357		
PostInc			0.745***			0.213
			(3.085)			(1.565)
*HiUE * PostInc*			-0.819**			-0.194
			(-2.291)			(-0.985)
*HiSIR * PostInc*			0.399			0.242
			(1.028)			(1.057)
*HiUE * HiSIR * PostInc*			-0.565			0.110
			(-0.849)			(0.292)
Observations	21,126	12,958	34,392	21,124	12,958	34,390
Adjusted R^2	0.096	0.103	0.091	0.042	0.064	0.030
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Robustness check using residual *P-Score*

This table replicates the results in Table 2 Panels B and Table 3 Panel A using the residual of *P-Score* obtained from regressing the logit transformation of *P-Score* on the log of market cap, the log of market cap squared, and the firm fixed effects. Panel A (B) tabulates the regression results focusing on the return windows of [-1, 5] ([6,10]), with full sample results in Column 1, results of top tercile of residual *P-Score* in Column 2, results of remaining two terciles of residual *P-Score* in Column 3, full sample results with triple interactions in Column 4, and quarterly Fama-MacBeth regression results in Column 5. In both panels, we report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between high versus low residual *P-Score* subsamples based on 1,000 random samples. All variables are defined in Appendix A. *t* statistics in parentheses in Columns 1 – 4 are based on standard errors clustered by firm. *t*-statistics in Column 5 are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: Residual *P-Score* and the buying pressure after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[-1,5](*100)*					
Sample	Full	*HiPScore* = 1	*HiPScore* = 0	Full	Fama-MacBeth
HiUE	5.367***	5.833***	5.175***	5.182***	5.006***
	(58.704)	(38.194)	(49.618)	(50.323)	(18.160)
HiSIR	-0.501***	-0.625***	-0.355***	-0.481***	-0.383***
	(-5.277)	(-3.575)	(-3.053)	(-4.472)	(-3.001)
*HiUE * HiSIR*	0.614***	0.298	0.862***	0.871***	0.733***
	(3.979)	(1.149)	(4.674)	(4.772)	(3.433)
Bootstrapping:		Col (2) = Col (3): *p* = 0.032			
HiPScore				-0.217**	-0.233***
				(-2.359)	(-3.994)
*HiUE * HiPScore*				0.538***	0.484***
				(3.275)	(2.879)
*HiSIR * HiPScore*				-0.110	-0.153
				(-0.652)	(-1.220)
*HiUE * HiSIR * HiPScore*				-0.736**	-0.637***
				(-2.469)	(-2.994)
Observations	160,074	52,687	106,669	160,074	159,811
Adjusted R^2	0.082	0.092	0.095	0.082	0.123
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Panel B: Residual *P-Score* and the reversals in the subsequent period

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[6,10](*100)*					
Sample	Full	*HiPScore* = 1	*HiPScore* = 0	Full	Fama-MacBeth
HiUE	0.147***	0.121	0.184***	0.165***	0.150**
	(3.271)	(1.639)	(3.290)	(3.007)	(2.651)
HiSIR	0.021	0.031	0.036	0.018	0.004
	(0.343)	(0.335)	(0.443)	(0.246)	(0.106)
*HiUE * HiSIR*	-0.232***	-0.186	-0.284***	-0.246**	-0.258***
	(-2.868)	(-1.383)	(-2.776)	(-2.457)	(-2.941)
Bootstrapping:		Col (2) = Col (3): p = 0.300			
HiPScore				0.056	-0.012
				(1.067)	(-0.446)
*HiUE * HiPScore*				-0.054	-0.023
				(-0.632)	(-0.414)
*HiSIR * HiPScore*				0.026	0.085
				(0.273)	(1.385)
*HiUE * HiSIR * HiPScore*				0.038	0.048
				(0.229)	(0.414)
Observations	160,062	52,683	106,661	160,062	159,799
Adjusted R^2	0.021	0.048	0.027	0.021	0.067
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Table 7: Funding shocks as a quasi-experiment for triggering short covering demand

This table reports results on how *P-Score* affects the losses of a hedged portfolio of buying (shorting) stocks in the bottom (top) quintile of short interest. The dependent variable is the daily hedged return in such a portfolio of the bottom *P-Score* (residual *P-Score*) quintile minus the daily hedged return in the portfolio of the top *P-Score* (residual *P-Score*) quintile in Columns 1 and 2 (Columns 3 and 4). The table reports the coefficients from time-series regressions of this hedge return difference on the five factors suggested by Fama and French (2015) and the sixth suggested by Carhart (1997). All variables are defined in Appendix A. Robust *t* statistics are reported in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

	(1)	(2)	(3)	(4)
DV = *HedgeReturnDiff*				
Portfolios created by sorting:	Raw *P-Score*	Raw *P-Score*	Residual *P-Score*	Residual *P-Score*
Constant	-0.069***	-0.049**	0.047***	0.056***
	(-4.031)	(-2.510)	(2.867)	(2.961)
RMRF	0.264***	0.265***	-0.024	-0.023
	(8.895)	(8.876)	(-0.905)	(-0.853)
SMB	0.098**	0.098**	-0.129***	-0.132***
	(2.353)	(2.349)	(-2.904)	(-2.965)
HML	0.039	0.043	0.033	0.030
	(0.590)	(0.658)	(0.522)	(0.479)
UMD	0.046	0.051	0.077**	0.078**
	(1.480)	(1.627)	(2.422)	(2.469)
CMA	0.018	0.026	-0.041	-0.029
	(0.213)	(0.316)	(-0.576)	(-0.411)
RMW	-0.394***	-0.394***	-0.026	-0.024
	(-7.030)	(-6.996)	(-0.465)	(-0.432)
$D_{RET(MKT)<2.5\sigma}$	0.006		-0.021	
	(0.044)		(-0.193)	
D_{QUANT}	-1.088***		-0.570***	
	(-7.765)		(-3.804)	
D_{LEHMAN}	-0.047		-1.024*	
	(-0.119)		(-1.660)	
$D_{Large\Delta VIX}$		-0.080**		-0.045
		(-2.163)		(-1.253)
Observations	3,423	3,423	3,419	3,419
Adjusted R^2	0.144	0.145	0.012	0.012

Table 8: Additional Analyses

This table reports the coefficients from time-series regressions of excess monthly portfolio returns (in excess of T-bill rate) on the five factors suggested by Fama and French (2015) and the sixth suggested by Carhart (1997). We put a stock meeting the sample requirement in the leftist column for 12 months. For each month, we calculate the equal-weighted portfolio returns. We first use all firm-months with monthly average short interest higher than 10% as in Markit. Then we split the sample based on whether the *P-Score* is in the top tercile each month among those highly-shorted stocks. The robust *t*-statistics are reported in parentheses.

Sample	Intercept	*RMRF*	*SMB*	*HML*	*RMW*	*CMA*	*UMD*	*Adj.* R^2
SIR >= 10%	-0.36	1.16	1.01	0.08	0.03	0.01	-0.36	95.01
	(-9.23)	(121.01)	(57.69)	(5.04)	(1.24)	(0.43)	(-37.97)	
SIR>=10% &	-2.10	1.33	1.07	-0.41	0.04	0.06	-0.42	64.52
HiPScore = 1	(-15.59)	(39.86)	(17.68)	(-7.78)	(0.42)	(0.71)	(-12.68)	
SIR>=10% &	-0.29	1.16	1.01	0.11	0.03	0.00	-0.36	95.57
HiPScore = 0	(-7.88)	(128.36)	(60.89)	(7.62)	(1.33)	(0.16)	(-40.01)	

Figure 1: The trend of *P-Score* and its related elements over time

This figure plots the *P-Score* (solid red line), quasi-indexer ownership (long dash black line), dedicated institutional ownership (short dash green line), and insider ownership (dash dot blue line) each month from January 2006 to December 2019. All variables are defined in the Appendix A.