In Search of Shares: Passive Ownership and Short Covering

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Abstract:

Passive ownership could help short-sellers by increasing lendable shares as previously documented, or hurt them by reducing the number of shares available to buy-to-cover their positions. Using earnings announcements as the setting, we find that heavily-shorted firms experience higher announcement returns and greater subsequent reversals after positive earnings surprises, and this pattern exists only for firms with relatively high passive ownership. The higher returns around positive earnings announcements are the result of higher volume and greater price impact of short covering. Our inferences are robust to a placebo test based on negative earnings surprises, alternative samples using large changes in passive ownership, alternative definitions of passive ownership, and exogenous macro funding shocks that trigger short-covering. Generalizing these results using calendar-time approaches, we find that heavily-shorted firms with higher passive ownership have less negative returns. Our results suggest that passive ownership can affect the supply of shares and is a significant constraint faced by short-sellers when closing short positions.

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

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The biggest factor for short-sellers, and often the most overlooked, is actually passive investing. …… (W)hen passive buys, it pulls an active holder out of the float and replaces it with a passive, so your supply of stock ends up shrinking.

— *Short-seller Carson Block of Muddy Waters Capital*[1]

1. Introduction

Certain types of stock ownership are inelastic (i.e., less sensitive to price changes) for structural reasons and/or due to institutional constraints. These owners view each stock as a "unique work of art" (Scholes 1972), with no close substitutes. 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. Prior work has documented that these inelastic or passive owners can help short-sellers by increasing the supply of lendable shares, thereby making it easier for them to open short positions (Prado et al. 2016; Palia and Sokolinski 2021). However, these owners can also reduce the number of shares available to purchase, thereby making it harder for short-sellers to close positions. As a result, passive ownership, while facilitating initiation of short positions, can be a constraint when short-sellers try to close positions. In this paper we examine the effect of passive ownership as a constraint to short covering.

This is an important issue to study for at least two reasons. First, passive investing has attracted enormous attention from regulators, market participants, and academic researchers. There is a growing literature on various benefits and costs of passive investing (e.g., Israeli et al. 2017; Ben-David et al. 2018; Glosten et al. 2021). While the conventional wisdom indicates that passive ownership facilitates short selling, its potential detrimental effect might be overlooked as the

[1] See Carson Block's interview with Financial News in a Barron's Live event in September 2021. Available at https://www.fnlondon.com/articles/short-seller-carson-block-on-gamestop-china-and-why-a-potential-market-crash-will-be-much-larger-much-faster-than-ever-20210916.

renowned short seller Carson Block argues in the opening quote of the paper. Second, practitioners have long recognized the idea of “short squeeze” that short-sellers need to buy-to-cover their positions quickly due to an unexpectedly large increase in stock prices, which in turn triggers a cycle of additional price increases and further covering (SEC 2015; 2021; Engelberg et al. 2018; Allen et al. 2021). As short squeezes could cause short sellers to suffer huge losses and distort price efficiency as evidence in the recent GameStop case (Allen et al. 2022), it is important to understand the constraints to short covering that contributes to short squeezes.

To identify a setting with demand shocks, we initially build on Hong et al. (2012) and Lasser et al. (2010) and focus on “good news” earnings announcements of heavily-shorted firms, where short sellers are likely to rush to cover their positions. This is a powerful setting for us to detect the impact of supply constraints due to the urgent and immediate demand to purchase shares by short sellers. In addition, by focusing on firms with high short interest leading to earnings announcements, we alleviate the concern that those firms are constrained in opening short positions. We examine how the supply constraint driven by passive ownership affects event returns for firms with high short interest and positive earnings news. Specifically, as our main hypothesis we expect earnings announcement returns for firms with high demand to cover would be higher when their ownership structure is more passive (i.e., supply is more constrained and thereby less responsive to price changes).

We take a broad view of passive ownership and construct an index of passive ownership based on three easily identifiable groups that are least likely to sell their shares in response to demand shocks. We start with the quasi-indexer ownership following Bushee (1998), and also consider ownership by dedicated institutions as well as insiders because those two types are less likely to sell in response to price fluctuations as well. It is important to note that Bushee’s (1998) classification of quasi-indexers and dedicated investors is primarily based on portfolio turnover. As a result, it is particularly well-suited for our study as it captures the idea of supply elasticity of ownership independent of the individual composition of the owners (index funds, ETFs, sovereign wealth funds, pension funds, etc.). Our key inferences are robust if we focus on quasi-indexer ownership as classified by Bushee (1998), or if we only use index funds and ETFs to define passive ownership.

We construct the passive ownership index, *PassScore*, as the percentage of shares outstanding owned by those three types of owners: quasi-indexers, dedicated owners, and insiders. A higher *PassScore* indicates that more ownership is in the hands of owners who are not willing to sell their holdings (i.e., it is harder to purchase shares to cover short positions). During our sample period, we see a slight increase of *PassScore* from 46.2% in January 2006 to 48.1% in December 2019. The cross-sectional variation is considerable – the inter-quartile range is 40% (from 28% to 68%). Importantly, *PassScore* is highly positively correlated with the lendable supply, consistent with prior research documenting that passive ownership facilitates securities lending (Palia and Sokolinski 2021). The key goal of this paper is to highlight the intriguing contrast that passive ownership makes it easier for short sellers to open positions, but harder for them to close their positions.

Consistent with Hong et al. (2012), using returns from day -1 to day 5 around earnings announcement, we find 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 this effect does not exist for firms with low passive ownership and is concentrated in firms with relatively high passive ownership. The difference in price response between the two groups is significant and the inferences are robust to several alternative windows. Further, to confirm that it is short covering demand rather than something else that contributes to our results, we use the immediate market reactions to "bad news" earnings announcements as a placebo test. We do not expect short-sellers to rush to cover their positions immediately after bad earnings news, and indeed do not find that highly-shorted firms exhibit differentiated market reactions to "bad news" conditional on their *PassScores.*

The natural follow-up question is whether the differential price responses observed for the low and high *PassScore* groups is efficient. If the returns observed for these firms is attributable to the buying pressure driven by demand for short covering together with constrained supply, 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 a reversal in returns in a subsequent window (day 6 to 10) after the positive earnings announcements, indicating a general overreaction around the earnings announcement window. More importantly, we do not observe this reversal for firms where the passive ownership is low, consistent with the idea that the initial price response was not an overreaction. The reversal observed in the full sample is entirely driven by the subsample with relatively high *PassScore* where supply of shares is constrained, and the between-subsample difference is significant. Again, the inference is overall robust to several alternative windows. Taken together, these results suggest that type of ownership and their effect on supply of shares has an important role to play in short-term price efficiency.

We delve deeper into the adverse returns experienced by short-sellers when supply is constrained 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 high *PassScore* firms than for low *PassScore* firms after positive earnings news. We find that the greater price impact also leads to more short covering for heavily-shorted firms with high *PassScore* after positive earnings shocks.

One might argue for two potential endogeneity concerns. First, as ownership structure is not exogenous, it is possible that some omitted variables contribute to both *PassScore* and the documented effect. However, the variables that are commonly identified as suspected omitted variables are likely to bias against our results. For example, we know pricing inefficiencies are stronger for firms with smaller size, lower liquidity, and lower institutional ownership. However, the price inefficiency we find is stronger for firms with high *PassScore*, which are larger, more liquid, and with higher institutional ownership.[2] Nevertheless, to further alleviate any endogeneity concern of the *PassScore*, we conduct change analyses based on large quarter-over-quarter increases and decreases in *PassScore* (i.e., more than 10 percentage points change in *PassScore*). This approach essentially uses the firm as its own control. We find that after large increase (decreases) in *PassScore*, 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 *PassScore* provide additional support for the role of inelastic ownership in limiting arbitrage. Taken together, any arguments regarding endogeneity of *PassScore* have to explain all these results.[3]

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[2] We discuss the connection between *PassScore* and illiquidity in more detail Section 5.3.

[3] In addition, we conduct a two-stage approach to explicitly remove (1) the impact of size (Nagel 2005) and (2) any time-invariant factors in determining *PassScore*. Using the residuals of regressing the logit transformation of *PassScore* on the logged market cap and its square after controlling for firm fixed effects, we find that all our main inferences remain the same.

Another potential endogeneity concern is that earnings surprises are not exogenous. It is important to note that by construction, the "unexpected earnings" have already excluded all the information analysts use to forecast earnings, and earnings surprises could be viewed as exogenous to the market. Nevertheless, to provide an alternative setting to earnings surprises, we use the market-wide funding shocks used in Richardson et al. (2017) as a quasi-experiment to observe the impact of *PassScore* when there is an exogenous demand for 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 higher *PassScore* than with lower *PassScore*, providing additional support to our main results based on earnings announcements. While each of them has their individual advantages and disadvantages, together the two designs reinforce each other and provide greater confidence in the research inferences (Armstrong et al. 2022).

We conduct several sets of additional analyses. First, we measure *PassScore* based on only quasi-indexer ownership, or based on only index fund and ETF ownership, and we confirm that our inferences remain. Second, we broaden our analysis to examine the overall relation between *PassScore* 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 et al. (2002), we find that heavily shorted firms with relatively high *PassScore* have much less negative future abnormal returns than their counterparts with low *PassScore*. These results suggest that high passive ownership, while making it easier for short-sellers to enter short positions (e.g., Prado et al. 2016), also makes it harder for them to close their positions, therefore reducing their profits. Third, we discuss the relation between *PassScore* and liquidity. We emphasize that firms with high

PassScore are more liquid on average, and heavily-shorted firms with high *PassScore* see large spikes in illiquidity after positive earnings news.

Our paper contributes to the literature in several ways. First, it identifies a novel implication of passive ownership on short selling. In studying lendable shares, Prado et al. (2016) and Palia and Sokolinski (2021) show that passive ownership helps short-sellers by increasing the supply of lendable shares and relaxing short-selling constraints. 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 the price impact of the short covering. In this way, our paper contributes to the growing literature on the dark side of buy-and-hold ownership and especially ETFs (e.g., Ben-David et al. 2018; Israeli et al. 2017).

Implicit in the market efficiency argument is the unconstrained ability to buy and sell shares. In finance theory supply of stocks is generally not viewed as a significant constraint to setting prices, based on the idea of the existence of close substitutes (Shleifer 1986). Therefore, when prices rise due to non-fundamental reasons, asset owners will sell and move to the close substitutes, thereby keeping prices around fundamental value. The alternative is that some types of owners view each stock as a "unique work of art" (Scholes 1972) without substitutes and are therefore inelastic providers of supply which would indicate the possibility of inefficient pricing. Hong et al. 2012; Lasser et al. 2010 when examining short-seller driven demand shocks on stock returns do not explicitly discuss supply constraints but their long-horizon PEAD results suggest that supply is constrained. Our results indicate that the extent to which supply is constrained is determined by the nature of ownership. Certain owners view stocks as securities with substitutes while others view them as "unique works of art," and the mix of the two has implications for pricing inefficiencies.

Relatedly, our paper documents passive ownership as a specific type of constraint to short covering, therefore contributing to the emerging literature on short covering, which primarily focuses on the reasons for short covering (e.g., Hong et al. 2012; Lasser et al. 2010; Richardson et al. 2017; Stice-Lawrence et al. 2022) and the return implications (Blocher and Ringgenberg 2019; Boehmer et al. 2018). We also add to the existing research on short-selling constraints, which mostly focuses on the constraints in the first two stages of the short-selling ecosystem – initiating and maintaining short positions (e.g., see Reed (2013) and Jiang et al. (2022) for reviews). In contrast, we focus 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 a specific type of short covering constraint.[4]

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 et al. 2005) and earnings announcement premium (e.g., Ball and Kothari 1991; Savor and Wilson 2016). This 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 asymmetry 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

[4] There are a few studies focusing on specific cases of Volkswagen (Godfrey 2016 and Allen et al. 2021), and market corners (Allen et al. 2006). They 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.

result, researchers should account for the impact of short covering and its interaction with ownership structure when examining earnings announcement returns and ERCs.

2. Constructing *PassScore* and Descriptive Statistics

2.1 Constructing *PassScore*

We construct an index of passive ownership to measure the proportion of buy-and-hold shares that are not easily available for investors to buy. We start with the quasi-indexer ownership following Bushee (1998) and Bushee and Noe (2000), and also add ownership by dedicated institutions and insiders because those two types of owners are also less likely to sell in response to price fluctuations.[5] We believe that this broadly-defined passive ownership is better-suited for our study than narrowly focusing on index funds and ETFs for several reasons. First, Bushee's classification of quasi-indexer and dedicated investors is primarily based on portfolio turnover and turnover precisely capture what matters to our story – willingness to sell in the presence of demand for shares. For the same reason, we also include insider ownership, which is typically not considered as part of "free float" by practitioners, to reduce the noise of our measurement. Second, while index funds and ETFs witness rapid growth in recent decades, they are relatively less significant in earlier part of the sample (See Figure 1). Nevertheless, we also tabulate results based on two alternative definitions of *PassScore* (i.e., based on quasi-indexer ownership only, and based on index funds and ETF ownership), and all key inferences are the same.

For quasi-indexer and dedicated ownership, we use the permanent classification provided on Professor Brian Bushee's website to classify institutions. We primarily rely on Thomson Reuter

[5] 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.

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.

For insider ownership, 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 our tests, 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 in the previous three years prior to the month-end.[6] 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%*).

We then calculate *PassScore* as the sum of ownership percentage by quasi indexers, dedicated institutions, and corporate insiders.[7] As examples, Amazon and Microsoft have *PassScores* of 0.519 and 0.547, respectively, at the end of 2019. This evidence indicates that 51.9% (54.7%) of Amazon (Microsoft) stock is held by owners who are relatively unwilling to sell their shares.

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[6] There is a trade-off for using a longer or shorter period of insider trading transactions. If we use a 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.

[7] 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 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 *PassScore* accordingly. We find that our results continue to hold after making this modification to the *PassScore*.

2.2 Summary statistics

Figure 1 plots the means of monthly *PassScore*, and its three components in our sample period from January 2006 to December 2019, requiring non-missing values for any of those variables. We can see that the four lines are relatively stable, with *PassScore* (solid red line) ranging from 43.5% in late 2011 to 51.3% in early 2007. Quasi-indexer ownership (long dash black line) ranges from 29.9% in early 2011 to 37.3% in mid-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 daily data from 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*).[8] 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 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.

[8] 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.

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 *PassScore* is 0.490 (0.517), suggesting that roughly half of the outstanding shares are classified as passive, and less available for purchase if there is a demand uptick. However, there is considerable variation – the interquartile range is about 0.39, with the 1st quartile of 0.285 and the 3rd quartile of 0.676. A closer look at the statistics of the three types of ownership used to calculate *PassScore* 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 et al. (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, *PassScore* is highly positively correlated with ownership by quasi-indexers, dedicated investors, and insiders. Further, *PassScore* is highly positively correlated with lendable shares and negatively correlated with lending fees and utilization rate of lending supply, consistent with prior research that passive investors have a positive effect on lendable shares (e.g., Prado et al. 2016; Palia and

Sokolinski 2021). *PassScore* is also positively correlated with short interest, market cap, analyst coverage, and trading volume turnover, and negatively correlated with illiquidity and volatility.

3. *PassScore* and Short Covering after Positive Earnings Surprises

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.'s (2012) framework to examine the role of passive ownership when short-sellers likely rush to cover their short positions after positive earnings surprises.

3.1 *PassScore* and market reactions after positive earnings surprises

3.1.1 Model and variables

Hong et al. (2012) estimate a pooled regression of cumulative abnormal returns around quarterly earnings announcement dates on a high earnings surprise indicator variable, an indicator variable for whether a stock is highly shorted before the earnings date, and the interaction of the highly shorted indicator and the high earnings surprise indicator. 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:

$$\begin{aligned} CAR_{i,t} = {} & \alpha + \beta_1 HiUE_{i,t} + \beta_2\, HiSIR_{i,t} + \beta_3 HiUE_{i,t} * HiSIR_{i,t} + MKTCAP\ indicators_{i,t} \\ & + P/E\ indicators_{i,t} + DISAGREEMENT\ indicators_{i,t} + CONVDEBT\ indicator_{i,t} \\ & + VOLATILITY\ indicators_{i,t} + INDUSTRY\ indicators_{i,t} + EXCHANGE\ indicators_{i,t} \\ & + QUARTER\ indicators_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

CAR is the cumulative abnormal returns from day -1 (i.e., the trading day before the earnings announcement date) to day 5 in our main analyses and we examine other windows in robustness tests.[9] Abnormal returns are adjusted by the four-factor characteristic-based portfolio

[9] 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

return as in Daniel et al. (1997).[10] We replace the earnings announcement date with 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. This variable captures the main effect of long buying on returns in response to the earnings surprise. *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. The variable can be interpreted as the incremental price reaction resulted from the short-covering. All control variables are defined as in Hong et al. (2012). Specifically, we include the following series of indicators: *MKTCAP indicators* (market cap divided into 25 indicators by quarter), *P/E indicators* (price-to-earnings divided into 25 indicators by quarter and one additional indicator variable for negative earnings stocks), *DISAGREEMENT indicators* (the dispersion in analyst forecasts divided into 25 indicators by quarter), *CONVDEBT indicator* (an indicator for the firm having positive convertible debt), *VOLATILITY indicators* (return volatility of firms in the previous month calculated using daily returns divided into 25 indicators by quarter), Fama-French 49 industry fixed effects, stock exchange fixed effects, and quarter fixed effects. 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

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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.

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

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 pattern 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 *PassScore* in this sample tilts slightly toward the higher end, with a mean of 0.564 relative to the mean of 0.490 in the general stock-month level data tabulated in Table 1, largely because requiring analyst forecast data excludes smaller firms which tend to have lower passive ownership (and therefore lower *PassScore*). 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.

3.1.2 Regression results on market reactions after positive earnings surprises

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 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 *PassScore*. We argue that passive ownership is a key reason why short sellers' buy-to-cover pushes prices much higher after positive earnings shocks. Specifically, we create *PassScore* terciles within quarter and short interest tercile, and define an indicator of *LowPScore* equal to one for the bottom 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 bottom tercile of *PassScore* (Column 2) and the remaining two terciles (Column 3). We find that the results in Column 1 are primarily driven by the sample with high *PassScore*. 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 high *PassScore*, but their counterparts with low *PassScore* 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 low versus high *PassScore*. First, we follow Da et al. (2011) and Shroff et al. (2014) and use a bootstrapping method. Specifically, we randomly assign an observation into the bottom and the top two terciles of *PassScore*, and re-estimate the results in Columns 2 and 3 and take the difference in the coefficient of *HiUE * HiSIR*. We repeat this procedure 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 low versus high *PassScore* 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*

[11] Our results are similar if we focus on only the top and bottom tercile. We sort *PassScore* 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 *PassScore* 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.

* *HiSIR* differs between Columns 2 and 3 in a pooled regression. The triple interaction term is significant at the 10% level (Coeff. = -0.578; t = -1.786). Third, we estimate 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 passive 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 low *PassScore* sample, but highly significant at the high *PassScore* sample. The bootstrapping tests show that the difference in *HiUE* * *HiSIR* is significant at the 10% level for all four alternative windows.

3.1.3 Placebo test using market reactions after *negative* earnings surprises

We focus on "good news" earnings because they could trigger short covering. Short-sellers do not face the pressure to cover positions around "bad news" and therefore we do not expect *PassScore* to affect immediate price reactions. As a result, negative earnings surprises provide a nice setting for a placebo test. If it is something else rather than short covering demand that contributes to our results, we should still see that highly-shorted firms exhibit differentiated market reactions after bad earnings news conditional on their *PassScores.* In Panel D, we replace *HiSUE* with *LowSUE* (i.e., an indicator of bottom-tercile SUE) and reproduce Table 2 Panel B. We find that the coefficient on *LowSUE* is significantly negative, consistent with selling pressure as a result of the "bad news." The coefficient on *LowSUE * HiSIR* is also significantly negative, indicating that the returns are worse for bad news firms with high short interest. This evidence suggests that the short-sellers are informed in their short positions. Most importantly, when we partition the sample based on *PassScore* we find the interaction coefficients are similar across the two groups (-0.616 for low *PassScore* and -0.643 for high *PassScore*), and there is no statistical significance in the three tests we use to evaluate the differences between the subsamples. This result provides a powerful placebo test to our story that the short covering demand triggered by positive earnings surprise leads to the differentiated immediate market reactions between highly-shorted firms with low versus high *PassScores*. In addition, those results also help us to rule out a risk-based explanation, as short sellers take more losses shorting firms with high *PassScore* firms when they have good news, but do not take more profits when they have bad news.

3.2 *PassScore* 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 above fundamental value, we expect to see return reversals in a subsequent period. This effect should be stronger for stocks with high *PassScore* 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 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 low *PassScore* (Column 2) and high *PassScore* (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 low versus high *PassScore* 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 high *PassScore* provide strong evidence that their stock prices are pushed to an excessively high level after positive earnings shocks, due to passive ownership limiting shares available for short-sellers to buy-to-cover.[12] In other words, by constraining the supply of shares available to trade, passive ownership has an adverse effect on short-term price efficiency.

Echoing Table 2, Panel C, we also 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 low *PassScore* sample, but highly significant at the high *PassScore* sample. The bootstrapping

[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 high *PassScore* firms. However, this explanation would predict that the highly shorted firms with high *PassScore* continue to outperform their lightly-shorted counterparts in the subsequent period after the positive earnings announcements.

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 generally 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 overreactions 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.

A 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 low *PassScore* (Column 2) and high *PassScore* (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 high *PassScore* firms as compared with low *PassScore* 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 4 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 low *PassScore* (Column 2) and high *PassScore* (Column 3). While we find that the interaction term is significant for both groups, the magnitude is larger for the high *PassScore* group. This evidence is consistent with a feedback loop causing greater short covering in firms with high *PassScore*. The difference is significant at the 5% level based on the bootstrapping method and 10% level based on the other two methods.[13] Taken together, the two panels in Table 4 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.

3.4 Change analyses: evidence from large increases and decreases in *PassScore*

One might argue that firms with low versus high *PassScore* are inherently different, and some unobservable differences could drive the difference in return responses to the buying pressure caused by short covering. Note any correlated omitted variables would need to explain

[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 et al. 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.

the results using negative earnings surprises in Table 2 Panel D and 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. Furthermore, we find that the price inefficiency documented in this paper is stronger for firms with lower liquidity (Table 8 Panel B), smaller size (untabulated), and lower institutional ownership (untabulated), opposite to the predictions based on those subsamples that are normally related to price inefficiencies. While we do not have an alternative explanation in mind that we view as viable, we acknowledge this possibility. Therefore, we conduct change analyses, focusing on earnings announcements before and after large changes in *PassScore*. While still imperfect, our goal is to hold the firms' fundamentals largely constant while allowing *PassScore* to vary over a short period of time.

We calculate quarter-over-quarter changes in *PassScore* using the ending *PassScore* of each calendar quarter, retaining quarters with a decrease or increase in *PassScore* of at least 10 percentage-points over the prior quarter (e.g., from 40% to 30% or to 50%).[14] 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 increase-event *and* one decrease-event, or (2) between two increase-events or two decrease-events, because those observations have different pre-post classifications based on different events.[15]

[14] Those firm-quarters with large increase/decrease in *PassScore* witness significant decreases/increases in all three ownership types held by insiders, quasi-indexers, and dedicated investors. Also, some of those large changes in *PassScore* are associated with concurrent changes in shares outstanding, perhaps due to SEOs, stock options, or stock repurchases.

[15] For example, if firm A has large increases in *PassScore* 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 *PassScore* 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.

Further, we remove earnings announcements made in the event quarters (i.e., witnessing the large increases or decreases in *PassScore* relative to the prior quarters) to avoid misclassification of pre versus post. During our sample period, we identify 3,363 *PassScore* increase events, and 3,446 decrease events. After applying the above filters, we end up with 27,208 earnings announcements in the increase-event tests, and 34,392 earnings announcements in the decrease-event tests.

Table 5 Panel A report results using large increases in *PassScore*. 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 increases 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-increase 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 decreases in *PassScore*. 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 decreases 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 increases and large decreases in *PassScore* make it even less likely for an alternative story to explain our main results.

4. Macro Funding Shocks as An Exogenous Trigger of Short Covering Demand

We study whether passive ownership adversely affects short-term price efficiency by limiting the supply of shares available to short-sellers who 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 exogenous 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 funding capital becomes less available due to the heightened market uncertainty.[16] 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 setting different from 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

[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.

quasi-experiment for us to observe the impact of *PassScore* when there is an exogenous demand of short covering.[17]

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 that the losses to the hedged portfolio constructed above would be even greater for high *PassScore* firms as the short covering triggered by funding shocks would push prices even

[17] One possible setting to observe exogenous variation in *PassScore* 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 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 to switch indexes (e.g., Appel et al. 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 et al. (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.

higher. Specifically, we follow Richardson et al. (2017) to sort *PassScore* into quintiles within each daily quintile of short interest, and construct a hedged portfolio based on quintiles of short interest for each *PassScore* quintile. We again confirm that the significant losses after market-wide shocks are evident in each *PassScore* quintile. To compare the loss differences attributed to *PassScore*, we regress the difference in hedged returns between the top and bottom quintiles of *PassScore* 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 top quintile of *PassScore* minus the daily hedged return in the portfolio of the bottom quintile of *PassScore*. *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 find that in Column 1, $D_{RET(MKT)<2.5\sigma}$ is positive but insignificant, D_{QUANT} is highly significantly negative at the 1% level, and D_{LEHMAN} is negative but insignificant. In Column 2, $D_{Large\Delta VIX}$ is negative and significant at the 5% level. 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 cover their positions.

5. Additional Analyses

5.1 Alternative definitions of *PassScore*

In our main analyses we define *PassScore* broadly as the sum of ownership held by quasi-indexers, dedicated institutions, and insiders. We assess the robustness of our main results by considering two alternative definitions of *PassScore.* First, we only consider ownership by quasi-indexers as passive. Table 8, Panel A presents the results. Second, rather than relying on the turnover pattern at the 13F filer level, we focus on the ownership held by index funds and ETFs. We identify ETFs based on the et_flag (i.e., "F") and index funds based on the index_fund_flag (i.e., "B", "D", and "E") in the CRSP Survivor-Bias-Free Mutual Fund database (MFDB) (Appel et al. 2016). As we can observe in Figure 1 (the purple dot line), the ownership by those two types of funds was rather small but has increased monotonically during our sample period. Because the ownership by index funds and ETFs is rather low in early parts of the sample, sorting on it could not generate meaningful separation between low versus high passive ownership. As a result, we report results based on two later sample periods (2011-2019, and 2016-2019). Table 8, Panel B presents the results. Overall, we find that the pattern that the interaction term *HiUNEX*HiSIR* is insignificant in the subsample with low *PassScore*, but highly significant in the subsample with high *PassScore.* It is worth noting that the results based on index funds and ETF ownership in 2016-2019 is particularly strong. In other words, using those alternative approaches to measure *PassScore,* we still find that highly-shorted after positive earnings shock witness overall reaction around earnings announcements and subsequent reversals only when they face with lower supply of shares constrained by the passive ownership.

5.2. *PassScore* and short-sellers' overall returns

While the analyses so far have focused on short horizon returns around an event that likely pushes short-sellers to cover their positions, the question is whether this result 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 high *PassScore* than for firms with low *PassScore*.

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 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 *PassScore* is in the bottom monthly tercile among those highly-shorted stocks, we find that the alpha for stocks with low *PassScore* is much more negative than stocks with high *PassScore* (-210 versus -29 bps).[19] This finding is consistent with our prediction that the buying pressure caused by short-sellers' covering pushes stock prices higher, thereby eating up their profits in stocks with high passive ownership. In untabulated robustness analyses, we confirm that our inferences are robust if we focus on firm-months with average short interest higher than 5% rather than 10%, if we construct calendar-time portfolio at the daily level rather at the monthly level, or if we focus on the subsamples with low lending fees (i.e., General collateral or GC) or with high lending fees (i.e., on Special).

5.3 *PassScore* and illiquidity

As discussed earlier in the paper, there is a negative correlation between *PassScore* and Amihud (2002) illiquidity (correlation coefficient = -0.26 in Table 1 Panel C). This observed correlation reduces the likelihood that our results are driven by *PassScore* proxying for average underlying illiquidity. To further bolster confidence in the results, In Table 8 Panel C 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* shares turnover (*Turnover*). Taken together, these results suggest that our findings are unlikely to be driven by illiquid firms.

However, some might find the relationship between *PassScore* and illiquidity puzzling. Specifically, since high *PassScore* firms have fewer shares to meet the demand, why do these firms have lower illiquidity as measured by Amihud (2002)? As those firms are more liquid, we would normally expect them to have more efficient prices, so why is the price impact from short-covering greater among those firms? To the first question, the negative correlation between *PassScore* and average illiquidity is because higher *PassScore* firms tend to be larger and have higher institutional ownership. Both these variables are negatively correlated with illiquidity. To the second question, while high *PassScore* firms are overall more liquid, it does not automatically imply that the liquidity is adequate to meet sudden spikes in demand. We argue that ownership structure (*PassScore*) reflects the ability of liquidity suppliers to meet *sudden increases* in liquidity demand. Consistent with this argument, we find evidence that highly-shorted firms with high *PassScore* witness a larger spike in illiquidity after positive earnings news. Specifically, we regress the decile rank of increase in illiquidity (Amihud 2002) on each day in [-1, 5] relative to the prior-month average on *HiUNEX, HiSIR,* and *HiUNEX * HiSIR,* and the interaction term is highly positively significant for the high *PassScore* subsample, and insignificant for the low *PassScore* subsample for six out of the seven trading days in [-1, 5]. In other words, our results suggest that while high *PassScore* firms have high liquidity on average, these firms tend to have difficulty supplying liquidity when there are sudden increases in demand, driving up the prices. Taken together, our paper suggests passive ownership as a potentially important primitive construct that affects both levels and shifts in liquidity. We leave a more thorough study on this issue for future research.

5.4 Additional untabulated robustness analyses

We also conducted a battery of additional robustness analyses. First, in the main analyses we follow Hong et al. (2012) and create 25 indicators for market cap, P/E ratio, disagreement, and volatility in Equation (1). This approach allows us to better control for the non-linear relation between those variables and the dependent variables. Nevertheless, untabulated analyses show that our main results are quantitatively similar if we replace those indicators with the raw values of the four variables in the regressions. Second, we argue that our results are not driven by constraints when short seller *open* their positions but driven by constraints when they *close* their positions, because we focus on firms with high short interest leading to earnings announcements. To further rule out short selling constraints as an alternative explanation, we remove those firms with average DCBS higher than 2 in the five trading dates prior to earnings announcements and we find our main inferences on the immediate market reaction and subsequent reversals remain the same. Third, in our main analyses, we compare the bottom tercile of *PassScore* with the top two terciles to highlight that unless firms have low level of passive ownership, otherwise short sellers are likely to suffer from the temporary price hikes after positive earnings surprises. The inferences remain similar (although the between-subsample difference gets weaker) when we exclude the middle tercile and compare the bottom versus top terciles.

6. Conclusion

The rise of passive investing has attracted enormous attentions from practitioners and researchers alike. Prior researchers document that passive ownership could facilitate short selling and improve market efficiency through increasing supply of lendable shares (e.g., Prado et al. 2016), we argue that it could also have an opposing effect of hurting short sellers by constraining supply of shares available for purchase when they need to buy-to-cover their positions.

Following the research design of Hong et al. (2012), we find that highly-shorted firms experience an overreaction around positive earnings surprises followed by greater reversals in subsequent periods when passive ownership is relatively high. Evidence also suggests that the overreaction for highly-shorted firms with passive 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 passive ownership. We find similar inferences using an alternative exogenous setting where short covering demand is caused by macro funding shocks (Richardson et al. 2017). Generalizing these results to a setting beyond earnings announcements, we find that highly-shorted firms with more passive ownership are less profitable to short-sellers.

Taken together, these results provide evidence that passive ownership constrains the supply of shares available to short-sellers who need 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 is considered as the most significant risk short-sellers face (Kumar 2015). Our results have implications for short-sellers. We identify passive ownership as a potential short covering risk and therefore an important factor for them to consider when initiating short positions. While the prior literature on short-selling constraints has focused on the costs and frictions in initiating and maintaining short positions, we are among the first to conduct a large-sample study documenting a constraint to short covering. In particular, our paper points to the interesting role of passive ownership in different stages of short-selling: while it makes it easier for short-sellers to enter into and maintain short positions by increasing lendable supply, it makes it harder for them to close positions by decreasing the real "float" and the supply of shares available to purchase. As we quote in the very beginning of the paper, renowned short-seller Carson Block recently referred to passive investing as "the biggest and most overlooked factor for short-sellers" precisely for this reason. Finally, we 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
PassScore	An index of broadly-defined passive ownership, measured as *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. In Table 8 Panel A, we alternatively define *PassScore = QIX%.* In Table 8 Panel B, we alternatively define *PassScore = IndexFund+ETF%*
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
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
IndexFund+ETF%	The proportion of shares owned by index funds and ETFs at the end of each month. We identify ETFs based on the et_flag (i.e., "F") and index funds based on the index_fund_flag (i.e., "B", "D", and "E") in the CRSP Survivor-Bias-Free Mutual Fund database (MFDB). Further, we include any funds whose names include the following keywords: "Index, Idx, Indx, Ind, Russell, S&P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, 3000, 5000."
SIR	The monthly average of the ratio of the daily shares on 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 not missing)	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
LowUE	An indicator equal one if a firm's earnings surprise is in the bottom 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
LowPScore	An indicator equal to one if the stock is in the bottom tercile of *PassScore* sorted for stocks in our sample within each quarterly 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 the 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

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 *PassScore* over the prior quarter, and zero for earnings announcements made in the 12 quarters before the quarter with such big increase in *PassScore*
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 *PassScore* over the prior quarter, and zero for earnings announcements made in the 12 quarters before the quarter with such big decrease in *PassScore*
$D_{RET(MKT)<2.5\sigma}$	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 *PassScore* minus the daily hedged return in the portfolio of the top quintile of *PassScore*. 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
HiIlliq	An indicator equal to one if the stock is in the top tercile of *Illiquidity* in the month prior to the earnings announcement each quarter, and zero otherwise

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
PassScore	0.490	0.517	0.260	0.000	0.053	0.285	0.676	0.928	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. PassScore	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 *PassScore* 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 bottom tercile of *PassScore* in Column 2, results of remaining two terciles of *PassScore* 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 bottom tercile of *PassScore* first, followed by results of remaining two terciles of *PassScore*. In Panel D, we use the negative earnings surprises as a setting for a placebo test, replacing *HiUE* in Panel B with *LowUE.* In Panels B – D, we report the bootstrapping p-value in testing the difference in *HiUE * HiSIR* (*LowUE * HiSIR* in Panel D) between low versus high *PassScore* 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 and Panel D 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
PassScore	0.564	0.583	0.225	0.000	0.151	0.425	0.711	0.961	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: *PassScore* and buying pressure after positive earnings announcements

DV = *CAR[-1,5](*100)*	(1)	(2)	(3)	(4)	(5)
Sample =	Full	*LowPScore* = 1	*LowPScore* = 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			
LowPScore				-0.094	-0.101
				(-0.753)	(-1.176)
*HiUE * LowPScore*				0.033	0.305**
				(0.183)	(2.122)
*HiSIR * LowPScore*				-0.330	-0.412***
				(-1.644)	(-2.848)
*HiUE * HiSIR * LowPScore*				-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: *PassScore* and 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]*	
Sample =	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 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)
Bootstrapping:	Col (1) = Col (2): $p = 0.053$		Col (3) = Col (4): $p = 0.053$		Col (5) = Col (6): $p = 0.054$		Col (7) = Col (8): $p = 0.062$	
Observations	51,930	107,441	51,930	107,441	51,923	107,438	51,923	107,436
Adjusted R^2	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

Panel D: Negative earnings announcements as a setting for a placebo test

DV = *CAR[-1,5](*100)*	(1)	(2)	(3)	(4)	(5)
Sample =	Full	*LowPScore* = 1	*LowPScore* = 0	Full	Fama-MacBeth
LowUE	-5.234***	-5.073***	-5.397***	-5.345***	-5.228***
	(-57.527)	(-32.977)	(-49.224)	(-49.941)	(-17.519)
HiSIR	-0.035	-0.339*	0.183*	0.119	0.037
	(-0.382)	(-1.683)	(1.738)	(1.164)	(0.269)
*LowUE*HiSIR*	-0.715***	-0.616**	-0.643***	-0.668***	-0.602***
	(-4.707)	(-2.193)	(-3.626)	(-3.787)	(-2.982)
Bootstrapping:		Col (2) = Col (3): $p = 0.487$			
LowPScore				-0.181	-0.003
				(-1.416)	(-0.028)
*LowUE*LowPScore*				0.286	0.138
				(1.639)	(0.802)
*HiSIR*LowPScore*				-0.462**	-0.542***
				(-2.363)	(-3.334)
*LowUE*HiSIR*LowPScore*				-0.060	-0.053
				(-0.187)	(-0.200)
Observations	160,074	51,930	107,441	160,074	159,811
Adjusted R^2	0.081	0.078	0.088	0.081	0.125
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	/

Table 3: *PassScore* and reversals in the subsequent period after positive earnings announcements

This table examines the impact of *PassScore* 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 bottom tercile of *PassScore* in Column 2, results of remaining two terciles of *PassScore* 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 bottom tercile of *PassScore* first, followed by results of remaining two terciles of *PassScore*. In both panels, we report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between low versus high *PassScore* 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: *PassScore* and reversals in the subsequent period

	(1)	(2)	(3)	(4)	(5)
DV = *CAR[6,10](*100)*					
Sample =	Full	*LowPScore* = 1	*LowPScore* = 0	Full	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			
LowPScore				0.076	0.037
				(1.008)	(0.717)
*HiUE * LowPScore*				-0.048	0.011
				(-0.514)	(0.193)
*HiSIR * LowPScore*				-0.112	-0.112
				(-0.901)	(-1.255)
*HiUE * HiSIR * LowPScore*				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: *PassScore* and 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 =	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 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 *PassScore* 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 high *PassScore* 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 high *PassScore* 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 bottom tercile of *PassScore* in Column 2, results of remaining two terciles of *PassScore* 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	*LowPScore* = 1	*LowPScore* = 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			
LowPScore				-0.210*	-0.203**
				(-1.911)	(-2.142)
*HiUE * LowPScore*				-0.132	0.150
				(-0.836)	(0.970)
*ShortCov[-1, 5] * LowPScore*				0.788***	0.770***
				(4.633)	(7.935)
*HiUE*ShortCov[-1,5]*LowPScore*				-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: Short covering after positive earnings announcements

	(1)	(2)	(3)	(4)	(5)
DV = *ShortCov[-1,5](*100)*					
		LowPScore	*LowPScore*		Fama-MacBeth
Sample =	Full	= 1	= 0	Full	
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			
LowPScore				0.020***	0.018**
				(2.699)	(2.097)
*HiUE * LowPScore*				-0.020***	-0.022***
				(-2.691)	(-3.126)
*HiSIR * LowPScore*				-0.068***	-0.063***
				(-4.129)	(-3.434)
*HiUE * HiSIR * LowPScore*				-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 *PassScore* and buying pressure after positive earnings announcements

This table examines how large decreases (Panel A) and large increases (Panel B) in *PassScore* affects the return patterns due to the buying pressure of short covering after positive earnings announcements. We identify large decreases and large increases in *PassScore* 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-increase (decrease) in Columns 1 and 4, results in the subsample of post-increase (decrease) 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-increase (decrease) 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 increases in *PassScore* and 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	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)
	Col (1) = Col (2):			Col (4) = Col (5):		
Bootstrapping:	*p* = 0.057			*p* = 0.010		
PostInc			-0.076			-0.119
			(-0.328)			(-0.936)
*HiUE*PostInc*			-0.479			0.159
			(-1.184)			(0.647)
*HiSIR*PostInc*			-0.153			0.521*
			(-0.356)			(1.949)
*HiUE*HiSIR*PostInc*			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 decreases in *PassScore* and 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	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)
	Col (1) = Col (2):			Col (4) = Col (5):		
Bootstrapping:	$p = 0.355$			$p = 0.357$		
PostDec			0.745***			0.213
			(3.085)			(1.565)
*HiUE*PostDec*			-0.819**			-0.194
			(-2.291)			(-0.985)
*HiSIR*PostDec*			0.399			0.242
			(1.028)			(1.057)
*HiUE*HiSIR*PostDec*			-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: Funding shocks as a quasi-experiment for triggering short covering demand

This table reports results on how *PassScore* 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 top *PassScore* quintile minus the daily hedged return in the portfolio of the bottom *PassScore* quintile in Columns 1 and 2. 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)
DV =	*HedgeReturnDiff*	*HedgeReturnDiff*
Constant	-0.069***	-0.049**
	(-4.031)	(-2.510)
RMRF	0.264***	0.265***
	(8.895)	(8.876)
SMB	0.098**	0.098**
	(2.353)	(2.349)
HML	0.039	0.043
	(0.590)	(0.658)
UMD	0.046	0.051
	(1.480)	(1.627)
CMA	0.018	0.026
	(0.213)	(0.316)
RMW	-0.394***	-0.394***
	(-7.030)	(-6.996)
$D_{RET(MKT)<2.5\sigma}$	0.006	
	(0.044)	
D_{QUANT}	-1.088***	
	(-7.765)	
D_{LEHMAN}	-0.047	
	(-0.119)	
$D_{Large\Delta VIX}$		-0.080**
		(-2.163)
Observations	3,423	3,423
Adjusted R^2	0.144	0.145

Table 7: Alternative approaches to define *PassScore*

This table replicates the results in Table 2 Panels B and Table 3 Panel A using two alternative definitions of *PassScore.* In Panel A, we define *PassScore* as quasi-indexer ownership. Columns 1-4 (5-8) tabulates the regression results focusing on the return windows of [-1, 5] ([6,10]), with results of bottom tercile of *PassScore*, results of remaining two terciles of *PassScore*, full sample results with triple interactions, and quarterly Fama-MacBeth regression results, respectively. We report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between low versus high *PassScore* subsamples based on 1,000 random samples. In Panel B, we define *PassScore* as ownership by index funds and ETFs, and we report results based on two sample periods. Columns 1-2 (3-4) tabulates the regression results focusing on the return windows of [-1, 5] ([6,10]), with results of bottom tercile of *PassScore* in Column 1 (3), and results of remaining two terciles in Column 2 (4) based on sample 2011-2019. Columns 5-6 (7-8) tabulates the regression results focusing on the return windows of [-1, 5] ([6,10]), with results of bottom tercile of *PassScore* in Column 5 (7), and results of remaining two terciles in Column 6 (8) based on sample 2016-2019. We report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between low versus high *PassScore* subsamples based on 1,000 random samples. All variables are defined in Appendix A. *t* statistics in parentheses in Columns 1, 2, 3, 5, 6, and 7 of Panel A and all columns in Panel B are based on standard errors clustered by firm. *t*-statistics in Columns 4 and 8 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: Defining *PassScore* based on only quasi-indexer ownership

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV =	*CAR[-1,5](*100)*				*CAR[6,10](*100)*			
Sample =	*LowPScore* = 1	*LowPScore* = 0	Full	Fama-MacBeth	*LowPScore* = 1	*LowPScore* = 0	Full	Fama-MacBeth
HiUNEX	5.857***	5.115***	5.123***	4.860***	0.135	0.151***	0.143***	0.127*
	(33.592)	(51.182)	(51.602)	(18.178)	(1.314)	(3.468)	(3.306)	(1.842)
HiSIR	-0.700***	-0.308***	-0.417***	-0.284**	-0.200	0.126**	0.073	0.083*
	(-3.009)	(-3.172)	(-4.316)	(-2.229)	(-1.273)	(2.144)	(1.243)	(1.746)
*HiUNEX*HiSIR*	0.167	0.876***	0.878***	0.806***	-0.128	-0.265***	-0.284***	-0.275***
	(0.541)	(5.162)	(5.176)	(4.523)	(-0.700)	(-3.220)	(-3.487)	(-3.409)
Bootstrapping	Col (1) = Col (2): *p* = 0.005				Col (5) = Col (6): *p* = 0.228			
LowPScore			-0.385***	-0.403***			0.162*	0.106
			(-2.786)	(-3.468)			(1.718)	(1.424)
*HiUNEX*LowPScore*			0.693***	0.854***			0.006	0.042
			(3.697)	(4.286)			(0.055)	(0.485)
*HiSIR*LowPScore*			-0.229	-0.407***			-0.195	-0.160*
			(-1.059)	(-3.420)			(-1.442)	(-1.704)
*HiUNEX*HiSIR*LowPScore*			-0.710**	-0.721***			0.162	0.128
			(-2.122)	(-3.349)			(0.842)	(0.689)
Observations	52,030	107,421	160,074	159,811	52,022	107,417	160,062	159,799
Adjusted R-squared	0.074	0.089	0.082	0.124	0.006	0.031	0.021	0.068
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No

Panel B: Defining *PassScore* based on ownership by index funds and ETFs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV =	*CAR[-1,5]*		*CAR[6,10]*		*CAR[-1,5]*		*CAR[6,10]*	
Sample =	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0	*LowPScore* = 1	*LowPScore* = 0
Sample period:	2011-2019				2016-2019			

HiUNEX	5.277***	4.870***	0.197*	0.019	4.894***	5.118***	0.155	0.047
	(24.832)	(41.886)	(1.729)	(0.423)	(14.746)	(30.950)	(0.791)	(0.579)
HiSIR	-0.650**	-0.253**	-0.038	0.067	0.243	0.175	-0.194	0.123
	(-1.997)	(-2.176)	(-0.217)	(0.969)	(0.427)	(0.897)	(-0.598)	(0.930)
*HiUNEX*HiSIR*	0.452	0.609***	-0.134	-0.286***	-0.034	0.935***	-0.028	-0.418**
	(1.186)	(3.008)	(-0.591)	(-2.941)	(-0.057)	(3.049)	(-0.074)	(-2.453)
Bootstrapping	Col (1) = Col (2): $p = 0.297$		Col (3) = Col (4): $p = 0.190$		Col (1) = Col (2): $p < 0.001$		Col (1) = Col (2): $p = 0.016$	
Observations	34,552	72,067	34,548	72,061	16,804	35,413	16,803	35,411
Adjusted R-squared	0.063	0.089	0.003	0.021	0.059	0.097	-0.006	0.016
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Additional Analyses

This table reports two sets of additional analyses. Panel A 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 *PassScore* is in the bottom tercile each month among those highly-shorted stocks. The robust *t*-statistics are reported in parentheses of Panel A. In Panel B, Columns 1-4 (5-8) tabulates the regression results focusing on the return windows of [-1, 5] ([6,10]), with results of top tercile of *illiquidity*, results of remaining two terciles, full sample results with triple interactions, and quarterly Fama-MacBeth regression results, respectively. We report the bootstrapping *p*-value in testing the difference in *HiUE* * *HiSIR* between two subsamples based on 1,000 random samples. *t* statistics in parentheses in Columns 1, 2,3, 5, 6, and 7 are based on standard errors clustered by firm, while *t*-statistics in Columns 4 and 8 are Newey-West adjusted with four lags to control for heteroskedasticity and autocorrelation. All variables are defined in Appendix A. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ (two-sided tests)

Panel A: *PassScore* and short-sellers' overall returns

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	0.950
	(-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	0.645
LowPScore = 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	0.956
LowPScore = 0	(-7.88)	(128.36)	(60.89)	(7.62)	(1.33)	(0.16)	(-40.01)	

Panel B: The role of illiquidity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
DV =		*CAR[-1,5](*100)*				*CAR[6,10](*100)*		
Sample	*HiIlliq* = 1	*HiIlliq* = 0	Full	Fama-MacBeth	*HiIlliq* = 1	*HiIlliq* = 0	Full	Fama-MacBeth
HiUNEX	6.411***	4.540***	4.534***	4.264***	0.297***	0.061	0.066*	0.061
	(40.324)	(48.521)	(48.608)	(17.185)	(3.354)	(1.563)	(1.686)	(1.426)
HiSIR	-0.678**	-0.661***	-0.574***	-0.459***	-0.029	0.026	0.019	0.057
	(-2.323)	(-7.346)	(-6.248)	(-3.667)	(-0.148)	(0.518)	(0.366)	(1.360)
*HiUNEX * HiSIR*	0.322	1.208***	1.198***	1.099***	-0.265	-0.205***	-0.190**	-0.228***
	(0.813)	(7.835)	(7.813)	(6.081)	(-1.125)	(-2.694)	(-2.522)	(-3.131)
Bootstrapping	Col (1) = Col (2): $p < 0.001$				Col (5) = Col (6): $p = 0.300$			
HiIlliq			-0.671***	-0.552***			-0.133	-0.051
			(-3.887)	(-3.531)			(-1.021)	(-0.675)
*HiUE * HiIlliq*			1.900***	2.043***			0.184**	0.168*
			(10.835)	(11.651)			(1.963)	(1.940)
*HiSIR * HiIlliq*			-0.205	-0.459*			-0.066	-0.215
			(-0.739)	(-1.774)			(-0.357)	(-1.590)
*HiUE * HiSIR * HiIlliq*			-0.778*	-0.331			-0.004	0.280
			(-1.865)	(-0.676)			(-0.018)	(1.077)
Observations	52,655	106,904	160,074	159,811	52,648	106,899	160,062	159,799
Adjusted R-squared	0.086	0.085	0.083	0.126	0.018	0.023	0.021	0.069
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	No	Yes	Yes	Yes	No

Figure 1: The trend of ***PassScore*** and its related elements over time

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