The Invisible Hand in the Dark:

The Disciplinary Effect of Dark Pools on Firm Overinvestment

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Abstract

We propose that the availability of dark pools incentivizes informed traders to acquire information ex-ante and thus induces stronger monitoring effects on corporate decisions. Utilizing the trade-at rule provision in the SEC's Tick Size Pilot Program, we find that restrictions on dark pool trading lead to higher levels of corporate overinvestment for medium- and small-cap securities. The results are more pronounced for firms with a larger short-selling flow before the Program. The overinvestment due to the restrictions in dark trading worsens the firms' future performance. Overall, we identify a novel external governance mechanism via informed trading in the dark pools.

JEL Classification: G10, G18, G30, M41

Keywords: dark pools; tick size pilot program; informed trading; short selling; disciplinary effects; overinvestment

1. Introduction

Dark pools have become increasingly important trading venues, as they account for 47% of the total equity trading volume in the U.S. as of January 2021.[1] With the rising relevance of dark pools, accounting and finance scholars have been debating the influences of dark trading on the stock market. On the one hand, a line of the literature shows that dark trading improves market quality and leads to greater information acquisition.[2] On the other hand, another strand of literature finds that trading in the dark pools impedes price discovery.[3] However, whether the trading activities of dark pools exert any *real impact* on corporate decisions remains unexplored. The question is important and relevant given the large literature on the real effects of financial markets (e.g., Edmans, Goldstein, and Jiang, 2012; Bond, Edmans, and Goldstein, 2012). Our study intends to bridge this research gap and pin down a disciplining effect of dark pools on corporate overinvestment.

Utilizing the trade-at rule during Tick Size Pilot Program (the Program, hereafter) in 2016, we test whether the restrictions of dark pool trading alter the incentives of information acquisition and monitoring among investors for medium- and small-cap firms, thereby disciplining the investment decisions of these corporate managers. The gist is that investors face a trade-off between potential benefits and costs of obtaining private information (Grossman and Stiglitz, 1980). The availability of dark pools affects this trade-off, as investors

[1] See the "Prepared Remarks at the Global Exchange and FinTech Conference" by the Chair of SEC, Gary Gensler at https://www.sec.gov/news/speech/gensler-global-exchange-fintech-2021-06-09#_ftn1.
[2] See Boulatov and George (2013), Zhu (2014), Foley and Putninš (2016), Balakrishnan, Gkougkousi, Landsman, and Taori (2021), and Brogaard and Pan (2022).
[3] See Comerton-Forde and Putniņš (2015), Hatheway, Kwan, and Zheng (2017), and Thomas, Zhang, and Zhu (2021).

who possess valuable private information could "hide in the dark" and thus potentially enjoy larger gains by trading in dark pools without disclosing their identities.[4] *Ceteris paribus*, the expected profits of investors to obtain private information becomes larger with the presence of dark pools. With a higher intensity of information gathering and the consequent monitoring, corporate managers' self-maximizing behaviors are more likely to be uncovered by the concerned market participants. While managers reap private benefits of control from empire-building ex-ante, they are less likely to overinvest in an improved information and governance environment ex-post.[5] Accordingly, we propose our main hypothesis that *dark pools discipline managers from overinvestment*.

The Program, launched on October 3rd, 2016, divides stocks into three test groups and one control group based on a stratified random sampling process. Stocks in Test Group One (TG1) are quoted in \$0.05 increments in tick size but continue to trade at their current price increment. Stocks in Test Group Two (TG2) and Test Group Three (TG3) are quoted and traded in \$0.05 increments. Stocks in TG3 are subject to an additional trade-at rule, which restricts dark trading by preventing dark pools from executing a trade at the national best bid and offer (NBBO) without also displaying the NBBO. The trade-at rule is designed to shift trading in the TG3 from dark venues to exchanges and has been shown to significantly reduce dark trading (Thomas, et al., 2021; Boggard and Pan, 2022). This rule offers an ideal opportunity for us to

[4] See Ye and Zhu (2020) and Balakrishnan et al. (2021).
[5] It is well established in the literature that managers benefit from empire-building behaviors. For example, see Murphy (1985), Jensen and Murphy (1990), Goel and Thakor (2008), Pikulina, Renneboog, and Tobler (2017). For the literature on the governance effect for firm investment, see Richardson (2006), McNichols and Stubben (2008), Hope and Thomas (2008), and Chang, Lin, and Ma (2019).

evaluate the causal effects of dark trading on corporate overinvestment.[6] To this end, we employ a difference-in-difference (DID) design that uses TG3 as the treatment group and TG2 as the control group, as they only differ in the restrictions on dark trading.

We focus on corporate investment in that managers incline to invest inefficiently without proper external or internal governance (e.g., Biddle, Hilary, and Verdi, 2009; Roychowdhury, Shroff, and Verdi, 2019; Durnev and Mangen, 2020). Moreover, overinvestment is one of the worst kinds of agency problems that can be detrimental to shareholder value.[7] Therefore, we follow Biddle et al. (2009) and use firms' abnormal investment (*ABINV*) as our main dependent variable to measure how effective the dark pools' monitoring and disciplinary effects are on corporate investment decisions.

We first validate the regulation shock by testing the impact of the trade-at rule on dark trading. We find that the percentage of trading volume in dark pools over the total trading volume (*DARK*) drops by 11.1% during the Program for the treated firms, consistent with the findings in Thomas et al. (2021). Next, we examine whether restrictions on dark trading disproportionately affect informed traders who tend to hide orders from the general market and reduce the likelihood of being front-run (Ye and Zhu, 2020; Balakrishnan, Gkougkousi, Landsman, and Taori, 2021). We measure the trading activities of informed investors by short-selling flow, which has been shown to be more informative (e.g., Wang, Yan, and Zheng, 2020).

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[6] One of the caveats of Tick Size Pilot Program is that only meidium- and small-cap firms are included. Howbeit, it will not invalidate our argument of the discipline effects of dark pool on overinvestment through informed trading as informed traders tend to focus on mediaum- and small-cap firms considering their innate opaqueness. The profitability on private information of such firms are more salient (Drake et al., 2015; Zhao, 2020; Brendel and Ryans, 2021).

[7] See Jensen (1986), Berger and Ofek (1995), Titman, Wei, and Xie (2004), Richardson (2006), Hope and Thomas (2008), Cooper, Gulen, and Schill (2008), Chang, Lin, and Ma (2019).

The result indicates that the short-selling flows in dark pools (*SHORT_DARK*) and lit markets (*SHORT_LIT*) decrease by 9.7% and 2.3%, respectively. Overall, these findings suggest that the trade-at rule effectively restricts the trading activities in dark pools, especially among informed investors.

We then test the disciplinary effect of the trade-at rule on corporate overinvestment. Consistent with our hypothesis, the treated firms exhibit a significantly higher abnormal investment level (*ABINV*) during the Program. The result indicates that restrictions on dark trading lead to a higher level of corporate abnormal investment. The abnormal investment level increases by 0.734, which accounts for 18.2% of its standard deviation (4.017) in our quarterly sample. Moreover, the parallel trend analysis shows that our results are not affected by firms' pre-existing characteristics and thus are likely to be causal.

To show that the increase in abnormal investment is not driven by the under-invested firms improving their investment efficiency during the Program, we further partition the sample into the overinvestment (*OVER*) and underinvestment (*UNDER*) groups based on the sample median.[8] We find that the results are significant only for the *OVER* group, in which the trade-at rule increases the firms' abnormal investment by 0.978 (24.3% increase compared to the standard deviation).

The literature has shown that short sellers function as an external governance mechanism to discipline managers and reduce agency problems (e.g., Massa, Zhang, and Zhang, 2015;

[8] In the International Appendix (Table IA3), we use investment inefficiency (*INV_INEFF*), the absolute value of *ABINV*, as a dependent variable. The results show that the trade-at rule increases the overall investment inefficiency. It further demonstrates that our main result is not driven by the under-invested firms improving their investment efficiency during the program.

Fang, Huang, and Karpoff, 2016; Chang et al., 2019). We thus examine the cross-sectional effects by partitioning the sample into two groups based on their short-selling flows before the trade-at rule. We conjecture that the trade-at rule limits short-selling activities at dark pools, thereby weakening the disciplinary effect on managers' investment decisions. That is, firms with a higher short-selling flow before should be more affected by the Program. We find consistent evidence that the abnormal investment increases by 1.255 for the treated firms in the high short-selling flow group during the Program. In contrast, the restrictions on dark trading do not significantly affect the firms in the low short-selling flow group. The results suggest that the short-selling activities are a crucial mechanism for dark venues to discipline corporate overinvestment.[9]

Finally, we find that the increase in overinvestment for the medium- and small-cap firms due to the restrictions on dark trading indeed hurts firms' future performance. The return on assets (ROA) for the four quarters in the next year are all negatively associated with the trade-at rule. We further use the trade-at rule as an instrumental variable (IV) for overinvestment to show that overinvestment *causes* this deterioration in firm performance. The results suggest that a one-standard-deviation increase in abnormal investment reduces firms' return on assets by around 2.8% in each quarter of the following year. Therefore, overinvestment in our sample is unlikely a result of managers focusing on long-term growth (Arthur, Vashishtha, and

[9] In the International Appendix (Table IA4 to IA7), we further show that the positive correlation between $TREAT_i \times DURING_t$ and overinvestment concentrates on firms with high agency costs and less financial constraints. Firms with higher agency costs, proxied by financial restatements, higher bankruptcy risks, and excess executive compensation are more likely to become the targets of short- sellers (Massa et al. 2015; Chen, Harford, and Lin, 2015; Fang et al., 2016; Hope, Hu, and Zhao, 2017). Meanwhile, firms with fewer financial constraints are capable of investing more (Campello, Graham, and Harvey, 2010). These findings further complement the argument that by trading in the dark venues, informed traders can effectively discern the problematic firms and discipline the less financially constrained firms which need timely surveillance.

Venkatachalam, 2018). Rather, the overinvestment behavior can be largely attributed to the lack of external governance and thus harm firms' future performance.

To the best of our knowledge, our paper is the first to show the real effects of dark pools on corporate decisions. Previous studies about dark pools focus mainly on their impact on the market microstructure (e.g., Boulatov and George, 2013; Zhu, 2014; Foley and Putniņš, 2016; Hatheway, Kwan, and Zheng, 2017; Blakrishnan, et al., 2021) and whether they are more attractive to informed or uninformed traders (Reed Samadi, and Sokobin, 2020; Ye and Zhu, 2020; Balakrishnan et al., 2021). However, none of the existing studies examine whether dark pools would have any real effects on corporate behaviors in the spirit of Bond, Edmans, and Goldstein (2012), who discuss the feedback effects of the secondary financial markets on the real economy. We extend the studies of dark pools to a broader scope and provide novel causal evidence that dark pools, as one of the important trading venues, can alleviate the agency problems between managers and shareholders and exert a disciplinary effect on corporate overinvestment.

Our paper also contributes to the burgeoning literature on the disciplinary effect of the secondary markets. This stream of studies argues that informed traders such as short-sellers and hedge funds can discipline managerial misbehaviors, including earnings management (Massa et al., 2015; Fang et al., 2016), value-destroying mergers and acquisitions (Chang et al., 2019), and empire buildings (Gantchev, Sevilir, and Shivdasani, 2020; Wu and Chung, 2022). Nevertheless, there is no research about whether trading venues matter for these informed traders to enforce the disciplinary function. Since dark pools incentivize information acquisition by helping informed investors to hide their identities and profit from their private information (Brogaard and Pan, 2022), these traders would have lower incentives to gather information without dark pools. We show that as a consequence, managers are less disciplined from overinvestment.[10] Our paper thus supplements the literature about the disciplinary effects of the "invisible hand" on corporate managers by showing the bright side of dark pools as trading venues.

2. Literature Review and Hypothesis Development

2.1 Dark Pool Trading

Dark pools differ from lit venues in many ways, including the sub-penny price improvement, price derivation process, and pre-trade transparency. Traditional exchanges are subjected to constraints on the quoted bid-ask spreads, resulting in a buildup of depth in the limit order books when the trading interest is high. As dark pools offer sub-penny price improvements, traders often migrate their order flows to dark pools to bypass existing limit order queues on lit markets (Kwan, Masulis, and McInish, 2015).

Besides, dark pools may provide limited price discovery as they derive execution prices from lit markets by matching orders at the midpoint of the national best bid and offer (NBBO) or executing orders at prices bounded between the NBBO. Nevertheless, they can change the price discovery process indirectly and thus affect the market quality. Several prior studies have

[10] There are limitations to generalize our results to large-cap companies since the Tick Size Pilot Program only applies to medium- and small-cap securities. Large firms are under greater scrutiny and are more transparent. Hence, whether the existence of dark pools can exert the same magnitudes of disciplinary effects remains as an empirical question to be explored. The medium- and small-cap firms are more likely to be the targets of informed traders to gain private information due to the intrinsic opaqueness (e.g., Drake et al. 2015; Zhao 2020; Brendel and Ryans 2021). Therefore, the trade-at rule for medium- and small-cap firms offers a more appropriate setting to study the impact of dark pool's disciplinary effect on overinvestment through informed trading.

shown that dark trading improves the market quality in lit markets (Boulatov and George, 2013; Zhu, 2014; Foley and Putniņš, 2016; Blakrishnan et al., 2021). However, others find that the opposite is more plausible (Hatheway, Kwan, and Zheng, 2017; Thomas et al., 2021).

Another important feature of dark pools is the lack of pre-trade transparency compared to traditional exchanges. Thus, dark pools can facilitate the trading of large blocks of shares without alarming the broad market, thereby reducing the risk of being front-run. Although the existing studies argue that dark trading is less informed in general (Zhu, 2014; Comerton-Forde and Putniņš, 2015; Reed et al., 2020), informed traders still utilize dark pools to hide their orders. For example, Ye and Zhu (2020) show that dark trading increases with informed trading, especially when the value of information is higher. Balakrishnan et al. (2021) find an increase in the dark market share during the weeks around earnings announcements. In addition, Nimalendran and Ray (2014) and Forde and Putniņš (2015) find that informed traders submit orders to dark pools alongside lit markets.

Overall, the extant research shows that informed traders can execute orders in dark pools for (i) minimizing price impacts, (ii) avoiding front-running, (iii) gaining sub-penny price improvements, and (iv) maximizing the probability of order executions. Therefore, the existence of dark pools can lead to greater information acquisition (Brogaard and Pan, 2022), as the expected trading profits from informed investors are higher.

2.2 Dark Pool Trading and Overinvestment

As we discussed in the previous section, the dark pools are important trading venues for informed traders to hide their identities and optimize order executions, thereby providing them with opportunities to better profit from their private information. Short sellers are shown to be informed investors and have disciplinary effects on firms' decision-making processes (e.g., Christophe, Ferri, and Angel, 2004; Boehmer and Wu, 2013; Massa, Zhang, and Zhang; Fang, Huang, and Karpoff, 2016). The disciplining hypothesis suggests that short sellers serve as an external governance mechanism by increasing stock price efficiency and monitoring managerial decisions. They increase the probability and speed with which markets uncovers managerial misbehavior and thus reduce managers' incentives to engage in value-destroying activities ex-ante. The relaxation of short-selling constraints can reduce earnings management and assist financial fraud detection (Massa et al., 2015; Fang, Huang, and Karpoff, 2016). Moreover, short-selling threats mitigate managerial myopia in investment decisions by disciplining mergers and acquisitions (Chang, Lin, and Ma, 2019), encouraging long-term investments (Massa et al., 2015), and increasing innovative activities (He and Tian, 2016). Similarly, other informed traders, such as activist hedge funds, can also discipline managers by reducing overall mergers and acquisitions practices and curtailing empire buildings (Gantchev, Sevilir, and Shivdasani, 2020; Wu and Chung, 2022).

Our study focuses on corporate overinvestment, one of the notorious agency problems that can be destructive to shareholder value (e.g., Jensen, 1986; Berger and Ofek, 1995; Titman et al., 2004; Richardson, 2006; Hope and Thomas, 2008; Campbell Gallmeyer, Johnson, Rutherford, and Stanley, 2011). Managers are prone to overinvestment without external or internal governance, as it provides private benefits of control via (i) increasing their power and prestige, (ii) helping to meet short-term goals, and (iii) resonating with their overconfident personalities.

The agency cost hypothesis suggests that managers make self-maximization choices by aggressively growing the firm (Richardson, 2006; McNichols and Stubben, 2008; Hope and Thomas, 2008). Such behaviors come from managers' desires for status, power, and prestige and can lead to better compensation and less unemployment risk (Amihud and Lev, 1981; Murphy, 1985; Shleifer and Vishny, 1989; Jensen and Murphy, 1990; Goel and Thakor, 2008). In addition, managerial myopia is another determinant of overinvestment (Bebchuck and Stole, 1993; Xiong and Jiang, 2022). Moreover, CEOs are more likely to be overconfident. Such personal attributes affect corporate investment decisions and lead to excess investment (Malmendier and Tate, 2005, 2015; Goel and Thakor, 2008; Gervais, Heaton, and Odean, 2011; Pikulina, Renneboog, and Tobler, 2017).

In contrast, managers would allocate resources more efficiently when agency problems are mitigated by better information environments (Biddle et al., 2009; Roychowdhury et al., 2019; Durnev and Mangen, 2020). With the existence of dark pools, informed investors (e.g., short sellers and hedge funds) are more incentivized to acquire valuable private information about stocks that can be traded in dark pools (Brogaard and Pan, 2022). Consequently, the disciplinary effect of informed traders on managers will be weaker for stocks with restrictions on dark trading. When managers are less disciplined, we expect them to be more obsessed with aggressively growing their companies by overinvestment. Based on the discussion above, we propose our hypothesis as follows.

Hypothesis: *Dark pool trading disciplines managers from overinvestment.*

Nevertheless, it is unclear ex-ante whether dark pools can effectively reduce firms' overinvestment. According to the quiet life hypothesis, when disciplinary effects are weakened, managers can also enjoy the quiet life and involve in underinvestment (Bertrand and Mullainathan 2003; Giroud and Mueller 2010). In addition, a line of literature argues that dark pools imped the price discovery process (Comerton-Forde and Putniņš, 2015; Hatheway et al, 2017; Thomas et al., 2021), which might provide managers more space to temporarily fool the market and weaken the disciplinary force on corporate overinvestment. Even without dark pools, informed traders can still place the order in the lit market and exhibit disciplinary force but with certain higher transaction costs. Thus, whether there exists a disciplinary effect of dark pools on corporate investment is still an empirical question that is worth exploring.

3. Data and Methodology

3.1 Data Sources and Sample Construction

The SEC implemented a Tick Size Pilot Program in 2016 for medium- and small-capitalization stocks as a natural experiment. The program is announced in September 2016 by the SEC and commences on October 31, 2016. We first obtain the list of firms that participate in the Program from the FINRA.[11] We follow Brogaard and Pan (2022) and Thomas et al. (2021) to use Test Group Three (TG3) as the treatment group and Test Group Two (TG2) as the control group. Both TG2 and TG3 are subject to the same quoting and trading increments, but the trading in dark pools decreases for TG3 due to the restrictions imposed by the trade-at rule. This natural experiment provides a clean setting for us to directly examine the dark pool

[11] https://www.finra.org/rules-guidance/key-topics/tick-size-pilot-program/data-collection-securities-and-pilot-securities-files.

restrictions on firm overinvestment for medium- and small-cap firms. We remove the stocks that change primary listing venues and those whose prices drop below $1 during the Program from our sample. We further delete the stocks that join the Program after October 31, 2016, and those that leave the Program during the Program period. There are in total 225 and 242 firms in our treatment and control groups after the sample filtering, respectively.

For our tests at the daily level, we follow Chung et al. (2021) and use October 1, 2015, to September 23, 2016, as the pre-Program period and October 31, 2016, to October 31, 2017, as the Program period. For our analysis at the quarterly level, we follow Ahmed, Li, and Xu (2020) and use quarters from April 1, 2015, to September 31, 2016, as the pre-Program period and quarters from January 1, 2017, to June 30, 2018, as the Program period.

For the daily analysis sample, we combine four datasets, including dark trading volume from TAQ, total trading volume from CRSP, and off- and on-exchange shorting data from FINRA and CBOE.[12] We calculate *DARK* as the ratio of dark trading volume from TAQ over total trading volume from CRSP. *SHORT_DARK* is the dark pool short-selling flow, which is calculated as the aggregated daily short volume over total volume for off-exchange trades from FINRA. *SHORT_LIT* is the lit exchange short-selling flow, which is calculated as the aggregated daily short volume over total volume from CBOE.

For the quarterly analysis sample, we use data from Compustat. The main variable of interest, abnormal investment (*ABINV*), is calculated based on Biddle et al. (2009) as the signed

[12] The two largest exchanges in the U.S. are the Nasdaq and NYSE, which charges fees for their short sale information. The short sale data from the third-largest exchange, CBOE, is available from https://www.cboe.com/us/equities/market_statistics/short_sale/.

residual from the cross-sectional regression below:

$$Investment_{i,t+1} = \beta_1 + \beta_2 \times Sales\ Growth_{i,t} + \varepsilon_{i,t+1} \quad (1)$$

This equation is estimated for each industry quarter based on SIC 2-digit classification with at least eight observations in each quarter. $Sales\ Growth_{i,t}$ is a measure of growth opportunity. The signed residual represents the level of abnormal investment. Higher values of the residuals are associated with higher levels of overinvestment, and vice versa.

Our control variables are also constructed based on Biddle et al. (2009) by using data from CRSP and Compustat. A detailed description of our variable definition can be found in Table IA1 of the online supplement. We winsorize all continuous variables at the 1% level to remove potential errors and outliers. There are 78,616 and 4,514 observations for the daily and quarterly datasets, respectively.

The summary statistics and correlations for the regression variables are reported in Table 1. Panel A shows the summary statistics of the quarterly sample.[13] The mean (median) for the main dependent variable, abnormal investment, is –0.287 (–0.578). The summary statistics for the daily dark trading and short-selling flow measures are shown in Panel B. On average, dark trading takes up 30% of the trading volume. Around 43.5% of the off-exchange trading is short selling. The on-exchange short-selling takes up a higher percentage of 56.1%.[14] Panel C shows the Pearson's correlation coefficients among the main variables of interest. Firms that tend to overinvest are more likely to have a larger firm size (*lnME*), higher market-to-book ratio (*MTB*), and more cash holdings (*CASH*).

[13] Sample disctribution across industry and year-quarter are represented in International Appendix (IA2).
[14] Our statistics on short selling is consistent with the literature (Reed, Samadi, and Sokobin, 2019).

3.2 Methodology

To provide causal evidence for our hypothesis, we adopt a standard difference-in-difference design as follows:

$$Y_{i,t} = \beta_1 + \beta_2 TREAT_i \times DURING_t + \gamma X_{i,t} + TimeFE + FirmFE + \varepsilon_{i,t} \quad (2)$$

where $Y_{i,t}$ is one of the dependent variables of interest. The dummy variable, $TREAT_i$ equals one for firms in the treatment group (TG3), and zero otherwise. The dummy variable, $DURING_t$ equals one after Program commencement, and zero otherwise. The estimated average treatment effect of the trade-at rule on the dependent variables is measured by β_2, the interaction term between $TREAT_i$ and $DURING_t$. We use this model to examine the effects of the trade-at rule on dark trading and short-selling flow using the daily sample (Table 2).

We then use this model to examine the effect of dark trading on abnormal investment using the quarterly sample (Table 3). The variable $X_{i,t}$ represents a vector of control variables following Biddle et al. (2009). A firm fixed effect is used to control for cross-sectional variations in firm characteristics. We also control for a day (year-quarter) fixed effect for our daily (quarterly) dataset.

4. Results

4.1 Effect of Trade-at Rule on Dark Trading and Shorting-Selling Flow

We report estimation results of three models based on Equation (2) in Table 2. Since the dependent variables are all at the daily frequency, we use the daily sample to give us more accurate estimations. Column 1 verifies that the trade-at rule is effective in reducing dark trading. Following Thomas, et al. (2021), we use the percentage of trading volume in dark pools over the total trading volume, *DARK*, as our proxy for dark trading activity. The coefficient on $TREAT_i \times DURING_t$ is negative and statistically significant at the 1% level. The magnitude of the coefficient is similar to that of Thomas et al. (2021), showing that the percentage of shares traded in dark venues dropped by 11.1% during the Program for the treatment group.

We then show that short selling decreases due to the trade-at rule since the dark pools help informed traders to hide their orders from the general market and reduce the price impact. We use short-selling flow as a proxy for informed trading, as it has been shown to contain information about future stock prices (e.g., Wang et al., 2020). Column 2 shows that short-selling flow in dark pools (*SHORT_DARK*) decreases by 9.7% for the treatment firms during the Program. This result is statistically significant at the 1% level and amounts to 22.2% of the total short-selling flow in dark venues (0.435).

Last, we show that the restrictions in dark trading have a spillover effect on informed trading in lit markets. Since it is inconvenient for short sellers to trade in dark pools after the trade-at rule, they are less willing to acquire information about stocks in the treatment group. Therefore, they might reduce their overall trading for the treatment stocks, instead of fully migrating their trading from dark venues to lit markets. As is reported in Column 3, the short-selling flow in the lit market (*SHORT_LIT*) is reduced by 2.3%. While the magnitude of the reduction is smaller compared to the coefficient in Column 2, the result is nontrivial. It is statistically significant at the 1% level and accounts for 4% of the average short-selling flow in the lit market (0.561). To conclude, the trade-at rule curtails dark trading for treatment stocks during the Program and leads to a reduction in informed trading measured by short selling.

4.2 Effect of Trade-at Rule on Firm Overinvestment

In this section, we test our hypothesis by examining whether the restrictions in dark trading have real consequences on corporate investment based on the quarterly sample. In particular, Tables 3 and 4 exhibit how the trade-at rule affects firms' abnormal investment, measured by *ABINV*. In Column 1 of Table 3, the coefficient on $TREAT_i \times DURING_t$ is 0.511 and significant at the 5% level without controlling for year-quarter fixed effects and firm fixed effects. The coefficient on *TREAT* is insignificant, suggesting that the treatment and control firms are not significantly different in abnormal investment levels before the Program. The coefficient on *DURING* is not significant either, indicating that the control firms' abnormal investment levels are similar before and during the Program.

With firm and year-quarter fixed effects added, Column 2 shows that the abnormal investment level increases by 0.734 for treatment firms during the Program. The increase accounts for 18.2% of the standard deviation of *ABINV* (4.017) and is significant at the 1% level. Our results are robust by changing the measure of abnormal investment by the recent one in Bae, Biddle, and Park (2022).[15] For control variables, we find that abnormal investment is positively associated with firm size (*lnME*), operating cash flow volatility (*σCFO*), capital structure (*KSTRUC*), and negatively associated with cash holdings (*CASH*) after controlling for the fixed effects.

Although we find that the restriction to dark pool trading leads to higher abnormal investment levels, it could be the case that the effect is driven by a reduction in underinvestment

[15] See the detail of the construction of the measurement in IA1 and the regression results in IA3 Panel C.

for the treated firms after the Program. To tease out this alternative channel and provide further support to our hypothesis, we separate the sample into the overinvestment ($OVER$) group and underinvestment ($UNDER$) group based on the sample median. Specifically, if the firm's abnormal investment level is above the median, it is categorized into the $OVER$ group and vice versa. We then re-run the regression for each group.

The coefficient on $TREAT_i \times DURING_t$ in Column 3 of Table 3 for the $OVER$ group is positive and statistically significant at the 5% level. The magnitude of the coefficient is larger than that for the full sample in Column 2. The result indicates that the trade-at rule increases firms' overinvestment by 0.978 (24.3% compared to the standard deviation of *ABINV*). In contrast, the coefficient on $TREAT_i \times DURING_t$ in Column 4 for group $UNDER$ is negative at −0.37 and not statistically significant. The p-value of the difference between the two coefficients is 0.016, which is statistically significant. We also find the trade-at rule decreases investment efficiency (*INV_EFF*) and overall corporate investment such as capital expenditure ($CAPX\_Q$) and change of the net value of property, plant, and equipment (*CHPPE_Q*), as shown in International Appendix (IA3 Panel A and B). These results suggest that our finding is not driven by a reduction in firms' underinvestment, corroborating our hypothesis.

Next, we use a parallel trend analysis to alleviate the concern of the pre-existing trends. Specifically, we run a regression using the following model:

$$
\begin{aligned}
Y_{i,t} = \beta_1 + \beta_2 TREAT_i \times PRE6 + \beta_3 TREAT_i \times PRE5 + \beta_4 TREAT_i \times PRE4 \\
+ \beta_5 TREAT_i \times PRE3 + \beta_6 TREAT_i \times PRE2 \\
+ \beta_7 TREAT_i \times DURING1 + \beta_8 TREAT_i \times DURING2 \\
+ \beta_9 TREAT_i \times DURING3 + \beta_{10} TREAT_i \times DURING4 \\
+ \beta_{11} TREAT_i \times DURING5 + \beta_{12} TREAT_i \times DURING6 + \gamma X_{i,t} \\
+ YearQuarterFE + FirmFE + \varepsilon_{i,t} \qquad (3)
\end{aligned}
$$

where $Y_{i,t}$ is the abnormal investment (*ABINV*). Variables from *PRE6* to *DURING6* are dummy variables that equal one for quarter *t* concerning the Program commencement period. For instance, *DURING1* equals one if it is the first quarter after the Program, 2017 Q1, and zero otherwise. The coefficient for the quarter preceding the Program, 2016 Q3, is normalized to zero and serves as a benchmark. We run this regression for the sample period starting from the second quarter of 2015 to the second quarter of 2018.

Table 4 presents the regression results for the parallel trend tests. The coefficients β_2 to β_{12} capture the average difference between the treatment and control groups for each quarter relative to the third quarter of 2016. Columns 1 and 2 show the results without controls and with controls, respectively, and they are quantitatively similar. The coefficients are not statistically significant before the Program, indicating parallel trend assumption for DID is satisfied.

To conclude, we find that restrictions in dark trading lead to a weaker disciplining effect on managers and corporate overinvestment, consistent with our hypothesis.

4.3 Validating the Short Selling Channel

Brogaard and Pan (2022) find that the inclusion of dark pools leads to greater information acquisition. A sizable literature has shown that short sellers exert a disciplining effect on managers (e.g., Massa et al., 2015). Hence, we conjecture that the increase in the overinvestment for the treatment group is at least partially a result of the reduction in short sellers' activity after the trade-at rule.

To validate this informed investor channel, we examine whether the impact of the trade-at rule is concentrated among the treatment firms with the higher short-selling flow before the Program. We use short-selling flow (*SHORT_DARK*) as the proxy for short-selling activity. Specifically, a higher short-selling flow indicates a stronger disciplinary effect of informed investors on managers. If a firm's short-selling flow is above (below) median one quarter prior to the Program, it is grouped into the *HIGH_SHORT* (*LOW_SHORT*). We then run the regression following Equation (2) for each group.

The coefficient on $TREAT_i \times DURING_t$ in Table 5 is positive and significant in the *HIGH_SHORT* group in Column 1 at 1.255, corresponding to a 31.2% increase in abnormal investments compared to its standard deviation. The coefficient for the *LOW_SHORT* group in Column 2 is much lower in magnitude at 0.349 and not statistically significant. The p-value of the difference between the two coefficients is 0.055, which is statistically significant. The finding confirms our conjecture that the effect of the dark pools is concentrated among stocks with higher informed trading before the Program, as these stocks suffered a greater reduction in short-selling threat during the Program.

To further complement the argument of the disciplinary function of informed trading in the dark pool, we test whether the positive correlation between the restriction of dark pools and overinvestment concentrates on firms with higher agency costs. Since firms with higher agency costs, proxied by financial restatements, higher bankruptcy risks, and excess executive compensation are more likely to become the targets of short-sellers (Massa et al. 2015; Chen, Harford, and Lin, 2015; Fang et al., 2016; Hope, Hu, and Zhao, 2017). As shown in Internaltional Appendix IA4, the coefficient on *TREAT* × *DURING* × *RESTATE* is positive and significant at a 5% confidence level, indicating the positive effect of restrictions to dark pool on overinvestment is concentrated on restated firms. For Table IA5 and IA6, we only find significant results for firms with high bankruptcy risk and firms with high excess executive compensation before the rule.

Meanwhile, firms with fewer financial constraints are capable of investing more (Campello, Graham, and Harvey, 2010). Thus, the positive relationship between dark pool restrictions and overinvestment concentrates on firms with fewer financial constraints before the rule as shown in Table IA7. Together, the evidence supports our argument that by trading in the dark venues, informed traders can effectively discern the problematic firms and discipline the less financially constrained firms.

4.4 Consequences on Firm Performance

While we find an increase in overinvestment for treatment firms during the Program, the behavior per se does not necessarily harm the performance. Firms may overinvest compared to industry peers due to a longer vision of growth, which is associated with better future performance (Arthur, Vashishtha, and Venkatachalam 2018). Hence, in this section, we study whether overinvestment due to the treatment effect is detrimental to firms' performance, measured by future return on assets (ROA). The coefficients on $TREAT_i \times DURING_t$ in Panel A of Table 6 are all negative and statistically significant for Columns 1 to 4, indicating that the restrictions to dark trading cause worse operating performance for the four quarters of the next year.

We further validate that the reduction in firm performance is a result of overinvestment using the two-stage least-squares (2SLS) approach. Specifically, we use the Program as an instrumental variable (IV) to test the impact of overinvestment on firms' future performance based on the regression model as follows:

$$ROA_{i,t+j} = \beta_1 \widehat{ABINV}_{i,t} + \gamma X_{i,t} + YearQuarterFE + FirmFE + \varepsilon_{i,t} \quad (4)$$

where j = 4, 5, 6, 7, representing the four quarters of the next year. The first stage regression estimates the predicted abnormal investment ($\widehat{ABINV}$) by regressing $ABINV$ on $TREAT_i \times DURING_t$ and a set of control variables using Equation (2).[16]

Panel B of Table 6 demonstrates that the coefficients on $\widehat{ABINV}$ are negative and significant for the first three quarters in the following year, and remain negative for the fourth quarter in the next year. Overall, the results indicate that corporate overinvestment that is driven by restrictions on trading in dark pools indeed worsens firms' future operating performance.

5. Conclusion

In this paper, we study whether the presence of dark pools has a disciplining effect on firms' overinvestment. To the best of our knowledge, our paper is the first to examine the real effects of dark trading on corporate decisions. We argue that dark pools can discipline the behavior of

[16] The regression result is shown in Table 3 Column 2.

overinvestment for medium- and small-cap firms as the dark venues incentivize information acquisition of informed investors who can hide their orders from the general market and profit from their private information. Thus, we expect firms to increase overinvestment when restrictions are put on dark trading.

We test our hypothesis and provide a plausible causal relationship using a natural experiment conducted by the SEC during the Tick Size Pilot Program. During the Program, a trade-at rule is imposed on the last treatment group, which effectively restricted off-exchange trading. We show that the firms in the treatment group tend to overinvest, and the disciplining effect of the dark pools comes from informed trading. As a consequence, overinvestment is associated with negative future performance. These results support the disciplining effect of dark pools and shed light on the bright side of dark trading.

References

Ahmed, A. S., Y. Li, and N. Xu. 2020. Tick Size and Financial Reporting Quality in Small-Cap Firms: Evidence from a Natural Experiment. *Journal of Accounting Research* 58 (4):869-914.

Altman, E. I. 1968. Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance* 23 (4):589-609.

Amihud, Y., and B. Lev. 1981. Risk Reduction as a Managerial Motive for Conglomerate Mergers. *The Bell Journal of Economics*:605-617.

Armstrong, C. S., C. D. Ittner, and D. F. Larcker. 2012. Corporate Governance, Compensation Consultants, and CEO Pay Levels. *Review of accounting studies* 17 (2):322-351.

Bae, J., G. C. Biddle, and C. W. Park. 2022. Managerial Learning from Analyst Feedback to Voluntary Capex Guidance, Investment Efficiency, and Firm Performance. *Management Science* 68 (1):583-607.

Balakrishnan, K., X. Gkougkousi, W. R. Landsman, and P. Taori. 2021. Dark Market Share around Earnings Announcements and Speed of Resolution of Investor Disagreement. *The Accounting Review*, forthcoming.

Bebchuk, L. A., and L. A. Stole. 1993. Do Short-Term Objectives Lead to Under-or Overinvestment in Long-Term Projects? *The Journal of Finance* 48 (2):719-729.

Berger, P. G., and E. Ofek. 1995. Diversification's Effect on Firm Value. *Journal of Financial Economics* 37 (1):39-65.

Bertrand, M., and S. Mullainathan. 2003. Enjoying the Quiet Life? Corporate Governance and Managerial Preferences. *Journal of Political Economy* 111 (5):1043-1075.

Biddle, G. C., G. Hilary, and R. S. Verdi. 2009. How Does Financial Reporting Quality Relate to Investment Efficiency? *Journal of Accounting and Economics* 48 (2):112-131.

Boehmer, E., and J. Wu. 2013. Short Selling and the Price Discovery Process. *Review of Financial Studies* 26 (2):287-322.

Bond, P., A. Edmans, and I. Goldstein. 2012. The Real Effects of Financial Markets. *Annual Review of Financial Economics* 4 (1):339-360.

Boulatov, A., and T. J. George. 2013. Hidden and Displayed Liquidity in Securities Markets with Informed Liquidity Providers. *Review of Financial Studies* 26 (8):2095-2137.

Brendel, J., and J. Ryans. 2021. Responding to Activist Short Sellers: Allegations, Firm Responses, and Outcomes. *Journal of Accounting Research* 59 (2):487-528.

Brogaard, J., and J. Pan. 2022. Dark Pool Trading and Information Acquisition. *The Review of Financial Studies* 35 (5):2625-2666.

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. 2011. CEO optimism and forced turnover. *Journal of Financial Economics* 101 (3): 695-712.

Campello, M., J. R. Graham, and C. R. Harvey. 2010. The Real Effects of Financial Constraints: Evidence from a Financial Crisis. *Journal of Financial Economics* 97 (3):470-487.

Chang, E. C., T.-C. Lin, and X. Ma. 2019. Does Short-selling Threat Discipline Managers in Mergers and Acquisitions Decisions? *Journal of Accounting and Economics* 68 (1):101223.

Chen, T., J. Harford, and C. Lin. 2015. Do Analysts Matter for Governance? Evidence from Natural Experiments. *Journal of Financial Economics* 115 (2):383-410.

Christophe, S. E., M. G. Ferri, and J. J. Angel. 2004. Short-Selling Prior to Earnings Announcements. *The Journal of Finance* 59 (4):1845-1876.

Chung, K. H., A. J. Lee, and D. Rösch. 2020. Tick Size, Liquidity for Small and Large Orders, and Price Informativeness: Evidence from The Tick Size Pilot Program. *Journal of Financial Economics* 136 (3):879-899.

Comerton-Forde, C., and T. J. Putnins. 2015. Dark Trading and Price Discovery. *Journal of Financial Economics* 118 (1):70-92.

Cooper, M. J., Gulen, H., & Schill, M. J. 2008. Asset Growth and the Cross-Section of Stock Returns. *the Journal of Finance* 63(4): 1609-1651.

Drake, M. S., L. A. Myers, S. Scholz, and N. Y. Sharp. 2015. Short Selling Around Restatement Announcements: When do Bears Pounce? *Journal of Accounting, Auditing & Finance* 30 (2):218-245.

Durnev, A., and C. Mangen. 2020. The Spillover Effects of MD&A Disclosures for Real Investment: The Role of Industry Competition. *Journal of Accounting and Economics* 70 (1):101299.

Edmans, A., I. Goldstein, and W. Jiang. 2012. The Real Effects of Financial Markets: The Impact of Prices on Takeovers. *The Journal of Finance* 67 (3):933-971.

Fang, V. W., A. H. Huang, and J. M. Karpoff. 2016. Short Selling and Earnings Management: A Controlled Experiment. *The Journal of Finance* 71 (3):1251-1294.

Foley, S., and T. J. Putniņš. 2016. Should We be Afraid of The Dark? Dark Trading and Market Quality. *Journal of Financial Economics* 122 (3):456-481.

Gantchev, N., M. Sevilir, and A. Shivdasani. 2020. Activism and Empire Building. *Journal of Financial Economics* 138 (2):526-548.

Gervais, S., J. B. Heaton, and T. Odean. 2011. Overconfidence, Compensation Contracts, and Capital Budgeting. *The Journal of Finance* 66 (5):1735-1777.

Giroud, X., and H. M. Mueller. 2010. Does Corporate Governance Matter in Competitive Industries? *Journal of Financial Economics* 95 (3):312-331.

Goel, A. M., and A. V. Thakor. 2008. Overconfidence, CEO Selection, and Corporate Governance. *The Journal of Finance* 63 (6):2737-2784.

Grossman, S. J., and J. E. Stiglitz. 1980. On the Impossibility of Informationally Efficient Markets. *The American Economic Review* 70 (3):393-408.

Hadlock, C. J., and J. R. Pierce. 2010. New Evidence on Measuring Financial Constraints: Moving beyond the KZ index. *The Review of financial studies* 23 (5):1909-1940.

Hatheway, F., A. Kwan, and H. Zheng. 2017. An Empirical Analysis of Market Segmentation on U.S. Equity Markets. *Journal of Financial and Quantitative Analysis* 52 (6):2399-2427.

He, J., and X. Tian. 2016. Do short Sellers Exacerbate or Mitigate Managerial Myopia? Evidence from Patenting Activities. *Working Paper*.

Hope, O.-K., D. Hu, and W. Zhao. 2017. Third-party Consequences of Short-selling Threats: The Case of Auditor Behavior. *Journal of Accounting and Economics* 63 (2-3):479-498.

Hope, O.-K., and W. B. Thomas. 2008. Managerial Empire Building and Firm Disclosure. *Journal of Accounting Research* 46 (3):591-626.

Jensen, M. C. 1986. Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review* 76 (2):323-329.

Jensen, M. C., and K. J. Murphy. 1990. Performance Pay and Top-Management Incentives. *Journal of Political Economy* 98 (2):225-264.

Kraft, A. G., R. Vashishtha, and M. Venkatachalam. 2018. Frequent Financial Reporting and Managerial Myopia. *The Accounting Review* 93 (2):249-275.

Kwan, A., R. Masulis, and T. H. McInish. 2015. Trading Rules, Competition for Order Flow and Market Fragmentation. *Journal of Financial Economics* 115 (2):330-348.

Lev, B., and Y. Amihud. 1981. Risk Reduction as a Managerial Motive for Conglomerate Mergers. *The Bell Journal of Economics* 12 (2):605-617.

Malmendier, U., and G. Tate. 2005. CEO Overconfidence and Corporate Investment. *The Journal of Finance* 60 (6):2661-2700.

———. 2015. Behavioral CEOs: The Role of Managerial Overconfidence. *Journal of Economic Perspectives* 29 (4):37-60.

Massa, M., B. Zhang, and H. Zhang. 2015. The Invisible Hand of Short Selling: Does Short Selling Discipline Earnings Management? *Review of Financial Studies* 28 (6):1701-1736.

McNichols, M. F., and S. R. Stubben. 2008. Does Earnings Management Affect Firms' Investment Decisions? *The Accounting Review* 83 (6):1571-1603.

Nimalendran, M., and S. Ray. 2014. Informational Linkages between Dark and Lit Trading Venues. *Journal of Financial Markets* 17:230-261.

Pikulina, E., L. Renneboog, and P. N. Tobler. 2017. Overconfidence and Investment: An Experimental Approach. *Journal of Corporate Finance* 43:175-192.

Reed, A. V., M. Samadi, and J. S. Sokobin. 2020. Shorting in Broad Daylight: Short Sales and Venue Choice. *Journal of Financial and Quantitative Analysis* 55 (7): 2246-2269.

Richardson, S. 2006. Over-investment of Free Cash Flow. *Review of Accounting Studies* 11 (2):159-189.

Roychowdhury, S., N. Shroff, and R. S. Verdi. 2019. The Effects of Financial Reporting and Disclosure on Corporate Investment: A review. *Journal of Accounting and Economics* 68 (2-3):101246.

Shleifer, A., and R. W. Vishny. 1989. Management Entrenchment: The Case of Manager-specific Investments. *Journal of Financial Economics* 25 (1):123-139.

Titman, S., Wei, K. J., & Xie, F. 2004. Capital Investments and Stock Returns. *Journal of financial and Quantitative Analysis* 39 (4): 677-700.

Thomas, J., F. Zhang, and W. Zhu. 2021. Dark Trading and Post-Earnings-Announcement Drift. *Management Science* 67 (12):7785-7811.

Wang, X., X. S. Yan, and L. Zheng. 2020. Shorting Flows, Public Disclosure, and Market Efficiency. *Journal of Financial Economics* 135 (1):191-212.

Wu, S.-Y., and K. H. Chung. 2022. Hedge Fund Activism and Corporate M&A Decisions. *Management Science* 68 (2):1378-1403.

Xiong, Y., and X. Jiang. 2022. Economic Consequences of Managerial Compensation Contract Disclosure. *Journal of Accounting and Economics*:101489.

Ye, M., and W. Zhu. 2020. Strategic Informed Trading and Dark Pools. *Working Paper* Available at SSRN 3292516.

Zhao, W. 2020. Activist Short-selling and Corporate Opacity. *Working Paper* Available at SSRN 2852041.

Zhu, H. 2014. Do Dark Pools Harm Price Discovery? *Review of Financial Studies* 27 (3):747-789.

Table 1 Descriptive Statistics

	Mean	SD	p25	Median	p75
Panel A: Summary of quarterly data (N=4,514)					
ABINV	–0.287	4.017	–2.152	–0.578	0.084
LnME	13.029	1.203	12.212	13.137	13.973
MTB	1.863	1.346	1.056	1.347	2.092
σCFO	0.025	0.029	0.008	0.018	0.032
σSALE	0.025	0.031	0.004	0.015	0.033
σINV	4.294	8.136	1.015	1.998	4.158
KSTRUC	0.180	0.200	0.001	0.108	0.290
IND_KSTRUC	0.196	0.105	0.102	0.189	0.260
CFO/SALE	–0.563	4.661	0.007	0.099	0.220
OPECYCLE	6.813	1.800	5.751	6.323	7.177
CASH	0.167	0.210	0.030	0.078	0.217
DIV	0.480	0.500	0.000	0.000	1.000
AGE	20.328	14.759	9.000	18.000	27.000
LOSS	0.260	0.438	0.000	0.000	1.000
AMIHUD	0.192	0.828	0.002	0.006	0.036
SPREAD	0.005	0.007	0.001	0.002	0.006
Panel B: Summary of daily data (N=78,616)					
DARK	0.299	0.098	0.238	0.282	0.338
SHORT_DARK	0.435	0.201	0.283	0.429	0.579
SHORT_LIT	0.561	0.168	0.450	0.572	0.684

Panel C: Correlation

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) *TREAT*	1.00											
(2) *ABINV*	0.04***	1.00										
(3) *LnME*	0.01	0.04***	1.00									
(4) *MTB*	0.01	0.16***	0.20***	1.00								
(5) *σCFO*	–0.01	0.08***	–0.13***	0.31***	1.00							
(6) *σSALE*	–0.03***	0.03**	–0.08***	0.14***	0.64***	1.00						
(7) *σINV*	0.02*	0.12***	–0.13***	0.20***	0.20***	0.03***	1.00					
(8) *CFO/SALE*	0.01	–0.14***	0.01	–0.25***	–0.10***	0.03**	–0.26***	1.00				
(9) *CASH*	0.01	0.12***	–0.07***	0.52***	0.32***	0.04***	0.42***	–0.41***	1.00			
(10) *DIV*	–0.02	–0.10***	0.13***	–0.21***	–0.18***	–0.08***	–0.17***	0.15***	–0.32***	1.00		
(11) *AGE*	0.04***	–0.11***	0.04***	–0.11***	–0.01	0.10***	–0.15***	0.10***	–0.23***	0.27***	1.00	
(12) *LOSS*	0.00	0.14***	–0.14***	0.21***	0.21***	0.10***	0.20***	–0.27***	0.42***	–0.35***	–0.17***	1.00

This table shows the descriptive statistics. Panel A is the summary statistics of the quarterly sample. Panel B is the summary statistics of the daily sample. Panel C is the Pearson correlation matrix for some key variables in the quarterly sample. The variable definitions can be found in Table A1. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 2 The impact of the trade-at rule on dark pool trading and short selling

	(1) *DARK*	(2) *SHORT_DARK*	(3) *SHORT_LIT*
TREAT × DURING	–0.111***	–0.097***	–0.023***
	(–25.061)	(–13.363)	(–2.929)
LnME	–0.028***	0.009	0.025**
	(–5.401)	(0.913)	(2.501)
MTB	0.006***	0.002	0.002
	(2.978)	(0.515)	(0.364)
σCFO	–0.062	0.073	0.003
	(–0.613)	(0.668)	(0.036)
σSALE	0.118**	–0.116	–0.080
	(2.006)	(–0.818)	(–0.554)
σINV	–0.000	0.000	0.000
	(–0.045)	(0.297)	(0.216)
KSTRUC	0.014	0.050	0.012
	(0.853)	(1.615)	(0.420)
IND_KSTRUC	0.003	0.048	0.058
	(0.088)	(0.681)	(0.874)
CFO/SALE	0.000	–0.001	–0.000
	(0.437)	(–0.988)	(–0.488)
OPECYCLE	0.001	–0.004	–0.006
	(0.498)	(–0.892)	(–1.201)
CASH	0.005	–0.006	0.012
	(0.288)	(–0.175)	(0.314)
DIV	0.007	0.002	–0.010
	(1.174)	(0.176)	(–1.050)
AGE	–0.003	0.012	0.014
	(–0.198)	(0.483)	(0.618)
LOSS	–0.003	–0.002	–0.003
	(–1.110)	(–0.495)	(–0.558)
AMIHUD	–0.003	0.007	0.002
	(–0.356)	(0.611)	(0.352)
SPREAD	4.014***	2.320**	0.224
	(5.565)	(2.394)	(0.216)
Constant	0.710**	0.108	–0.018
	(2.462)	(0.209)	(–0.037)
Firm FE	Yes	Yes	Yes
Day FE	Yes	Yes	Yes
Obs.	78,614	78,614	78,614
R-squared	0.874	0.150	0.235

This table presents the impact of the trade-at rule on dark pool trading activities and short-selling flow using Equation (2). The dependent variables from Columns 1 to 3 are dark trading (*DARK*), short-selling flow in dark pools (*SHORT_DARK*), and short-selling flow in lit markets (*SHORT_LIT*). We use the current quarter's financial data to construct control variables in the tests. Standard errors are clustered at the firm level and the day level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 3 The impact of the trade-at rule on overinvestment

	ABINV			
	FULL	*FULL*	*OVER*	*UNDER*
	(1)	(2)	(3)	(4)
TREAT × DURING	0.511**	0.734***	0.978**	–0.037
	(1.991)	(2.903)	(2.319)	(–0.403)
TREAT	–0.081			
	(–0.328)			
DURING	–0.022			
	(–0.129)			
LnME	–0.009	0.793**	1.503***	–0.158
	(–0.081)	(2.299)	(2.679)	(–1.282)
MTB	0.367***	0.060	–0.344	0.163***
	(3.013)	(0.384)	(–1.089)	(3.174)
σCFO	3.805	7.822**	7.536	1.583
	(0.666)	(2.255)	(0.968)	(0.773)
σSALE	2.162	6.826	24.606**	–1.291
	(0.521)	(1.388)	(2.331)	(–0.841)
σINV	0.024	0.011	–0.013	0.004
	(1.488)	(0.661)	(–0.436)	(0.879)
KSTRUC	–1.180**	3.745***	8.099***	–0.872**
	(–2.265)	(3.422)	(4.130)	(–2.302)
IND_KSTRUC	3.482***	1.019	1.736	–1.696*
	(2.795)	(0.413)	(0.461)	(–1.763)
CFO/SALE	–0.094**	–0.040	0.011	–0.017
	(–2.206)	(–0.796)	(0.153)	(–1.363)
OPECYCLE	0.110**	0.178	–0.125	–0.163
	(2.273)	(0.601)	(–0.244)	(–1.548)
CASH	–1.112	–4.851***	–12.555***	0.383
	(–1.459)	(–3.204)	(–3.417)	(0.729)
DIV	–0.342*	–0.257	–0.116	0.214
	(–1.808)	(–0.997)	(–0.293)	(1.570)
AGE	–0.019***	–0.030	0.518	–0.323***
	(–2.959)	(–0.120)	(0.890)	(–2.848)
LOSS	1.044***	0.399*	0.873**	0.068
	(4.350)	(1.871)	(2.395)	(0.847)
AMIHUD	0.044	–0.049	–0.002	–0.050
	(0.360)	(–0.633)	(–0.022)	(–1.333)
SPREAD	–34.542*	–7.495	6.652	11.062
	(–1.916)	(–0.444)	(0.230)	(1.460)
Constant	–1.830	–11.966*	–26.228**	7.785**
	(–1.149)	(–1.661)	(–1.993)	(2.550)
Firm FE	No	Yes	Yes	Yes
Year-Quarter FE	No	Yes	Yes	Yes
Obs.	4,514	4,503	2,191	2,198
R-squared	0.071	0.365	0.527	0.598
Equality Test			p = 0.016	

This table presents the impact of the trade-at rule on firms' abnormal investment using Equation (2). The dependent variable from Columns 1 to 4 is the abnormal investment, *ABINV*, calculated as the signed residual based on the regression model in Equation (1). Column 2 includes Firm and Year-Quarter fixed effects. Columns 1 and 2 contain the full sample. Column 3 shows the sub-sample regression of the overinvestment group where the *ABINV* is above the median value. Column 4 shows the results of the underinvestment group where the *ABINV* is below the median value. The equality test shows the statistical difference between the coefficient on *TREAT × DURING* in Columns 3 and 4. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 4 Parallel trend analysis

	ABINV	
	(1)	(2)
TREAT × PRE6	0.371	0.323
	(0.783)	(0.687)
TREAT × PRE5	–0.118	–0.096
	(–0.231)	(–0.190)
TREAT × PRE4	0.214	0.258
	(0.432)	(0.530)
TREAT × PRE3	–0.127	–0.096
	(–0.223)	(–0.171)
TREAT × PRE2	0.446	0.453
	(1.014)	(1.037)
TREAT × DURING1	0.805*	0.800*
	(1.778)	(1.796)
TREAT × DURING 2	1.141**	1.096**
	(2.415)	(2.368)
TREAT × DURING 3	0.935**	0.926**
	(2.102)	(2.099)
TREAT × DURING 4	0.694*	0.653
	(1.717)	(1.601)
TREAT × DURING 5	1.005**	0.989**
	(2.189)	(2.148)
TREAT × DURING 6	0.830*	0.796*
	(1.757)	(1.686)
Controls	No	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	4,503	4,503
R-squared	0.351	0.365

This table presents the results of dynamic analysis using Equation (3). The dependent variable is the abnormal investment, *ABINV*. *DURING* in table 3 has been decomposed into the quarters relative to the commencement of the trade-at rule. The benchmark is one quarter before the compliance of the trade-at rule (2016 Q3). Column 2 includes all control variables as in Table 3. Both columns add Firm and Year-Quarter fixed effects. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 5 Cross-sectional tests on short-selling flows

	HIGH_SHORT	*LOW_SHORT*
	(1)	(2)
TREAT × DURING	1.255***	0.349
	(3.115)	(1.029)
LnME	1.434***	0.539
	(3.244)	(0.795)
MTB	0.017	–0.261
	(0.089)	(–0.957)
σCFO	9.829*	5.177
	(1.705)	(1.248)
σSALE	18.798***	2.842
	(2.622)	(0.399)
σINV	0.007	0.024
	(0.299)	(1.273)
KSTRUC	3.648**	4.650***
	(2.053)	(2.914)
IND_KSTRUC	2.184	3.902
	(0.755)	(0.986)
CFO/SALE	–0.063	–0.058
	(–1.313)	(–0.811)
OPECYCLE	0.709*	0.066
	(1.671)	(0.134)
CASH	–7.888***	–4.704**
	(–2.687)	(–2.458)
DIV	–0.217	–0.462
	(–0.772)	(–0.877)
AGE	–0.458	0.163
	(–1.382)	(0.576)
LOSS	0.325	0.397
	(0.985)	(1.217)
AMIHUD	–0.028	–0.155
	(–0.194)	(–1.048)
SPREAD	–12.779	–5.334
	(–0.475)	(–0.174)
Constant	–15.066	–11.544
	(–1.555)	(–1.051)
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	2,042	2,038
R-squared	0.409	0.412
Equality Test	p = 0.055	

This table presents the cross-sectional tests conditional on the short-selling level before the trade-at rule. The dependent variable is the abnormal investment, *ABINV*. Column 1 shows the sub-sample regression of the *HIGH_SHORT* group where the quarterly averaged *SHORT_DARK* for the firm before the rule is above the median. Column 2 shows the results of sub-sample regression of the *LOW_SHORT* group. The equality test shows the statistical difference between the coefficient on *TREAT × DURING* in Columns 1 and 2. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table 6 Consequence tests

Panel A: Future firm performance- next year' ROA

	ROA			
	(1) *Year t+1 Q1*	(2) *Year t+1 Q2*	(3) *Year t+1 Q3*	(4) *Year t+1 Q4*
$TREAT \times DURING$	–0.005**	–0.005**	–0.006**	–0.004*
	(–1.974)	(–2.160)	(–2.382)	(–1.866)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	4,457	4,432	4,401	4,369
R-squared	0.612	0.612	0.609	0.619

Panel B: Trade-at rule as IV for overinvestment

	ROA (2SLS)			
	(1) *Year t+1 Q1*	(2) *Year t+1 Q2*	(3) *Year t+1 Q3*	(4) *Year t+1 Q4*
$\widehat{ABINV}$	–0.007*	–0.007*	–0.008*	–0.006
	(–1.734)	(–1.810)	(–1.796)	(–1.512)
Controls	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
Obs.	4,457	4,432	4,401	4,369
R-squared	0.429	0.456	0.404	0.487

This table presents the consequence tests. Panel A shows the rule's impact on future firm performance, proxied by 4 quarter's ROAs in the next year. The dependent variables in Columns 1 to 4 are separated ROA for next year in each quarter. Panel B uses the trade-at rule as an instrumental variable for overinvestment. After regressing overinvest (*ABINV*) on $TREAT \times DURING$ in the first stage (the result is shown in Table 3), we get predicted $ABINV$ ($\widehat{ABINV}$). Panel B shows the results of the second stage where we regress future ROA on $\widehat{ABINV}$. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Internet Appendix

"The Invisible Hand in the Dark:

The Disciplinary Effect of Dark Pools on Firm Overinvestment"

The purpose of this internet appendix is to provide additional robustness tests to our findings. These additional tests are labeled with the extension "IA" for "Internet Appendix" (e.g., Table IA), while the tables reported in the main text are labeled with the original table name. We discuss the supplementary tables below.

Table IA1 provides variable explanations for the variables used in the regression analysis both in the main text and International Appendix.

Table IA2 shows the sample distribution of the quarterly sample used in the main regression. As shown in Panel A, our observations mainly focus on finance (24.7%), manufacturing (15.4%), and business equipment (14.1%) industry.[17] Panel B suggests our observations are evenly distributed across year quarters. Each year-quarter constitutes around 8% of the total observations.

Table IA3 provides additional tests on the effect of the Program on overinvestment. In Panel A, we use two direct measures of firms' investment, capital expenditure (*CAPX_Q*) and property, plant, and equipment growth (*PPECH_Q*), as the independent variables. The coefficients on *TREAT* × *DURING* in Columns (1) and (2) are significant at a 5% level. In Panel B, we use the absolute value of *ABINV*, investment inefficiency (*INV_INEFF*), as the independent variables. We find that $TREAT_i \times DURING_t$ is positively associated with investment inefficiency, suggesting that restrictions on dark pools hinder the overall corporate investment efficiency. Lastly, our findings are robust to alternative measures of abnormal

[17] Our main result still holds when teasing out all the observations in financial industry.

investment used in Bae, Biddle, and Park (2021), as shown in Panel C. The results are consistent with our main findings.

Table IA4 to IA6 shows the cross-sectional tests on agency conflicts. Prior studies document that short sellers tend to focus on problematic firms such as firms with financial restatements or higher bankruptcy risk (Massa et al. 2015; Fang et al., 2016; Hope et al., 2017). While excess compensation is associated with lower corporate governance and higher agency costs (Chen et al., 2015; Armstrong, Ittner, and Larcker 2012). In this section, we use three measures, restatements, bankruptcy risks, and excess executive compensation as proxies for agency costs. The results show that the positive relationship between the restriction of dark pools and overinvestment is mainly concentrated on restated and distressed firms, and firms with excessive executive compensations.

In Table IA4, the benchmark regression in Column 1 shows restatement is positively associated with overinvesting, suggesting problematic firms with financial restatements tend to engage in overinvestment. Column 2 shows the results of the Difference-in-Difference-in-Difference (DDD) model.[18] The coefficient on *TREAT* × *DURING* × *RESTATE* is positive and significant at a 5% confidence level, indicating the positive effect of restrictions to dark pool on overinvestment is concentrated on restated firms.

In Table IA5, we partition the sample based on the median value of bankruptcy risk before the commencement of the Pilot program. Consistently, we only find significant results in Column 1, where the bankruptcy possibility is high. The coefficient on $TREAT_i \times DURING_t$ in Column 1 is 1.071 and significant at a 5% level. Similarly, in Table IA6, we only find significant results for the group with high excess executive compensations. The coefficient on $TREAT_i \times DURING_t$ in Column 1 is 0.972 and significant at a 5% level. Together with these

[18] Since only 7.5% of firms have restatements within the quarterly sample, the sample partition based on restatements before the program will lead to highly unbalanced sub-samples. Thus, we use DDD model to test the cross-sectional variations in firms with and without restatements.

findings, we conclude the main effect focuses on the firms with higher agency costs or firms that are more likely to be the potential targets of short sellers, which further validates the short selling channel in Section 4.3.

Table IA7 shows the cross-sectional tests on financial constraints. From an objective point of view, short sellers tend to focus on firms with higher agency costs, so the disciplinary effects tend to center on firms with more agency problems. Yet, from a subjective perspective, companies with less financial constraints could actively invest more (Campello et al., 2010) while constrained firms would be more cautious to overinvest and even cut technology and capital spending. Thus, we predict the positive impact of restriction of dark pools on corporate overinvestment should concentrate on firms with lower financial constraints before the program. Empirically, we partition the sample based on *HP* index (Hadlock and Pierce 2010), firm size, and age and find significant results for less constrained firms while no significance for constrained firms as shown in Panel A to C in Table IA7. In Panel A, the coefficient on $TREAT_i \times DURING_t$ is only significant for groups with low *HP* index (less financially constrained firms) and remains insignificant for high *HP* index before the program. Consistently in Panel B and C, we only find significant results for older firms and larger firms regarded as less financially constrained companies.

Table IA1. Variable definition

ABINV	Follow Biddle et al. (2009). *ANINV* is the abnormal investment calculated as the signed residual of the cross-sectional regression below. $$Investment_{i,t+1} = \beta_1 + \beta_2 \times Sales\ Growth_{i,t} + \varepsilon_{i,t+1}$$ The equation is estimated for each industry-quarter based on SIC 2-digit classification with at least 8 observations in each quarter. Positive residual represents overinvestment, negative residual represents underinvestment. Investment is the sum of R&D expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment multiply by 100 and scaled by last quarter total assets.
INV_INEFF	*INV_INEFF* is the absolute value of *ANINV*. The higher the value of *INV_INEFF*, the lower the investment efficiency.
ABINV_BBP	Follow Bae, Biddle, and Park (2022). *ABINV_BBP* is the abnormal investment calculated as the signed residual of the cross-sectional regression below. $$CPX_{i,t+1} = \beta_1 + \beta_2 \times TOBINQ_{i,t} + \beta_3 \times CF_{i,t+1} + \varepsilon_{i,t+1}$$ *CPX* is capital expenditure scaled by beginning total asset for firm *i* in year-quarter *t*, multiplied by 100. *TOBINQ* is the beginning of quarter Tobin's Q, calculated as the market value of equity plus total assets minus book value of equity, then scaled by total asset. *CF* is cash flow is current year-quarter operating cash flow scaled by beginning total asset.
CAPX_Q	Quarterly capital expenditure (derived from *CAPXY*) scaled by beginning quarter total asset (ATQ).
PPECH_Q	Quarterly change of net value of property, plant, and equipment (*PPENTQ*) scaled by beginning quarter total asset (*ATQ*).
LnME	The natural logarithm of the market value of equity. *ME* is the number of common shares outstanding (*CSHOQ*) multiplied by stock price (*PRCCQ*).
MTB	Market to book ratio. The number of common shares outstanding (*CSHOQ*) multiplied by stock price (*PRCCQ*), divided by the book value of equity (*CEQQ*).
σCFO	The standard deviation of the quarterly operating cash flow deflated by average quarterly total assets from quarter *t*-5 to *t*-1.
σSALE	The standard deviation of the sales deflated by total assets from quarters *t*-5 to *t*-1.
σINV	The standard deviation of investment (*CAPX_Q*) from quarters *t*-5 to *t*-1.
KSTRUC	Capital structure. The ratio of long-term debt (*DLTTQ*) to the sum of long-term debt and the market value of equity (*DLTTQ*+*PRCCQ***CSHOQ*).
IND_KSTRUC	The mean of *KSTRUC* for firms in the same SIC 3-digit industry.
CFO/SALE	The ratio of *CFO* to sales (*SALEQ*).
OPECYCLE	The log of receivables to sales (*RECTQ*/*SALEQ*) plus inventory to *COGSQ* (*INVTQ*/*COGSQ*) multiplied by 360.
CASH	The ratio of cash to total assets (*CHEQ*/*ATQ*).
DIV	An indicator variable that takes the value of one if the firm paid a dividend, and zero otherwise
AGE	The difference between the first year when the firm appears in CRSP and the current year.
LOSS	An indicator variable that takes the value of one if net income before extraordinary

	items (*IBQ*) is negative, and zero otherwise.
ROA	Return of assets calculated as income before extraordinary items (*IBQ*) scaled by total assets (*ATQ*)
AMIHUD	The quarterly average of daily Amihud's illiquidity ratio times 10^6. The daily Amihud's illiquidity ratio is calculated as the absolute value of daily stock return over daily dollar volume.
SPREAD	The quarterly average of the daily bid-ask spread. The daily close bid-ask spread is calculated as ask price minus bid price divided by the bid-ask mid-point (the mean of bid price and ask price) at market close.
DARK	The ratio of dark pool trading volume over total volume. Dark pool trading volume is calculated as the sum of shares traded during regular trading hours from TAQ and coded as EX = "D". Total volume (*VOL*) is obtained from CRSP.
SHORT_DARK	The short-selling flow in off-exchange markets, obtained from FINRA. Calculated as the ratio of short volume across different markets over the aggregate total volume.
SHORT_LIT	The short-selling flow in on-exchange markets, obtained from CBOE. Calculated as the ratio of short volume across different markets over the aggregate total volume.
RESTATE	*RESTATE* =1 if the firm has at least one restatement in the year. The data source is from Audit Analytics. We use the real restatement period instead of restatement announcement year to create the dummy variable.
BANKRUPT	Bankruptcy index or Z-score used in Altman (1968) and Biddle et al. (2009) but calculated at quarterly level*. *BANKRUPT* = 3.3×Pretax Income (PIQ) + 1×Sales (SALEQ) + 0.25×Retained Earnings (REQ) + 0.5×Working Capital ((ACTQ-LCTQ)/ATQ)
EXCOMP	Excess executive compensation used in (Chen, Harford, and Lin 2015), defined as the residuals from the OLS regression of natural logarithm of CEO total compensation on the natural logarithm of firm's total market value adding industry and year fixed effects in the universal sample of ExecuComp firms.
HP	HP index used in (Hodlock and Pierce 2010). *HP* = -0.737×SIZE +0.043×SIZE^2 - 0.04×AGE, where SIZE is capped at log of ($4.5 billion) and AGE is capped as 37 years.

* We follow the Z-score calculation used in Biddle et al., (2009) to create the Bankruptcy risk in the paper. For robustness, we also follow the original Altman (1968) to create bankruptcy risk based on the following equation. BANKRUPT = 1.2 × Working Capital/ Total asset ((ACTQ-LCTQ)/ATQ) +1.4×Retained Earnings/Total assets (REQ/ATQ) + 3.3×Earnings before interest and taxes/Total assets (OIADPQ/ATQ) + 0.6×Market value equity/ book value of total debt (MCQ/DLTTQ+DLCQ) + 1×Sales/ Total assets (SALEQ/ATQ). The results are qualitatively similar.

Table IA2. Sample distribution

Panel A: Sample distribution by industry

Industry	Number of Obs.	Percentage
Consumer Nondurables	178	3.9%
Consumer Durables	35	0.8%
Manufacturing	694	15.4%
Oil, Gas and Coal Extraction	47	1.0%
Chemicals and Applied Products	117	2.6%
Business Equipment	638	14.1%
Telephone and Television Transmission	144	3.2%
Utilities	73	1.6%
Wholesale, retail and Some Services	474	10.5%
Healthcare, Medical Equipment and Drugs	537	11.9%
Finance	1115	24.7%
Other	462	10.2%
Total	4,514	100.0%

Panel B: Sample distribution by year-quarter

Year-quarter	Number of Obs.	Percentage
2015 Q2	319	7.1%
2015 Q3	336	7.4%
2015 Q4	371	8.2%
2016 Q1	359	8.0%
2016 Q2	360	8.0%
2016 Q3	372	8.2%
2017 Q1	391	8.7%
2017 Q2	387	8.6%
2017 Q3	386	8.6%
2017 Q4	438	9.7%
2018 Q1	395	8.8%
2018 Q2	400	8.9%
Total	4,514	100.0%

This table presents the sample distribution across industry and year quarter. Panel A shows the sample distribution based on Fama-French 12 industry classification. Panel B shows the sample distribution of year-quarter. 2016 Q4 is removed from the sample period.

Table IA3. Additional tests

Panel A: Investment measured by CAPX and change of PPE

	(1) *CAPX_Q*	(2) *PPECH_Q*
TREAT × DURING	0.002**	0.004**
	(2.364)	(2.386)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	4,503	4,503
R-squared	0.353	0.154

Panel B: Investment inefficiency

	(1) *INV_INEFF*	(2) *INV_INEFF*
TREAT × DURING	0.610***	0.555***
	(3.281)	(2.746)
Controls	No	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	4,503	4,503
R-squared	0.347	0.373

Panel C: Overinvestment based on Bae et al. (2022)

	(1) *ABINV_BBP*	(2) *ABINV_BBP*
TREAT × DURING	0.126**	0.112**
	(2.233)	(2.072)
Controls	No	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	4,503	4,503
R-squared	0.518	0.533

This table presents the additional analysis. Panel A uses the quarterly *CAPX* and quarterly change of *PPE* as dependent variables. Panel B uses the absolute value of *ABINV* as the measure of investment inefficiency as the dependent variable. Panel C adopts another measure of firm overinvestment, *ABINV_BBP*, based on Bae et al. (2022). We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table IA4. Cross-sectional tests on restatement

	ABINV	
	(1)	(2)
TREAT × DURING × RESTATE		1.615**
		(2.520)
TREAT × DURING	0.727**	0.545*
	(2.474)	(1.777)
RESATE	0.522*	0.072
	(1.687)	(0.209)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	3629	3629
R-squared	0.356	0.358

This table presents the cross-sectional tests conditional on the financial restatements based on DDD analysis. The dependent variable is the abnormal investment, *ABINV*. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table IA5. Cross-sectional tests on bankruptcy risks

	HIGH_BANKRUPT	*LOW_BANKRUPT*
	(1)	(2)
TREAT × DURING	1.071**	0.619
	(2.395)	(1.192)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	1614	1561
R-squared	0.313	0.424

This table presents the cross-sectional tests conditional on excess compensation before the trade-at rule. The dependent variable is the abnormal investment, *ABINV*. Sample partition is based on the median value of annually excess executive compensations before the program. We obtain the executive compensation from ExecuComp. Since the database only covers S&P firms, the observations drop dramatically. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table IA6. Cross-sectional tests on excess compensation

	HIGH_EXCOMP	*LOW_EXCOMP*
	(1)	(2)
TREAT × DURING	0.972**	0.209
	(2.081)	(0.414)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	972	923
R-squared	0.413	0.307

This table presents the cross-sectional tests conditional on excess compensation before the trade-at rule. The dependent variable is the abnormal investment, *ABINV*. Sample partition is based on the median value of annually excess executive compensations before the program. We obtain the executive compensation from ExecuComp. Since the database only covers S&P firms, the observations drop dramatically. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.

Table IA7. Cross-sectional tests on financial constraints

Panel A: HP index

	HIGH_HP	*LOW_HP*
	(1)	(2)
TREAT × DURING	0.542	0.799***
	(1.273)	(2.892)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	2006	2118
R-squared	0.413	0.263

Panel B: Firm age

	YOUNG	*OLD*
	(3)	(4)
TREAT × DURING	0.522	0.736**
	(1.354)	(2.373)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	2006	2118
R-squared	0.357	0.361

Panel B: Firm size

	SMALL	*LARGE*
	(5)	(6)
TREAT × DURING	0.632	0.762***
	(1.431)	(2.732)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Quarter FE	Yes	Yes
Obs.	2038	2086
R-squared	0.415	0.232

This table presents the cross-sectional tests conditional on financial constrain before the trade-at rule. The dependent variable is the abnormal investment, *ABINV*. Panel A shows the sample partition based on the median value of the HP index before the program. A high *HP* index represents high financial constrain. Panel B shows the sample partition based on the median value of firm age before the program. Panel C shows the sample partition based on the median value of firm size before the program. We use the current period financial data to construct control variables in the tests. Standard errors are clustered at the firm level, and the corresponding *t*-statistics are included in parentheses. Levels of significance are presented as follows: *p<0.1; **p<0.05; ***p<0.01.