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Short selling and dark pool volume

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Abstract

Purpose – Prior research posits that traders with short-lived information favor lit exchanges over dark pools due to execution certainty. This paper aims to focus on the relation between informed trading based on firm fundamentals and dark pool volume because the preferred venue for traders with longer-lived information is less certain.

Design/methodology/approach – The authors examine the effect of short interest, a proxy for informed traders with long-lived information, on dark pool volume using fixed effects, first difference and instrumental variable approaches. They examine the effect of dark pools on the profitability of long-lived information using market- and characteristic-adjusted returns.

Findings – The proportion of trading volume executed in dark pools is positively correlated with short interest. This result is stronger for stocks that suffer from greater uncertainty and stocks targeted by transient institutional investors. Short sellers profit substantially from their information as subsequent returns are lower for heavily shorted stocks with greater dark pool volume.

Research limitations/implications – In 2014, the Financial Industry Regulatory Authority began making trading data available for dark pools. Before that, only limited information was publicly available. The authors use that data to shed more light on dark pools activity.

Practical implications – The evidence presented in the paper helps inform the current discussion about the role and regulation of dark pools.

Originality/value – This is the first study to show that informed traders with long-lived information favor dark pools due to their opacity and the possibility of price improvement.

Keywords Dark pools, Informed trading, Liquidity, Short selling, Stock returns

Paper type Research paper

1. Introduction

The term "dark pool" describes a venue for trading securities that lack transparency. Dark pools were introduced in the late-1980s to provide institutional investors with an outlet away from the traditional exchanges to trade blocks of stock with minimal price impact. In recent years, the fraction of the total trading volume executed in dark pools has increased substantially. For example, the CFA Institute estimates that off-exchange trading, which includes trading in dark pools, increased from 16 to 40% of the total trading volume from 2010 to early 2017 [1]. The increased prevalence of dark pool trading has raised concerns among regulators, academics, and other market participants. For instance, some believe that large amounts of off-exchange trading are associated with a deterioration in the market quality and price efficiency.

Hatheway *et al.* (2017) suggest that dark pools' negative impact on market quality is due to their ability to segment order flow based on information asymmetry risk, which has led researchers to study the factors that influence investors' choice of trading venue. Zhu (2014) models the choice of venue by informed and uninformed traders and predicts that traders with

JEL Classification — G10; G12

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short-lived information minimize execution risk by transacting on exchanges, while uninformed traders favor dark pools because of the potential for price improvement. However, Hendershott and Mendelson (2000) predict that the profitability of long-lived information is greater when traders have the option to trade in dark pools. Thus, the preferred trading venue for informed traders with longer-lived information is an open empirical question.

We combine open short interest with dark pool trading volume to study the relation between short selling and the proportion of total trading volume executed in dark pools. We find that the dark pool volume as a percentage of total trading volume is positively correlated with the ratio of short interest to total trading volume, which is commonly referred to as days-to-cover (DTC). The relation between short interest and dark pool activity is evident for subsamples with different market capitalizations and robust to instrumental variable and first difference approaches that address endogeneity between short selling and dark pool activity.

The positive relation between short interest and dark pool activity is consistent with two explanations. One possibility is that informed traders with long-lived information drive the increased use of dark pools. Informed traders might favor dark pools because of their opacity, which helps them sustain their information advantage, and the potential for price improvement. An alternative explanation is that liquidity traders are responsible for the increased fraction of volume executed in dark pools. This could be the case if liquidity traders deliberately avoid informed traders, which may result in a preference for trading in a dark pool when the level of informed trading in the lit markets is high.

We attempt to distinguish between these explanations in several ways. First, we identify stocks that are more likely to pose greater value uncertainty to investors. We find that the relation between short interest and dark pool volume is stronger for firms with higher market-to-book ratios, greater capital expenditures to assets ratios, greater research and development to assets ratios and higher dispersion of investor expectations. Second, we explore the effect of institutional investor type on the relation between informed trading and dark pool volume and find that it is stronger for stocks targeted by transient institutional investors, who invest based on firm fundamentals and mispricing. Third, we examine whether the profits available to short sellers are related to dark pool volume. Consistent with Hendershott and Mendelson (2000), we find that subsequent returns are lower for stocks that experience a large proportion of their trading volume in dark pools. When we sort on both short interest and dark pool volume, we find that returns to short sellers are substantially larger for stocks with more dark pool volume. Thus, although we cannot directly observe short sellers' venue choices, our results are consistent with the notion that fundamentals-based informed traders drive the increase in dark pool volume.

This study contributes to the growing literature on dark pools by providing evidence that short interest and dark pool volume are correlated. The most closely related studies are Garvey *et al.* (2016), which investigates why traders choose dark markets, and Reed *et al.* (2018), which considers the implications of short sellers' trading venue decisions. This study differs from prior studies, in that we focus on the relation between short selling based on firm fundamentals and dark pool volume. In addition, this is the first study to document the strong negative relation between dark pool volume and subsequent returns.

2. Related literature and hypothesis development

2.1 Dark pools

Dark pools provide traders with an opaque venue for executing trades. This allows traders to pursue their objectives with less concern that activities such as imitation, front running and quote stuffing will negatively affect their trading profits. Because dark pools are not required to provide real-time information, traders can transact in dark pools with less fear that other investors will take advantage of their intentions.

Dark pools also offer greater potential for price improvement than the exchanges because they tend to match trades at the mid-point of the exchange-quoted bid–ask spread. Garvey *et al.* (2016) find that most dark pool trades benefit from price improvement, but that price improvement is rare for lit orders. However, they also point out that dark pools contribute to market fragmentation that could negatively affect market quality and price efficiency.

Zhu (2014) considers the tradeoff between execution certainty and price improvement that traders face when deciding whether to trade on an exchange or in a dark pool. Investors with short-lived information seek to exploit their information advantage quickly. Thus, they favor trading venues that provide immediate and certain execution, which leads them to transact on the exchanges. Because liquidity traders do not have time-sensitive information, they may accept greater execution risk in exchange for the potential for price improvement in dark pools. Consistent with Zhu's (2014) predictions, Garvey and Wu (2011) report that informed traders tend to favor trading venues that offer faster execution speed, while liquidity traders sacrifice speed for lower transaction costs.

Reed *et al.* (2018) use short selling as a proxy for informed trading to provide additional evidence consistent with Zhu (2014). They find that, while short sellers are responsible for a substantial fraction of dark pool trading, the proportion of short sales is greater on the exchanges than in dark pools. Reed *et al.* (2018) find that short sales executed on exchanges contribute more to price informativeness than short sales executed in dark pools. They also find that short sales on exchanges and their contribution to price informativeness are even greater around corporate news events, which suggests that event-driven short selling (i.e. time-sensitive information advantages) may explain the difference in short selling between the exchanges and dark pools.

2.2 Short sellers as informed traders

Early support for the notion that short sellers are informed traders is found in Figlewski (1981), who suggests that the amount of unfavorable information excluded from market prices increases with the level of short interest because stocks with higher short interest are more difficult to sell short. According to Diamond and Verrecchia (1987), short sale constraints change the information content of observed transactions by increasing the cost of short selling, which drives less-informed short sellers out of the market. Subsequent studies examine the trading strategies of short sellers and find evidence consistent with the view that short sellers are informed traders. For example, Boehmer *et al.* (2020) report that short sellers target stocks prior to earnings announcements. Because of the time-sensitive nature of firm-specific events, execution certainty is a first-order consideration for short sellers pursuing these strategies. Thus, event-driven short sellers are likely to prefer to trade on the exchanges where execution risk is limited (Zhu, 2014).

Other studies find evidence that short sellers target stocks based on fundamentals and mispricing. For example, Dechow *et al.* (2001) find that short sellers use fundamental-to-price ratios to identify overpriced stocks and profit from subsequent price declines. Engelberg *et al.* (2012) find that short sellers' information advantage stems from their superior ability to analyze public information. Unlike event-driven short selling, short selling based on fundamental analysis and mispricing is less time-sensitive. Therefore, fundamentals-based short sellers may accept some execution risk in exchange for protection from imitation and front running that might erode their trading profits.

2.3 Hypothesis development

While Zhu (2014) posits that investors with time-sensitive information prefer exchanges to dark pools because of higher execution risk associated with dark pools, the venue where investors with a sustainable information advantage prefer to trade is less certain. As Hendershott and Mendelson (2000) explain, investors with long-lived information do not incur a delay cost. Therefore, they may take advantage of the opacity and possibility of price improvement offered by dark pools because they can tolerate greater execution risk. We use short interest to identify stocks targeted by traders who have a sustainable information advantage. If these traders favor dark pools because of their opacity, which allows them to sustain their information advantage longer, we predict a positive relation between the level of short interest and the proportion of total trading volume executed in dark pools. We formalize this prediction in the following hypothesis:

Investors with a sustainable information advantage drive a positive relation between short selling and dark pool volume.

Another possibility is that liquidity traders use dark pools to avoid trading with informed traders when they are active in the lit markets. Support for the notion that liquidity traders attempt to avoid informed traders is found in Admati and Pfleiderer (1988) and Foster and Viswanathan (1990), who posit that trading patterns in stock markets are influenced by strategic decisions made by discretionary liquidity traders faced with the prospect of trading with informed traders, and Chowdhry and Nanda (1991) who suggest that liquidity traders may gravitate to markets that discourage informed trading. We would also expect to find a positive relation between short interest and dark pool volume if liquidity traders exhibit a preference for trading in dark pools when the level of informed trading in the lit markets is high.

Because we cannot directly observe short sellers' venue choices, we perform several tests designed to distinguish our hypothesis from a liquidity trader-based explanation. Our first set of tests examines whether the correlation between short selling and dark pool volume is sensitive to firm-level uncertainty. If informed traders drive the relation, we expect it to be stronger for stocks likely to suffer from greater uncertainty. Next, we study the effect of institutional investor type on the relation between short selling and dark pool volume. After identifying institutions' investment strategies (Bushee *et al.*, 2000), we explore whether the relation between short selling and dark pool volume is stronger for stocks targeted by institutions that trade on firm-fundamentals and mispricing. Finally, Hendershott and Mendelson (2000) predict that the profitability of long-lived information is greater when traders have the option to trade in dark pools. If informed traders drive the relation between short selling and dark pool volume, we expect to find that subsequent returns are lower for stocks with high levels of short interest and dark pool volume.

3. Data and methodology

The Financial Industry Regulatory Authority (FINRA) began making trading information available for all alternative trading systems (ATSs) on June 2, 2014 [2]. According to the Securities and Exchange Commission (SEC), all current ATSs are dark pools [3]. Each ATS is required to report trading information for a given week to FINRA within seven business days following the end of that week. FINRA releases that information after a two-week delay for actively traded stocks that are mandatorily added to the National Market System (NMS Tier 1 stocks). Information for less actively traded stocks that are added voluntarily (NMS Tier 2 stocks) or traded over the counter is released after a four-week delay. Therefore, we obtain weekly ATS volume for the period May 12, 2014, through December 29, 2017 [4].

We retrieve short interest, which corresponds to the number of uncovered shares sold short for transactions settled on or before the last business day of the month, from Compustat. Comerton-Forde *et al.* (2016) find that short interest reflects short sellers' beliefs about mispricing due to firm fundamentals that are likely to correct over longer time horizons. From the center for research in security prices (CRSP), we gather monthly data on returns, prices, shares outstanding and trading volume for NYSE- and Nasdaq-listed US common stocks (i.e. CRSP share codes 10 and 11). We exclude stocks with a closing price below US$1 on April 30, 2014, current and lagged monthly closing prices below US$5 and zero monthly trading volume. We also exclude months for which the cumulative price adjustment factor changes more than 20% (i.e. stock splits) or a stock's listing exchange changes.

We aggregate weekly ATS trading volume and calculate dark pool volume as the cumulative ATS monthly trading volume divided by the total number of shares traded in the month. We set dark pool volume equal to zero for stocks with no reported ATS volume but positive total trading volume. For consistency, we also divide short interest by monthly trading volume. As constructed, this measure, commonly referred to as the DTC ratio, equals the fraction of a month that it would take for short sellers to cover their open short positions given recent trading volume.

The choice of DTC as the response variable is inspired by Hong *et al.* (2016), who report that DTC is not strongly related to turnover measures or to the market-to-book effect. They also find that the effect of DTC on subsequent stock returns is stronger than the effect of shares shorted as a percentage of the shares outstanding and remains significant after controlling for lending fees, dispersion of opinions and binding short-sales constraints. High DTC levels indicate that informed traders expect a stock to underperform due to poor fundamentals or mispricing. Prior research suggests that high DTC stocks should underperform low DTC stocks to reward informed traders for their superior ability to process public information (Engelberg *et al.*, 2012) or to compensate them for initiating short positions that are hard to cover (Hong *et al.*, 2016). In untabulated tests, we confirm that the results are similar when we use the ratio of shares shorted to shares outstanding instead of DTC.

We follow Buti *et al.* (2011) and control for the following variables in models used to explain the variation in dark pool activity: trading volume, market capitalization, absolute return, closing price and a binary variable that identifies Nasdaq-listed stocks. We use the standard deviation of the error terms from the market model estimated within the calendar month to control for differences of investor opinions and the Amihud illiquidity measure, which is the monthly average of the daily ratio of absolute return to dollar trading volume, to control for stock illiquidity. Because the Amihud illiquidity measure has a skewed distribution, we use a log transformation. For the same reason, we also log trading volume and market capitalization.

Table 1 reports the descriptive statistics for our sample. We winsorize all continuous variables at the 1 and 99% levels to mitigate the impact of outliers. The average (median) dark pool volume is 16.19% (15.88%) of the total trading volume. This is in line with Tuttle (2013), who reports that dark pools executed 12.1% (11.3%) of the total (dollar) volume traded between May 7 and 12, 2012. The average (median) Lag(DTC) is 30.56% (23.44%) of the total trading volume. This value indicates that it would take 0.3056 months, or 6.42 trading days over a 21-trading-day month, to cover the outstanding short interest given recent trading volume. Hong *et al.* (2016) report that DTC averages 5.45 days for their 1988–2012 sample. They also find that the DTC ratio increases over their sample period, which may explain the difference between our non-overlapping samples.

We calculate the predicted value of Lag(DTC) and its residual as alternatives to the actual lagged value. To predict DTC, we regress DTC on dark pool activity, price to 52-week high ratio, monthly stock return, stock turnover, standard deviation of the error term from the market model, log of the Amihud illiquidity measure, log of market value of equity, book-to-market ratio and a binary variable that identifies stocks listed on Nasdaq. Residual DTC is equal to the actual value minus the predicted value. The average (median) predicted Lag(DTC) is 30.50% (30.54%) or 6.41 (6.41) trading days, and the average (median) residual lag is 0.00% (−5.51%). Average (median) values for lagged monthly trading volume and market value of equity are 23.04 (6.69) million shares and US$6.94*bn* (US$1.20), respectively. Average (median) values for lagged monthly absolute return and closing price are 7.48% (5.25%) and US$40.10 (US$26.83), respectively.

Table 1.
Descriptive statistics

Variable	Mean	SD	P25	Median	P75	Obs.
Dark pool volume	0.1619	0.0625	0.1214	0.1588	0.1992	120,476
Lag(DTC)	0.3056	0.2436	0.1277	0.2344	0.4120	120,476
Pred. Lag(DTC)	0.3050	0.0818	0.2555	0.3054	0.3558	114,078
Residual	0.0000	0.2281	−0.1530	−0.0551	0.0968	114,078
Lag(vol)	23,038,516	46,382,682	1,789,150	6,686,300	21,756,450	120,476
Lag(mve)	6,944,924,324	19,495,115,876	361,014,051	1,195,783,898	4,136,125,546	120,476
Lag(abs. return)	0.0748	0.0742	0.0231	0.0525	0.1005	120,476
Lag(price)	40.10	40.15	14.22	26.83	50.89	120,476
Lag(illiq.)	0.3569	2.1246	0.0003	0.0017	0.0114	120,476
Lag(std. error)	0.0182	0.0118	0.0101	0.0148	0.0226	120,476
Nasdaq	0.5672	0.4955	0.0000	1.0000	1.0000	120,476

Note(s): This table shows the summary statistics for the variables used in our analysis. Dark pool volume is the ratio of monthly dark pool volume to monthly total trading volume. Lag(DTC) is the lagged days-to-cover, which is defined as the previous month short interest to total trading volume ratio. The predicted value of Lag(DTC) and its residual are estimated using a regression of Lag(DTC) on lagged dark pool activity and a set of control variables as described in Section 3. Lag(vol) is the trading volume in the previous month. Lag(mve) is the number of shares outstanding times the closing price, both at the end of the previous month. Lag(abs. return) is the lag of the monthly absolute return. Lag(price) is the lag of the closing price at the end of the month. Lag(illiq.) is the lag of the Amihud's (2002) illiquidity measure. Lag(std. error) is the standard deviation of the error terms from the market model, estimated over the previous calendar month. Nasdaq is a binary variable that identifies stocks listed on Nasdaq. All the continuous variables are winsorized at the top and bottom 1% levels

4. Empirical results

4.1 Determinants of dark pool volume

In our multivariate analysis, we use lagged explanatory variables and fixed effects to mitigate potential biases because of simultaneous causality, reverse causality and spurious correlation. Because truly exogenous instruments are difficult to find, lagged values are commonly used in response to endogeneity concerns when it is expected that past levels of the explanatory variables determine the current level of the response variable. Fixed effects control for the possibility that the explanatory variable and the response variable are spuriously connected through variables that are not included in the model. Except for the two-stage least squares and first-difference estimations, we include stock and month fixed effects in all reported regression specifications [5].

Table 2, Models 1 and 2, reports that the relation between dark pool volume and both first- and second-order Lag(DTC) is positive and significant at the 1% level. Recall that the standard deviation of Lag(DTC) is 24.36% and the average dark pool volume is 16.19%. Therefore, the coefficient on Lag(DTC) in Model 1 implies that a one standard deviation change in Lag(DTC) is associated with a 2.33% change in dark pool volume as a fraction of total trading volume. When we include both lags in the same model (Model 3), the first-order lag remains highly significant, while the second-order lag is no longer statistically significant. A one standard deviation change in Lag(DTC) is associated with a 2.24% change in dark pool volume as a percentage of the total trading volume in that case.

In Table 2, Models 4–6, we replace Lag(DTC) with the predicted value of Lag(DTC) and its residual. The estimated coefficients on the predicted value of Lag(DTC) and its residual are positive and significant when used individually or together. Therefore, the component of Lag(DTC) that is orthogonal to the other control variables has strong explanatory power. The coefficient on the predicted value can be interpreted as the permanent effect of Lag(DTC) on dark pool volume, while the coefficient on its residual is the effect of transitory variations from normal levels. Overall, Table 2 provides support for our hypothesis. The signs and significance of the coefficients on our proxies for trading volume and market capitalization are not always consistent with those reported by Buti *et al.* (2011). We include a more comprehensive set of control variables to help address endogeneity concerns. However, this may create multicollinearity issues, which may explain the inconsistencies when compared to Buti *et al.* (2011).

D'Avolio (2002) reports that the supply of shares available to short is correlated with the market value of equity, and O'Hara and Ye (2011) find that dark pool trading differs based on market capitalization. Motivated by these studies, we split our sample into terciles based on market capitalization, calculated as the number of shares outstanding multiplied by the closing price. We define small capitalization stocks as stocks with a market capitalization below US$540.3*m*, medium capitalization stocks as stocks with a market capitalization between US$540.3*m* and US$2,676.4*m*, and large capitalization stocks as stocks with a market capitalization equal to or above US$2,676.4*m*. Table 3 considers whether the relation between DTC and dark pool volume varies based on the market capitalization tercile. The models include the same control variables reported in Table 2, but we omit them to conserve space. We report the results for small, mid and large capitalization stocks in Panels A, B and C, respectively.

We find that the estimated coefficients on the first-order lag of DTC are positive and significant at the 1% level for all three size terciles (Model 1). In addition, the effect is economically significant. Standard deviations for Lag(DTC) are 28.18, 24.44 and 17.34%, while average dark pool volumes are 13.86, 17.62 and 17.06% for small-, mid- and large-cap stocks, respectively. Therefore, a one standard deviation change in Lag(DTC) is associated with a 2.66, 1.89 and 1.66% change in dark pool activity for small-, mid- and large-cap stocks, respectively. The coefficient on the second-order lag of DTC is significant in the absence of the first-order lag (Model 2), but loses

Table 2.
Dark pool volume and DTC

	(1)	(2)	(3)	(4)	(5)	(6)
Lag(DTC)	0.0155***(9.75)		0.0149*** (9.29)			
Lag2(DTC)		0.0099*** (7.29)	0.0008 (0.66)			
Pred. Lag(DTC)				0.0744*** (16.15)		0.0801*** (17.10)
Residual					0.0089*** (5.52)	0.0122*** (7.59)
Log[lag(vol)]	0.0002 (0.30)	−0.0012* (−1.74)	0.0002 (0.22)	0.0014** (2.01)	−0.0003 (−0.46)	0.0026*** (3.46)
Log[lag(mve)]	−0.0007 (−0.41)	−0.0009 (−0.58)	−0.0009 (−0.53)	0.0028*(1.80)	−0.0027* (−1.70)	0.0025 (1.59)
Lag(abs. return)	0.0017 (0.73)	−0.0010 (−0.45)	0.0014 (0.61)	−0.0037 (−1.54)	0.0016 (0.67)	−0.0022 (−0.94)
Lag(inv. price)	−0.1160*** (−4.70)	−0.1116*** (−4.49)	−0.1175*** (−4.77)	−0.1667*** (−6.58)	−0.1155*** (−4.47)	−0.1707*** (−6.80)
Log[lag(illiq.)]	−0.0031*** (−5.62)	−0.0034*** (−6.00)	−0.0031*** (−5.69)	0.0000 (0.01)	−0.0034*** (−5.96)	−0.0002 (−0.28)
Lag(std. error)	−0.1427*** (−5.94)	−0.1817*** (−7.50)	−0.1469*** (−6.04)	−0.0671*** (−2.61)	−0.1952*** (−7.97)	−0.0532** (−2.07)
Nasdaq	0.0050 (0.78)	0.0050 (0.78)	0.0050 (0.78)	0.0069 (1.00)	0.0085 (1.22)	0.0068 (0.99)
Constant	0.1776*** (4.92)	0.2056*** (5.72)	0.1823*** (5.05)	0.0873** (2.42)	0.2285*** (6.51)	0.0742** (2.06)
Stock fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.232	0.231	0.232	0.234	0.230	0.235
Observations	120,476	120,420	120,420	114,078	114,078	114,078

Note(s): The response variable is the ratio of dark pool volume to total trading volume. DTC is days-to-cover, defined as the ratio of outstanding short interest to total trading volume. The remaining variables are as described in Table 1. *t*-statistics based on standard errors clustered by stock are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively

Table 3. Dark pool volume and DTC by size group

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: small cap						
Lag(DTC)	0.0131*** (5.71)		0.0111*** (4.73)			
Lag2(DTC)		0.0095*** (4.73)	0.0031 (1.57)			
Pred. Lag(DTC)				0.0823*** (9.57)		0.0845*** (9.79)
Residual					0.0063** (2.55)	0.0080*** (3.27)
Stock fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.124	0.123	0.124	0.125	0.121	0.125
Observations	39,757	39,725	39,725	36,902	36,902	36,902
Panel B: mid cap						
Lag(DTC)	0.0136*** (5.01)		0.0129*** (4.78)			
Lag2(DTC)		0.0083*** (3.80)	0.0010 (0.50)			
Pred. Lag(DTC)				0.0489*** (6.64)		0.0580*** (7.55)
Residual					0.0107*** (3.91)	0.0139*** (5.00)
Stock fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.296	0.295	0.296	0.294	0.293	0.296
Observations	40,961	40,946	40,946	38,787	38,787	38,787
Panel C: large cap						
Lag(DTC)	0.0163*** (5.12)		0.0198*** (6.37)			
Lag2(DTC)		0.0073** (2.48)	−0.0048* (−1.78)			
Pred. Lag(DTC)				0.0512*** (7.16)		0.0656*** (8.50)
Residual					0.0110*** (3.62)	0.0173*** (5.50)
Stock fixed effects	YES	YES	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES	YES	YES
R^2	0.414	0.413	0.414	0.414	0.413	0.416
Observations	39,758	39,749	39,749	38,389	38,389	38,389

Note(s): The response variable is the ratio of dark pool volume to total trading volume. DTC is days-to-cover, defined as the ratio of outstanding short interest to total trading volume. Intercepts and control variables are omitted for sake of space. The results for the small-, mid- and large-cap stocks are reported in Panels A, B and C respectively. Stocks are sorted into terciles based on market capitalization. *t*-statistics based on standard errors clustered by stock are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively significance for small- and mid-cap stocks and is negative for large-cap stocks when we include first and second lags in the same model (Model 3). Collinearity is the usual suspect when the sign of an explanatory variable flips after adding other explanatory variables. However, it is important to note that the coefficient on the first-order lag of DTC remains positive and significant in all models. In Models 4–6, we report that the estimated coefficients on the predicted value of Lag(DTC) and its residual are both positive and statistically significant. Overall, Table 3 indicates that the positive relation between short selling and dark pool volume does not differ substantially based on stock market capitalization.

Lagging short selling relative to dark pool volumes may not address simultaneity and reverse causality biases if those variables are persistent over time. Additionally, the use of fixed effects to control for the omitted variable bias does not fully address concerns about spurious correlation if the omitted variable changes over time. Therefore, we follow Buti *et al.* (2011) and use stocks with the same Fama and French 48-industry classification, listing exchange and market capitalization tercile to construct an instrument for each stock-month combination in our sample. Because dark pool volume has significant industry, exchange and size components, the average monthly dark pool volume within these groups is correlated with dark pool volume for each stock in month t, which fulfills the relevance requirement for a good instrument. To satisfy the exclusion requirement, we exclude stock i from that average when calculating the value of our instrument for stock i to eliminate a source of correlation between the instrument and the error term. We use the same procedure to create an instrument for DTC. The instruments for dark pool volume and DTC for stock i at time t are $\_Dark\ pool_{i,t}$ and $\_DTC_{i,t}$, respectively. We estimate the following two-stage simultaneous model:

$$\mathrm{DTC}_{i,t} = a_1 + a_2\_\mathrm{Dark\ pool}_{i,t} + a_3\_\mathrm{DTC}_{i,t} + \varepsilon_{1,i,t} \tag{1}$$

$$\mathrm{Dark\ pool}_{i,t} = b_1 + b_2\mathrm{DTC}_{i,t} + b_3\_\mathrm{Dark\ pool}_{i,t} + \varepsilon_{2,i,t} \tag{2}$$

In Equation (2), we replace DTC with the fitted value from Equation (1), a regression of DTC on the instruments that we create for dark pool volume and DTC to account for the possibility that short interest and dark pool volume are jointly determined.

In Table 4, we report first- and second-stage estimation results for the full sample first, followed by results for the small, mid and large market capitalization subsamples. Consistent with earlier tables, the coefficients on the fitted values of DTC are positive and statistically significant, further confirming the positive relation between informed trading and dark pool volume.

We also use lagged and concurrent differences to examine how changes in the explanatory variables affect changes in the response variable. Like fixed effects, differences control for spurious correlation because of the variables that are not included in the model. Differences also help us examine the direction of causality between informed trading and dark pool volume. We report the results in Table 5. The estimated coefficients on the prior month's change in DTC are always significant, while the coefficients on changes that are concurrent to changes in dark pool volume are significant only for stocks in the large market capitalization tercile.

Tables 2–5 report consistent evidence of a positive relation between short selling and dark pool volume. Next, we turn our attention to determining whether informed traders with longer-lived information or liquidity traders drive this effect. We approach this by examining firm-level information asymmetry, institutional ownership and subsequent stock returns.

4.2 Firm information asymmetry

We follow prior literature and proxy for firm-level information asymmetry using the market-to-book ratio, capital expenditures to assets ratio, research and development to

Table 4. Two-stage least squares estimation

	All		Small cap		Mid cap		Large cap	
	First stage DTC	Second stage Dark pool	First stage DTC	Second stage Dark pool	First stage DTC	Second stage Dark pool	First stage DTC	Second stage Dark pool
_Dark pool	0.1565*** (8.53)	0.8148*** (189.33)	0.5180*** (12.81)	0.6672*** (55.18)	0.1302*** (3.65)	0.7730*** (99.42)	0.1670*** (5.89)	0.8260*** (111.06)
_DTC	0.5998*** (88.63)		0.4134*** (27.38)		0.4813*** (38.62)		0.3114*** (21.29)	
DTC		0.0096*** (3.67)		0.0697*** (7.84)		0.0112** (1.99)		0.0237** (2.06)
Constant	0.09778*** (28.80)	0.0266*** (28.68)	0.1143*** (18.97)	0.0233*** (11.00)	0.1673*** (22.20)	0.0356*** (15.63)	0.1336*** (23.75)	0.0240*** (9.47)
Observations	118,794	118,794	39,154	39,154	40,411	40,411	39,229	39,229

Note(s): The response variable is the ratio of dark pool volume to total trading volume. _Dark pool is an instrument for the ratio of dark pool activity constructed every month as the average dark pool activity of other stocks listed on the same exchange, in the same market capitalization grouping, and in the same Fama and French 48-industry classification, excluding stock *i*. DTC is replaced with the fitted value from a regression of DTC on _Dark pool and an instrument for DTC constructed in the same way. *t*-statistics based on two-way clustered standard errors (i.e. at both stock and month levels) are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively

Table 5. Change in dark pool volume and DTC

	All	Small cap	Mid cap	Large cap
Δ1DTC	0.0170 (1.60)	0.0090 (0.90)	0.0096 (0.81)	0.0351*** (2.62)
Δ2DTC	0.0359*** (3.28)	0.0196** (2.23)	0.0515*** (4.22)	0.0582*** (2.67)
ΔLog(vol)	−0.0191*** (−3.90)	−0.0100*** (−3.41)	−0.0409*** (−4.51)	−0.0339*** (−3.38)
ΔLog(mve)	−0.0326* (−1.70)	−0.0199* (−1.76)	−0.0497** (−2.22)	−0.0627** (−2.12)
Δ(abs. return)	0.0158 (1.30)	0.0121 (1.27)	0.0218 (1.56)	0.0157 (0.71)
Δ(inv. price)	0.0000 (0.10)	−0.0000 (−0.32)	0.0001 (0.83)	−0.0001 (−0.74)
ΔLog(illiq.)	−0.0170*** (−5.97)	−0.0081*** (−7.36)	−0.0398*** (−6.31)	−0.0372*** (−4.44)
Δ(std. error)	0.5978*** (3.09)	0.1441 (1.24)	1.0600*** (3.96)	1.5273*** (4.34)
ΔNasdaq	0.0132 (0.60)	−0.0298*** (−4.07)	0.0328 (1.09)	−0.0049 (−0.13)
Constant	0.0005 (0.09)	0.0005 (0.11)	0.0003 (0.04)	0.0004 (0.06)
R^2	0.028	0.012	0.058	0.067
Observations	119,263	38,845	40,731	39,687

Note(s): The response variable is the change in the ratio of dark pool volume to total trading volume. ΔDTC is the change in the ratio of outstanding short interest to total trading volume from month *t*-1 to month *t*. Δ2DTC is the previous month's change in the ratio of outstanding short interest to total trading volume. The remaining variables are as described in Table 1. *t*-statistics based on two-way clustered standard errors (i.e. at both stock and month levels) are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively

Table 6. Firm-level information asymmetry and dark pool volume

	(1)	(2)	(3)	(4)
Lag(DTC)	0.0123*** (6.71)	0.0148*** (9.12)	0.0139*** (7.99)	0.0129*** (6.29)
Lag(DTC) × Lag(market/book)	0.0010*** (3.99)			
Lag(market/book)	−0.0003** (−2.21)			
Lag(DTC) × Lag(capex/assets)		0.0430* (1.80)		
Lag(capex/assets)		−0.0236** (−2.56)		
Lag(DTC) × Lag(R&D/assets)			0.0836* (1.89)	
Lag(R&D/assets)			−0.0470 (−1.37)	
Lag(DTC) × Lag(std. error)				0.1512* (1.91)
Log[lag(vol)]	0.0005 (0.68)	0.0004 (0.48)	0.0004 (0.50)	0.0003 (0.36)
Log[lag(mve)], CRSP	−0.0020 (−1.30)	−0.0025 (−1.60)	−0.0025 (−1.61)	−0.0007 (−0.45)
Lag(abs. return)	0.0019 (0.81)	0.0013 (0.55)	0.0015 (0.64)	0.0020 (0.88)
Lag(inv. price)	−0.1237*** (−4.96)	−0.1305*** (−5.20)	−0.1311*** (−5.21)	−0.1185*** (−4.77)
Log[lag(illiq.)]	−0.0031*** (−5.65)	−0.0032*** (−5.72)	−0.0032*** (−5.75)	−0.0031*** (−5.64)
Lag(std. error)	−0.1555*** (−6.44)	−0.1557*** (−6.44)	−0.1528*** (−6.30)	−0.1785*** (−6.03)
Nasdaq	0.0079 (1.12)	0.0082 (1.18)	0.0082 (1.19)	0.0051 (0.79)
Constant	0.2007*** (5.72)	0.2116*** (6.01)	0.2122*** (6.02)	0.1791*** (4.95)
Stock fixed effects	YES	YES	YES	YES
Month fixed effects	YES	YES	YES	YES
Observations	115,155	115,699	115,699	120,476
R^2	0.232	0.231	0.231	0.232

Note(s): The response variable is the ratio of dark pool volume to total trading volume. DTC is days-to-cover, defined as the ratio of outstanding short interest to total trading volume. Variables *market/book, capex/assets, R&D/assets and std. error* proxy for firm-level information asymmetry. The remaining variables are as described in Table 1. *t*-statistics based on standard errors clustered by stock are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively assets ratio and dispersion of investor expectations* (e.g. Pástor and Veronesi, 2003; Kothari *et al.*, 2002; Danielsen; Sorescu, 2001). In Table 6, we add the firm-level information asymmetry measures and their interaction with DTC to our base regression model. If firms with more information asymmetry offer greater opportunity to investors who trade on firm fundamentals and mispricing, the coefficients on the interaction terms should be positive. Such a finding would provide support for our hypothesis, which predicts that traders with sustainable information advantages drive the positive relation between short selling and dark pool volume.

We continue to report a positive relation between DTC and dark pool volume after controlling for measures of firm-level information asymmetry. Interestingly, the coefficients on the four firm-level information asymmetry measures are negative and significant, which indicates that dark pools capture less of the total trading volume in stocks that pose greater information asymmetry risk. However, the positive coefficients on the interaction terms are consistent with fundamentals-based informed traders targeting stocks with greater uncertainty in dark pools to take advantage of their opacity and the potential for price improvement.

4.3 Institutional ownership type

To examine the impact of institutional investor type on the relation between short selling and dark pool volume, we follow Bushee and Noe (2000), who use principal factor analysis to generate factors that explain shared variance among variables that describe institutional trading behavior and portfolio characteristics. The authors then use k-means cluster analysis on the factor scores to classify institutional investors as one of the three types. First, quasi-indexers are institutions that hold large diversified portfolios and trade infrequently. Second, dedicated institutions hold concentrated portfolios with large and stable holdings. Finally, transient institutions pursue trading strategies informed by firm fundamentals that result in substantial portfolio turnover.

We obtain quarterly data on institutional holdings from Thomson Reuters as reported in Form 13-F and calculate the aggregate percentage of each firm's outstanding shares held by each of the three types of institutions at the end of each quarter. The variables *pct_ded*, *pct_qix* and *pct_tra* correspond to the cumulative percentage of total shares outstanding held by dedicated, quasi-indexer and transient institutions, respectively. If informed traders are responsible for the positive relation between short selling and dark pool volume, the coefficient on the interaction between short selling and transient institutional ownership should be positive. This would provide support for our hypothesis, because transient institutions are more likely to invest based on fundamentals and mispricing than other types of institutions. If liquidity traders drive the positive relation between DTC and dark pool volume, we would expect to observe a positive coefficient on the interaction of DTC and quasi-indexers and, to a lesser extent, dedicated institutions.

We report the results in Table 7. The relation between DTC and dark pool volume remains positive and significant when we control for institutional ownership. The positive and significant coefficient on the interaction of transient institutional holdings (*pct_tra*) and DTC is consistent with the notion that transient institutional investors help drive the positive relation between informed trading and dark pool volume [6]. Neither quasi-indexers nor dedicated institutional investors have a significant effect on the relation between DTC and dark pool volume.

4.4 Dark pool volume and subsequent stock returns

Hendershott and Mendelson (2000) predict that dark pools, which provide a lower-cost venue for trading than exchanges, have a positive effect on the profitability of long-lived information. In

	(1)	(2)	(3)
Lag(DTC)	0.0145*** (8.62)	0.0111*** (4.05)	0.0056*** (2.42)
Lag(DTC) × Lag(pct_ded)	0.0132 (1.03)		
Lag(pct_ded)	−0.0007 (−0.08)		
Lag(DTC) × Lag(pct_qix)		0.0098 (1.63)	
Lag(pct_qix)		−0.0024 (−0.48)	
Lag(DTC) × Lag(pct_tra)			0.0598*** (5.23)
Lag(pct_tra)			−0.0075 (−1.09)
Log[lag(vol)]	0.0000 (0.07)	−0.0001 (−0.07)	−0.0002 (−0.28)
Log[lag(mve)], CRSP	−0.0008 (−0.54)	−0.0007 (−0.47)	−0.0006 (−0.36)
Lag(abs. return)	0.0019 (0.81)	0.0019 (0.85)	0.0025 (1.08)
Lag(inv. price)	−0.1220*** (−5.04)	−0.1196*** (−4.92)	−0.1172*** (−4.83)
Log[lag(illiq.)]	−0.0027***(−4.98)	−0.0027*** (−5.03)	−0.0027*** (−5.02)
Lag(std. error)	−0.1519*** (−6.42)	−0.1499*** (−6.33)	−0.1411*** (−5.94)
Nasdaq	0.0060 (0.92)	0.0060 (0.94)	0.0065 (1.01)
Constant	0.1866*** (5.34)	0.1863*** (5.31)	0.1850*** (5.27)
Stock fixed effects	YES	YES	YES
Month fixed effects	YES	YES	YES
Observations	117,559	117,512	117,559
R^2	0.234	0.234	0.235

Note(s): The response variable is the ratio of dark pool volume to total trading volume. DTC is days-to-cover, defined as the ratio of outstanding short interest to total trading volume. Variables pct_ded, pct_qix and pct_tra measure the cumulative percentage of total shares outstanding held by dedicated, quasi-indexer and transient institutions, respectively (Bushee and Noe, 2000). The remaining variables are as described in Table 1. *t*-statistics based on standard errors clustered by stock are reported in parentheses. ***, ** and * indicate statistical significance at the 1, 5 and 10% levels, respectively

Table 7. Institutional ownership type and dark pool volume

our final tests, we examine the relation between short interest, dark pool volume and subsequent stock returns. We consider both market- and characteristic-adjusted returns. For the later, we follow Daniel *et al.* (1997), who compute characteristic-adjusted returns by subtracting the return of a benchmark group from the raw return of a stock. The benchmark groups are based on size, book-to-market ratio and 12-month momentum quintiles calculated at the end of June of each year.

In the untabulated results, we confirm that short interest and subsequent returns are negatively correlated for our sample. We find that market-adjusted (characteristic-adjusted) returns for stocks in the highest DTC quartile are 0.30% (0.34) lower than those for stocks in the lowest DTC quartile in the subsequent month of trading. Cumulative underperformance increases with time, reaching 5.21% (4.91) after 12 months. This pattern of returns is consistent with the notion that DTC captures informed traders with long-lived information.

If informed short sellers exhibit a preference for dark pools when they have a sustainable information advantage, Hendershott and Mendelson (2000) predict that we should find a negative correlation between dark pool volume and stock returns. To examine the relation between dark pool volume and stock returns, we sort stocks into quartiles-based dark pool volume and calculate returns for each quartile over the subsequent 12 months. We then compare the returns for stocks with high dark pool volume to stocks with low dark pool volume to determine the relation between dark pool volume and returns.

Table 8, Panel A reports that a long-short strategy that buys stocks in the lowest dark pool volume quartile and short sells stocks in the highest dark pool volume quartile generates market-adjusted returns of 1.14%, on average, over two months. The same strategy returns

	Quartile	[0]	[0,1]	[0,2]	[0,5]	[0,8]	[0,11]
Panel A							
MM AR	4	0.0000	−0.0009	−0.0006	0.0005	−0.0017	−0.0058
		(0.99)	(0.86)	(0.91)	(0.95)	(0.87)	(0.57)
	3	0.0039	0.0067	0.0104	0.0206	0.0288	0.0355
		(0.30)	(0.13)	(0.04)	(0.00)	(0.00)	(0.00)
	2	0.0040	0.0072	0.0112	0.0232	0.0351	0.0472
		(0.26)	(0.09)	(0.02)	(0.00)	(0.00)	(0.00)
	1	0.0058	0.0105	0.0163	0.0332	0.0502	0.0690
		(0.11)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
	1–4	0.0057	0.0114	0.0169	0.0326	0.0519	0.0748
		(0.04)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
Panel B							
DGTW AR	4	−0.0006	−0.0011	−0.0014	−0.0017	−0.0049	−0.0086
		(0.56)	(0.52)	(0.54)	(0.64)	(0.25)	(0.07)
	3	0.0031	0.0061	0.0090	0.0175	0.0241	0.0300
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	2	0.0026	0.0053	0.0079	0.0159	0.0236	0.0320
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	1	0.0034	0.0070	0.0103	0.0196	0.0289	0.0400
		(0.09)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)
	1–4	0.0041	0.0081	0.0117	0.0213	0.0338	0.0486
		(0.07)	(0.02)	(0.01)	(0.01)	(0.00)	(0.00)

Note(s): This table reports cumulative abnormal returns (CAR) within quartiles of dark pool trading volume as a percentage of total trading volume, measured in month *t*. Quartile 4 is the highest quartile. CAR windows are from the first month [0] to 12 months [0,11]. Market-adjusted returns based on CRSP value-weighted index in Panel A and characteristic-adjusted returns as described by Daniel, Grinblatt, Titman and Wermers (1997) in Panel B. Returns are winsorized at the 1 and 99% levels. *p*-values for differences from zero are reported in parentheses

Table 8.
Returns by dark pool volume quartiles

an average cumulative return of 7.48% over 12 months. In Panel B, we report similar results for characteristic-adjusted returns. A trading position that is long low and short high dark pool volume stocks generates an average characteristic-adjusted return of 0.81% (4.86) over the first two (12) months.

Table 9 examines the joint effect of short interest and dark pool activity on stock returns. We independently sort stocks into quartiles based on short interest and dark pool volume, and then calculate the returns from a strategy that focuses on stocks in the highest quartile of short interest, i.e. long stocks in the lowest quartile of dark pool volume and short stocks in the highest quartile of dark pool volume. We bold the returns to this strategy in the results for emphasis. We report both market-adjusted (Panel A) and characteristic-adjusted (Panel B) returns. For parsimony, we report two- and 12-month cumulative abnormal returns. We find that the long-short strategy previously described generates an average cumulative market-adjusted (characteristic-adjusted) return of 1.19% (0.92%) over the first two months and 8.25% (5.91%) over 12 months. Greater returns over longer horizons support the notion that short sellers prefer to trade in dark pools when they have a sustainable information advantage.

Another potential trading strategy is to buy stocks with low short interest and low dark pool volume while simultaneously shorting stocks with high short interest and high dark pool volume. At the bottom right of each panel and return window, we report the returns from this strategy. We highlight the results in italics for emphasis. We find that this strategy generates substantial market-adjusted (Panel A) and characteristic-adjusted (Panel B) returns. Namely,

Table 9. Returns by short interest and dark pool volume (double sorts)

MM model	[0,1]	Dark pool volume 4	3	2	1	*1–4*	[0,11]	Dark pool volume 4	3	2	1	*1–4*
Panel A												
Short interest	4	−0.0043	0.0068	0.0071	0.0075	**0.0119**	4	−0.0326	0.0265	0.0452	0.0498	**0.0825**
		(0.45)	(0.25)	(0.26)	(0.22)	*(0.03)*		(0.00)	(0.03)	(0.00)	(0.00)	**(0.00)**
	3	−0.0018	0.0070	0.0069	0.0078	0.0097	3	−0.0078	0.0305	0.0439	0.0539	0.0618
		(0.74)	(0.13)	(0.18)	(0.13)	(0.04)		(0.47)	(0.00)	(0.00)	(0.00)	(0.00)
	2	−0.0009	0.0035	0.0093	0.0056	0.0065	2	−0.0072	0.0235	0.0550	0.0422	0.0494
		(0.85)	(0.44)	(0.02)	(0.22)	(0.18)		(0.52)	(0.01)	(0.00)	(0.00)	(0.00)
	1	0.0066	0.0114	0.0054	0.0146	0.0080	1	0.0456	0.0701	0.0447	0.0924	0.0467
		(0.13)	(0.01)	(0.16)	(0.00)	(0.10)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
	1–4	0.0109	0.0046	−0.0017	0.0071		1–4	0.0783	0.0436	−0.0006	0.0426	
		(0.01)	(0.34)	(0.71)	(0.21)			(0.00)	(0.00)	(0.93)	(0.00)	
					11–44	*0.0189*					*11–44*	*0.1250*
						(0.01)						*(0.00)*
Panel B												
Short interest	4	−0.0048	0.0056	0.0063	0.0044	**0.0092**	4	−0.0347	0.0169	0.0374	0.0244	**0.0591**
		(0.09)	(0.02)	(0.02)	(0.10)	**(0.03)**		(0.00)	(0.00)	(0.00)	(0.00)	**(0.00)**
	3	−0.0019	0.0057	0.0042	0.0044	0.0063	3	−0.0100	0.0212	0.0235	0.0256	0.0356
		(0.36)	(0.01)	(0.03)	(0.17)	(0.11)		(0.04)	(0.00)	(0.00)	(0.00)	(0.00)
	2	−0.0008	0.0032	0.0061	0.0021	0.0029	2	−0.0110	0.0207	0.0331	0.0153	0.0263
		(0.71)	(0.09)	(0.01)	(0.41)	(0.47)		(0.06)	(0.00)	(0.00)	(0.04)	(0.04)
	1	0.0052	0.0116	0.0047	0.0113	0.0061	1	0.0351	0.0689	0.0343	0.0626	0.0274
		(0.04)	(0.00)	(0.03)	(0.02)	(0.24)		(0.00)	(0.00)	(0.00)	(0.00)	(0.03)
	1–4	0.0100	0.0060	−0.0016	0.0069		1–4	0.0698	0.0520	−0.0031	0.0382	
		(0.01)	(0.12)	(0.65)	(0.14)			(0.00)	(0.00)	(0.62)	(0.00)	
					11–44	*0.0161*					*11–44*	*0.0972*
						(0.01)						*(0.00)*

Note(s): This table reports the CAR independently sorted on both short interest and dark pool activity. Quartile 4 is the highest quartile. Short interest is the outstanding balance of shorted shares divided by total trading volume, measured at the end of month *t-1*. Dark volume is the dark pool volume divided by total trading volume, measured in the month *t*. CAR windows are for the first two months [0, 1] and for 12 months [0, 11]. Market-adjusted returns based on CRSP value-weighted index in Panel A, and characteristic-adjusted returns as described by Daniel, Grinblatt, Titman and Wermers (1997) in Panel B. Returns are winsorized at the 1 and 99% levels. *p*-values for differences from zero are reported in parentheses cumulative market-adjusted (characteristic-adjusted) returns are 1.89% (1.61%) over the first two months and 12.50% (9.72%) over 12 months.

The results reported in Tables 6–9 provide support for our hypothesis, which predicts that informed traders with longer-lived information drive the positive relation between short selling and dark pool volume. Namely, the effect is stronger for stocks with greater firm-level information asymmetry and for stocks targeted by institutional investors that invest based on firm fundamentals. The substantial underperformance among stocks with high levels of dark pool volume is consistent with the notion that traders with a sustainable information advantage prefer to trade in dark pools.

5. Conclusion

We contribute to a growing literature on dark pools by investigating the relation between short interest and the proportion of trading volume executed in dark pools. We use ATS data to measure dark pool activity and short interest to proxy for informed trading based on long-lived information. This allows us to investigate the following questions: Is there a relation between short selling and dark pool volume? If so, do informed traders or liquidity traders drive the change in dark pool volume?

We find that short interest is positively correlated with the fraction of trading volume executed in dark pools. Additional evidence supports the notion that it is informed traders with sustainable information advantages, not event-driven traders, who drive the relation between short selling and dark pool volume. Namely, the positive relation between short selling and dark pool volume is stronger for stocks likely to suffer from greater information asymmetry and stocks targeted by institutions who invest based on firm fundamentals. Finally, we find that subsequent returns are lower for stocks with a greater proportion of their trading volume executed in dark pools, especially among those stocks most targeted by short sellers.

Notes

1. See https://www.cfainstitute.org/en/advocacy/issues/dark-pools.
2. SEC release No. 34–71341 (January 17, 2014) and No. 34–76931 (January 19, 2016) provide details on the rule requiring ATSs to report transaction data to FINRA.
3. See https://www.investor.gov/additional-resources/general-resources/glossary/alternative-trading-systems-atss.
4. Over-the-counter transparency data are available at http://www.finra.org/industry/OTC-Transparency. ATS trading volume data can be accessed by clicking "OTC Data" and agreeing with the terms of use.
5. The demeaning process of time-invariant variables in fixed-effects models makes their values equal to zero. However, eight stocks change their listing exchanges between months during our sample period. Therefore, we include a binary variable that identifies those listing changes.
6. Alternative explanations for the positive relation between transient institutional holdings and dark pool volume include that transient institutions are (1) more likely to short sell stocks and (2) willing to pursue all available markets for liquidity. We thank a reviewer for pointing this out.

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