NBER WORKING PAPER SERIES

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Working Paper 31127
http://www.nber.org/papers/w31127

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
April 2023

We are thankful to Shilpa Aggarwal, Shashwat Alok, Apoorva Javadekar, Ram Thirumalai, Shekhar Tomar, and the seminar participants at the ISB for very useful comments. We are grateful to the BSE for making the trade and order data available to us for research. We thank Sai Sriramya Gorripati for excellent research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed additional relationships of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w31127

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NBER Working Paper No. 31127
April 2023
JEL No. G14,G15

ABSTRACT

We identify different roles traders play using data with trader identities for all transactions in SENSEX-index stocks on the Bombay Stock Exchange from January 2005 to December 2011. Individual day traders (IDT) are identified as "noise traders", who play an important role in the market microstructure literature. We measure the impact of their activity on market liquidity and trading of other market participants. IDT contribute 10% to volume while losing 3.2 bp (73% of the half-spread) on average on trades with others, including proprietary day traders (PDT), the primary intraday-liquidity providers, and longer-term traders. While we find some evidence that supports learning among IDT about their own ability and about how to trade, they continue to participate in the market even after losing for a long period. Instrumental variable regressions show that IDT activity reduces bid ask spread and increases intra-day volatility and total volume traded. The volume traded by PDT and the number of PDT active in the market also increase, but PDT profitability stays unchanged with increased IDT activity. This pattern is consistent with competition among PDT. Our results highlight the importance of IDT's presence in lubricating financial markets.

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1 Introduction

"Noise makes financial markets possible,

but also makes them imperfect."

- Fischer Black

The role of noise traders in securities markets has received wide attention in the academic literature and public debates. In models of market microstructure, noise traders are those without any informational advantage.[1] Market-makers and other liquidity providers make up their losses on trades with informed traders by their gains on trades with noise traders. Thus, noise traders' losses act as the grease that allows the wheels of financial markets to go around. In this paper, we identify individual day traders (IDT) as noise traders and measure the impact of their activity on market liquidity and trading by other market participants. Using an instrumental variable approach, we find that higher IDT activity leads to a lower bid ask spread, higher overall volume, and higher activity by sophisticated liquidity providers.

According to Black (1986), "Noise trading is trading on noise as if it were information." IDT are likely to fit Black's definition for multiple reasons. They carry little inventory overnight, and hence their trading is not likely to be motivated by liquidity needs. Barber, Lee, Liu, Odean, and Zhang (2020) document that they lose money on average; the vast majority of them are unprofitable, and many continue even after an extensive experience of losses. These patterns are inconsistent with the models of rational learning in the literature.[2] Further, Kuo and Lin (2013) show that IDT are overconfident and biased in their interpretation of information. Overall, they continue

[1]See Kyle (1985), Glosten and Milgrom (1985), and Dow and Gorton (2006).

[2]For example, see Mahani and Bernhardt (2007) for a rational model of learning to trade.

to trade despite not having any information advantage or liquidity needs, qualifying as noise traders.

We use a unique transaction-level database with masked trader identities for trades in stocks on the BSE (formerly the Bombay Stock Exchange) from January 2005 to December 2011. We classify traders into day traders (DT) and longer-term traders (LT) based on how much inventory they carry at the end of the day. We find that during this seven-year period, individual day traders (IDT) in the SENSEX index stocks lose money every year, on average. They use marketable and non-marketable orders roughly equally and lose similar proportions on both. Over the entire period, they lose on average 3.8 basis points on their trades with longer-term traders (LT). IDT lose money while trading with proprietary day traders (PDT) and other (non-individual) longer-term traders (OLT). However, they make a profit while trading with individual longer-term traders (ILT). PDT lose to OLT but more than recoup those losses by transacting with IDT and ILT. These patterns are consistent with OLT being informed traders, ILT being liquidity traders who trade to hedge or rebalance their portfolio, PDT being the liquidity providers, and IDT being noise traders.[3] We find that IDT continue to participate in the market even after losing for a long period, further supporting the interpretation of them as noise traders.

While ILT also make a marked-to-market loss on their trades at the end of the day of the trade, they have a holding period longer than a day.[4] Thus, the fact of this loss does not lead to the conclusion that they are noise traders. Indeed, there could be many reasons why individual investors

[3]See theoretical models of market microstructure for roles played by different traders, for example, Glosten and Milgrom (1985) and Kyle (1985).

[4]70% of IDT do not hold any inventory in any stock they trade. Overall, more than 90% of stock-days they are active on have zero inventory. In contrast, 100% of ILT hold inventory at least once in our sample and they hold zero inventory on less than 50% of stock-days.

trade. They may also be noise traders – after all, individual investors in general display several biases (Barber and Odean (2013)) and treat trading as substitute for gambling (Gao and Lin (2015)). But they could also trade for rational reasons. There is evidence that that retail investor imbalances predict returns over short horizons (Kaniel, Saar, and Titman (2008), Kaniel, Liu, Saar, and Titman (2012), Kelley and Tetlock (2013), Boehmer, Jones, Zhang, and Zhang (2021)), possibly consistent with liquidity provision as well as informed trading. Seru, Shumway, and Stoffman (2010) document that retail investors learn as they trade. Thus, ILT's losses at the end of the day of the trade could reflect the liquidity cost they bear for demanding immediacy as they trade for other reasons. Therefore, we focus on IDT instead of all individual traders, as they fit the noise-trader definition more closely.

Next, we examine how IDT activity affects bid ask spreads during the period from June 2009 to December 2011, for which we have the order data from the BSE. During this subsample, IDT lose 2.5 basis points to LT compared to the average bid ask spread of 8.8 basis points. So, IDT's loss on trades with LT is 57% of the average half-spread, a substantial fraction. IDT lose 6.5 bp on average on their trades with PDT, i.e., 148% of the average half-spread. We measure IDT Activity either by INR volume of or the number of IDT in trades between IDT and LT.[5]

Theoretically, there are two potential channels by which noise trading can affect market liquidity. As outlined at the beginning of the introduction, in the models with informed trading, greater noise trader activity reduces the risk of adverse selection faced by market makers and thus improves liq-

[5]We use only a subset of IDT trades – those with LT – so that we can examine the spillover effects on IDT's trades with other traders. But we also present results with measures based on all IDT trades, which are very similar to our main results.

uidity.[6] On the other hand, in the models with inventory risk and without informed trading (Grossman and Miller (1988), for example), noise trading can increase price fluctuations, leading to more inventory risk and consequently worse liquidity. To empirically investigate how noise trading affects bid ask spread, we need to address the simultaneity issue. Noise traders may be attracted to liquid markets[7] and their presence, in turn, may affect liquidity. We deal with this issue by using IDT Winners, the number of IDT making a profit the previous day, as an instrument for IDT Activity. We show that when IDT Winners are more, IDT trade greater numbers and larger volume, justifying the use of IDT Winners as an instrument. Statistical tests also show that IDT Winners is a strong instrument for IDT Activity.[8]

Using a stock-day panel, we run an instrumental variable regression of bid ask spread on IDT Activity. We control for trailing volatility of daily returns, lagged stock return, and lagged bid ask spread and include stock and date fixed effects. We find that IDT Activity reduces the bid ask spread significantly. One-standard-deviation higher IDT Activity reduces bid ask spread by around one basis point, which is 20% of the standard deviation of the bid ask spread and 11% of the mean bid ask spread, a large effect. This result is consistent with the microstructure models of informed trading, where higher noise trader activity results in improved liquidity.

We estimate a similar instrumental variable regression to examine the impact of IDT Profit, the total profit of IDT in their trades with LT, on

[6]As we discuss in detail in Section 4.1, in the presence of informed trading, both marketable and non-marketable orders by noise traders can reduce the cost of quoting for market makers, narrowing the bid ask spread.

[7]For example, see the theoretical model in Admati and Pfleiderer (1988).

[8]After controlling for other variables affecting bid ask spread, including its lagged value, IDT Winners will affect bid ask spread only through IDT Activity, satisfying the exclusion restriction.

the bid ask spread. As noise traders, if IDT subsidize the liquidity provision, their losses – which can be interpreted as the subsidy – should have a negative relationship with the bid ask spread. This implies a positive relationship between IDT Profit and BA spread, which is exactly what we find. A one-standard-deviation increase in IDT Profit results in a 0.35 standard-deviation increase in the bid ask spread, i.e., a rise of 1.5 basis points.

Next, we examine IDT Activity's impact on the stock's overall volume. In line with the expectation that loss-making IDT are unlikely to crowd out other traders, we find that IDT Activity increases the total volume. To better understand the channel by which IDT Activity reduces bid ask spread, we study its spillover effects on the volume and profitability of sophisticated day traders. In particular, we focus on PDT. Proprietary traders are known to be liquidity providers in the market.[9] Since PDT carry very little inventory, they can be considered sophisticated intraday liquidity providers.

We find that higher IDT Activity results in higher volume and total profits for PDT but not significantly different proportionate profit. This pattern is present for PDT's overall trading, as well as their trading with IDT and LT.[10] Further, the number of PDT also goes up with IDT Activity, indicating more competition. This evidence is consistent with the following interpretation: i) PDT become more active in response to higher IDT Activity; ii) competition among them keeps their profitability unchanged; and iii) even with lower bid ask spreads, they are able to earn the same proportionate profit because of the higher subsidy provided by IDT. These results are

[9]See Biais, Declerck, and Moinas (2017), and Bergman, Kadan, Michaely, and Moulton (2020), for example.

[10]While our measure of IDT Activity is based on trades between IDT and LT, this could be highly correlated with overall IDT volume. Thus, if IDT trade more with PDT, one may argue that PDT volume may go up mechanically as they take the other side of IDT trades. However, we find that PDT activity in transactions with LT also goes up, thus eliminating the concern about a mechanical relationship.

in line with theoretical market microstructure models with informed trading as in Kyle (1985) and Glosten and Milgrom (1985). Finally, we also find that IDT Activity increases the intraday volatility of the stocks, an implication of the model with inventory risk concerns in addition to informed trading. However, the decline in the bid ask spread would suggest that inventory risk concerns are more than offset by lower likelihood of taking the opposite side of informed traders. Our results are robust to averaging the coefficients from stock-by-stock regressions instead of using the panel regression.

Related Literature.

Our study contributes to two strands of literature. The first examines the role of noise traders in financial markets. In behavioral finance, noise traders are subject to decision-making biases, and their activity introduces additional risk in arbitrage activities and inhibits the price discovery role of arbitrageurs.[11] In the theoretical market microstructure literature, noise traders may improve the liquidity as in the models where adverse selection is the main concern (for example, Kyle (1985)) or worsen liquidity as in the models where inventory risk is the main concern (for example, Grossman and Miller (1988)). Bloomfield, O'hara, and Saar (2009), in an experimental setting, find support for the first channel.

Empirically, examining the causal effect of noise trader activity on liquidity is challenging, since noise trader activity could in turn depend on how liquid the markets are. The literature has used various approaches to get around this issue. Berkman and Eleswarapu (1998) study a ban on the forward trading facility (Badla) on the BSE to provide indirect evidence that a

[11] See Shleifer and Summers (1990) and Shleifer and Vishny (1997). De Long, Shleifer, Summers, and Waldmann (1989) argue in favor of a securities transactions tax to reduce excess volatility from noise traders. Summers and Summers (1989) examine the welfare effects of a US Securities Transfer Excise Tax and conclude that the benefits outweigh the costs.

reduction in short-term trading worsens liquidity. Greene and Smart (1999) use Wall Street Journal analyst recommendations as an exogenous shock to noise trader activity and find that noise trading improves liquidity and reduces the adverse selection component of the bid ask spread. Foucault, Sraer, and Thesmar (2011) use a stock market reform leading to an exogenous, permanent reduction in retail traders' activity and find that for the affected stocks, volatility goes down and liquidity improves, thus supporting the inventory risk channel. More recently, Peress and Schmidt (2020) use distracting news to identify exogenous reduction to noise trading activity. They find that, on the days biased investors are distracted, stocks owned predominantly by individual investors display reduced liquidity and volatility. Ozik, Sadka, and Shen (2021) document that pandemic-induced increase in retail trading attenuated the rise in illiquidity. Eaton, Green, Roseman, and Wu (2022), using brokerage outages, show a differential effect on market quality of shocks to Robinhood investors, who tend to herd, and retail investors at traditional brokerages. We contribute to this literature by identifying individual *day traders* as an important class of noise traders whose activity reduces the bid ask spread and increases volatility. Further, we document the spillover effects of noise trader activity on sophisticated liquidity providers' volume, profitability, and competition.

Our study also contributes to the literature on individual day traders. Linnainmaa (2003) finds that individual day traders transact in attention-grabbing and familiar stocks. Barber et al. (2020) show that these traders lose money on average and continue to trade even after substantial losses. Barber, Lee, Liu, and Odean (2014) document that there is significant variation in their skills and only a tiny fraction consistently make money. Kuo and Lin (2013) provide evidence that individual day traders display overconfidence and bias.[12] We add to this literature by showing the impact of individual day traders' activity on the bid ask spread, volume, volatility, and profits of and competition among professional traders.

Next, we proceed with the description of the data and the variable construction.

2 Data and Construction of Variables

In this section, we first describe the trade data that allows us to examine the profitability of different trader groups. Then we discuss the measurement of the bid ask spread using the orders data.

2.1 Trade and Prices Data and Trader Classes

We use a unique dataset of all trades executed on the BSE (formerly the Bombay Stock Exchange) for the period from January 1, 2005, to December 31, 2011. The data include the stock id, date, time of the trade, trade price, quantity traded, and an anonymized trader id. We focus on 33 stocks included in the S&P BSE SENSEX, a broad stock market index, at any time during our sample period. The BSE assigns traders to different categories. Additionally, we create a category called proprietary traders that corresponds to brokers who trade on their own accounts. We group traders not categorized as Corporations (CO), Foreign Institutional Investors (FII), Mutual Funds (MF), Individuals (IND), or Proprietary Traders (PROP) as Others (OTHERS). We also classify a given trader as a day trader (DT) if she ends up flat at the end of the day – i.e., has zero inventory at the end

[12]Other studies document profitability and trading pattern of individual day traders. Using data from two brokers Harris and Schultz (1998) show that SOES bandits trade profitably. Based on individual day traders' transactions from one brokerage over three months, Garvey and Murphy (2005) find that around half of those traders make money.

of the day – on at least 50% or more days in each of the stocks she trades over the entire sample period. Traders who do not satisfy this condition are classified as Longer-term Traders (LT). For our analysis, we collapse these classes into four broad categories, based on whether a trader is a DT or not: Individual Day Traders (IDT), proprietary day traders (PDT), day traders excluding IDT and PDT (XDT), Individual Longer-term Traders (ILT) and Other (non-individual) Longer-term Traders (OLT), as presented in Table 1. Overall, the average end-of-the-day inventory of LT 57% of quantity traded and of DT is 7%. We observe similar patterns for ILT (56%) and IDT (7%). In particular, IDT carry zero inventory 90% of the stock-days in which they trade. For ILT, this fraction is less than 50%. We discuss the rationale for our classification beyond the legal categories in Section 3.1.

2.2 Daily Trading Profit/Loss

For DT, who mostly close their positions by the end of the day, trading profit, defined as the profit till the end of the day, is the relevant measure of how much money they make/lose. For LT, who are relatively longer-term investors with a horizon of more than one day, the trading loss is a measure of the intraday liquidity cost they have to bear. For each trade, we can identify both parties to the trade and calculate trading profit for each party j, in trade k in stock s, on day d, as follows:

$$\begin{aligned}
Trading\ Profit_{j,k,s,d} &= (EODPrice_{s,d} - TradePrice_{j,k,s,d})Quantity_{j,k,s,d}, \\
&\quad \text{if } j \text{ is } buyer, \text{ and} \\
Trading\ Profit_{j,k,s,d} &= (TradePrice_{j,k,s,d} - EODPrice_{s,d})Quantity_{j,k,s,d}, \\
&\quad \text{if } j \text{ is } seller,
\end{aligned}$$

where $EODPrice_{s,d}$ is the price of stock s at the end of day d. $TradePrice_{j,k,s,d}$ and $Quantity_{j,k,s,d}$ are the price and quantity, respectively, for trade k, in stock s, on day d by trader j. Suppose trader TR_1, belonging to the category IDT, buys 100 shares at a price INR 200 from trader TR_2 belonging to the category LT. The stock price drops to INR 195 at the end of the day. Then, for this trade, quantity, volume, and trading profits for each trader are as follows:

	TR_1	TR_2	Total
Quantity traded	100	100	200
Trading Volume (INR)	20,000	20,000	40,000
Trading Profit (INR)	-500	500	0

Note that our total quantity traded and total volume are two-sided, i.e., counting volume for each party separately. So aggregated across all trades, our total volume is twice the INR volume reported by the exchange. We define Aggregate Trading Profit and Aggregate Trading Volume for a group as the sum of the respective quantities for all traders belonging to that group.

2.3 Bid Ask (BA) Spread

For a subsample of 607 trading days over June 1, 2009, to December 31, 2011, we have data of all orders placed on the BSE.[13] We call this sample the BA Spread Sample. The dataset includes the stock id, date, time of order, type of order (buy or sell), the limit price of the order, the total order quantity, whether the record is an order addition, modification, or deletion, and the anonymized trader id. We construct limit order book snapshots using these data at each modification to the order book. For each stock s,

[13] Order data is missing from March 9, 2010, to May 2, 2010.

each day d, each snapshot i, we calculate the best bid and the best ask. For each stock, each day, we define BA Spread, the average of proportionate bid ask spread across snapshots, as

$$BA\ Spread_{s,d} = \frac{1}{I_{s,d}} \sum_{i=1}^{I_{s,d}} \frac{Ask_{s,d,i} - Bid_{s,d,i}}{0.5(Ask_{s,d,i} + Bid_{s,d,i})},$$

where $I_{s,d}$ is the number of order book snapshots for stock s on day d. We also calculate volume-weighted average daily bid ask spread across stocks on a given day d as follows:

$$BA\ Spread_{d} = \frac{\sum_{s=1}^{S} BA\ Spread_{s,d} Volume_{s,d}}{\sum_{s=1}^{S} Volume_{s,d}},$$

where $Volume_{s,d}$ is the INR volume of stock s on day d and S is the total number of stocks.

Having described the data and variables, we now turn to the profitability patterns to understand the roles played by different traders.

3 Patterns of Trading Profits

In this section, we first examine the profitability of different groups of traders. Then we discuss potential reasons for continued trading by IDT while making losses.

3.1 Trading Profits Across Trader Categories

To understand the extent of a category's profits/losses while trading with other categories, we group them by combinations of a trader's category and the category of her counterparty. For each combination, we calculate Aggregate Trading Profit and Aggregate Trading Volume, as defined in Section

2.2, from the perspective of the first party. Aggregate Profit Ratio of the group is the ratio of Aggregate Trading Profit to Aggregate Trading Volume.

First, we examine the profitability of IDT, PDT, XDT, and LT against each other in Table 2. We see that IDT account for 9.8% of total two-sided volume (1.2%+0.69%+0.3%+7.2%, see Section 2.2 for explanation of how we measure volume). IDT lose money trading against PDT, XDT as well as LT (6.5bp, 3.4bp, and 3.8bp, respectively). LT lose when trading with PDT (3.8bp). This loss can be interpreted as the liquidity cost paid by LT, the longer-term investors, to PDT for intraday liquidity. Pattern of XDT profitability is similar to that of PDT but smaller in magnitude. Further, they lose money to PDT. Interestingly, LT make positive Trading Profit while trading with IDT and this reduces their overall trading costs, i.e., IDT subsidize what LT have to pay for intraday liquidity.

If IDT are noise traders, then as we argue later, they could lose on both their liquidity demanding marketable limit orders as well as their patient limit orders due to being too slow in responding to fast arriving news. We investigate this by tagging the orders on the two sides of every trade as marketable and non-marketable. The order placed later triggers the trade and hence is tagged as the marketable order, the other being non-marketable. Orders are numbered sequentially. So we proxy a non-marketable order in a trade as the one with the lower order number.[14] Similar to Table 2, we aggregate trading volume and profit by combinations of a trader's category and the category of her counterparty for each type of order. Table 3 presents the percentage of the aggregate volume for IDT and PDT coming from

[14]This is an approximation since if an order is updated, it retains the original order number. Further, less than 0.50% of volume is for trades in which the two order numbers are the same. We exclude such trades from the classification of orders into marketable and non-marketable. However, if we allocate volume and profit from such trades to the two order categories equally or in proportions based on other trades, the conclusions remain the same.

marketable and non-marketable orders placed by the first party. For each type of order, we also report Profit Ratio in basis points, defined as the profit of the first party till the end of the day divided by the INR volume. We see that IDT use marketable and non-marketable orders in roughly equal proportions. Most importantly, they lose money on both to a similar extent. Thus, it is not the case that IDT primarily use one type of order or lose money only on marketable orders.

To understand the distinction in profitability by finer categories, in Table 4, we present the profitability summary by by separating LT into ILT and OLT. IDT profit while trading with ILT to the extent of 3 basis points and lose nearly 9 basis points to OLT. On the other hand, PDT, who could be relatively sophisticated day traders, earn profits against ILT, earning 10 basis points. However, they lose 3.7 basis points to OLT, i.e., non-individual longer-term traders. Thus, while PDT, on average, earn compensation for providing intraday liquidity to LT (Table 2), the source of this profit is their trading with ILT. ILT lose money against all the counterparties, but their losses are less against IDT (3 basis points) than against PDT (10 basis points), XDT (8.5 basis points), and OLT (13.5 basis points).

These patterns of profits and losses provide the basis for the following characterizations of the various groups beyond their legal definitions (see Table 1).[15] OLT are composed of presumably a mix of traders with various trading motives, but their positive daily profits suggest that there are more informed traders in this group than in the others. That they profit, on average, within the day follows from the standard market microstructure model result that informed traders have an impact on the price, even within

[15] See Getmansky, Jagannathan, Pelizzon, Schaumburg, and Yuferova (2017) and Jagannathan, Pelizzon, Schaumburg, Sherman, and Yuferova (2022), who identify different roles traders play during normal times and fast crashes.

the day. That these "longer-term traders" maintain their position would follow from the observation that information is only revealed through time, and this time may be longer than a day. The traders will continue holding their position, perhaps even adding to it in subsequent days because they anticipate that more information will come out favorable to their position. The key observation here is that the OLT transactions are correlated with prices at the end of the day (as indicated by OLT's positive profit), and as such, these transactions are costly for liquidity suppliers.

The ILT results are consistent with this group consisting of what we might call liquidity traders. These are traders who are willing to pay transaction costs to liquidate a position to cover consumption, put on a position for investment purposes, or modify a portfolio for risk management/hedging purposes. Their average losses suggest, however, that these portfolio adjustments are not, to a great extent, motivated by short-term information about prices. However, these transactions could be correlated with future stock prices beyond one day. After all, consumption, investment, and hedging demand all factor into the demand for shares of a particular security and hence its price. That such changes in total demand are not, on average, manifested in a day should not be a surprise.[16]

That brings us to the individual day traders, IDT. They lose money on average and are mostly flat by the end of the day. It seems incomprehensible that their trading should be correlated with future prices, and for that reason, we classify them as, on average, noise traders. This classification, though, is not necessarily obvious. In the early days of market microstructure models like Kyle (1985) and Glosten and Milgrom (1985), noise traders referred to those who bought or sold independent of the terms of trade. This

[16]The Robinhood traders buying Gamestop are unlikely to have had information about future fundamentals, yet they seem to have had a non-trivial effect on Gamestop's price.

was, for the most part, a simplifying assumption. For such trading to be "rational" hedging, traders would have to have infinite risk aversion (Villa (1987)). In fact, we have evidence that the terms of trade do matter to IDT since they use both marketable and non-marketable orders, and they lose money, on average, from the use of both (Table 3).

Liquidity traders, in the old microstructure language, traded based on the quotes—their trade was endogenized. This did make things more complicated but yielded the theoretical possibility of a market closing down if the adverse selection problem became severe enough (Glosten (1989)). The more modern use of the term noise, we think, is accurately described as trade uncorrelated with future prices. This goes back to Black (1986), who defines noise trading as "trading on noise as if it were information."

Finally, PDT, who earn profits against the noise traders (IDT) and liquidity traders (ILT) but lose to informed traders (OLT), fit the role of intraday liquidity providers.[17]

3.2 Why IDT Keep Trading Despite Losing

There could be multiple reasons why IDT keep trading despite consistent losses. First, they could be trading to learn about their own ability and/or skills in trading.[18] Second, IDT could also be overconfident and display biased learning.[19] Third, there could be non-financial reasons for them to trade.

In our sample, we find some evidence of learning. Panel A of Figure

[17]XDT show a pattern of profitability similar to PDT but of smaller magnitude. Further, they lose money to PDT indicating that, as day traders, they are less successful, on average, than PDT.

[18]For example, see Mahani and Bernhardt (2007), Seru, Shumway, and Stoffman (2010), Linnainmaa (2011) for theoretical models and empirical results consistent with trading to learn.

[19]See the theoretical models of Gervais and Odean (2001)). Barber et al. (2020) also provide evidence more in line with learning that is not fully rational.

1 plots the profitability of IDT who are categorized according to Days in Sample (DIS) (the number of days they have traded). We show the IDT profitability for each category of DIS separately for their trades with other IDT, LT, and ODT (PDT and XDT combined). If we exclude the group that trades for 10 days or less, we see that the profitability of IDT, who trade a greater number of days, is generally higher. This could be the effect of i) IDT learning about their ability and/or ii) IDT getting better at trading over time. The first mechanism implies that more profitable IDT are more likely to continue, a pattern supported by our data. The pattern is also consistent with the second mechanism: the profitability of IDT, who continue to trade beyond 100 days, improves from their initial days to the latter days even though they continue to make a loss. (Figure 1, Panel B).[20]

We also examine if the IDT who are more active are also more profitable. Defining ActiveRatio for a trader as DIS/(Total market trading days between (including) first and last days of the trader),[21] we find that more active IDT, excluding those who are in the market for 10 days or less, are generally more profitable (Figure 1, Panel C). However, only the most active group (ActiveRatio between 0.9 and 1), which includes only 1% of IDT, is profitable overall; all other groups lose.

Since the vast majority of IDT lose even after long periods of active trading, the explanation could lie in non-financial reasons to trade, such as the entertainment value of trading (Dorn and Sengmueller (2009), Grinblatt and Keloharju (2009)) or trading as a form of gambling (Barber, Lee, Liu, and Odean (2009), Gao and Lin (2015)).

This subsection documents a pattern of persistent losses of IDT, despite

[20]Thus, as argued by Barber et al. (2020), the learning does not appear to be fully rational.

[21]ActiveRatio, by construction, lies between 0 and 1, with a higher ratio indicating a more active trader.

some improvement over time, and reinforces our interpretation of IDT as noise traders. Having empirically identified our noise traders, we examine the effect of their activities on the market in the following section.

4 IDT and Liquidity

In this section we discuss how the bid-ask spread, a measure of trading liquidity, will be affected by noise trading according to theory. We then discuss how we address the endogeneity issue due to noise traders choosing to increase their activities when market is more liquid that poses a challenge in establishing causality. Then we describe our approach to address this issue and discuss of our findings.

4.1 Noise Trading and Bid Ask Spread

Theoretically, noise trading may improve or worsen liquidity. In the models with informed trading, its impact can come through both marketable and non-marketable orders. As we saw in the previous section, IDT use both marketable and non-marketable orders in roughly equal proportions (Table 3). When noise traders use marketable orders based on no information, they simply reduce the adverse selection problem that high-speed liquidity providers face. In light of active quote competition, the presence of more marketable order-using IDT reduces the relative proportion of informed trade and reduces the spread as in Glosten and Milgrom (1985)). This is exactly true in a world in which adverse selection is driven by snipers who react faster to public news and pick off stale quotes (Budish, Cramton, and Shim (2015)). If, on the other hand, the informed are trading based on longer-lived information, then noise traders' effect on the spread is more nuanced. With more noise traders, the speed with which information is impounded in prices is lower, meaning that spreads do not decline as fast. Glosten and Milgrom provide an analysis that shows that the time until almost all the information is reflected in prices is increasing in the amount of noise trade. Given that we measure spread as the average spread over the trading day, the effect of noise trade on the average spread will depend upon how long-lived the information is.[22]

When IDT use non-marketable orders, there is both a direct and indirect effect. The direct effect is that IDT, being willing to lose money, evidently quote unprofitably tight spreads. That is, their greater presence will lead to more unprofitable quoting and smaller spreads. Noisy non-marketable orders also provide a benefit to the proprietary traders who do not expect to lose money quoting. The aggressively priced IDT orders provide an execution option for the fast liquidity suppliers in the following sense. In volatile markets, successful fast liquidity suppliers can often sense the direction the market is going.[23] In the event that, for example, the market is "crumbling up," the fast liquidity suppliers have been selling to active buyers. The presence of resting sell orders allows the liquidity suppliers to cover their short positions, remove the sell orders and quote new higher prices. In effect, the liquidity suppliers are "informed traders" trading against the uninformed quotes which provide the execution option.[24] The presence of this option makes quoting less costly and hence reduces the bid ask spread. On balance, and for the reasons listed above, we believe that we should see greater IDT market participation associated with smaller average daily spreads in the presence of informed trading.

On the contrary, in the absence of informed trading but with inventory

[22]This issue is considered by Glosten and Putniņš (2019).

[23]Just as IEX's "crumbling quote" functionality is able to forecast changes in prices.

[24]This is reminiscent of the early option-based microstructure theory of Copeland and Galai (1983).

risk (for example, Grossman and Miller (1988)), noise trading can add to price volatility, resulting in more inventory risk and wider bid ask spread.

To summarize, whether bid ask spreads widen or tighten with increased noise trader activity depends on whether the adverse selection channel dominates or the inventory risk channel.

4.2 IDT Activity, IDT Profit, and BA Spread

We measure IDT Activity in two different ways. Log IDT Volume is the log of the total INR volume of IDT for their trades with LT. Log IDT Number is the log of the number of IDT in transactions with LT. Our measures are based on only a subset of IDT trades – those with LT – so we can examine the spillover effects on IDT's trades with other traders. However, as robustness tests, we present the results based on measures using all IDT trades in Section 6. Panels A and B of Figure 2 plots the time-series of 5-day moving averages of aggregate BA spread (BA_d) defined in Section 2.3 and IDT Activity. We can see that the two series move in the opposite direction, supporting the idea that higher IDT Activity is associated with lower BA Spread.

If IDT lower the bid ask spread by providing a subsidy to other market participants via their losses, higher profit by them should be associated with a higher bid ask spread. We define IDT Profit as the profit in INR of IDT from their trades with LT. We are interested in total profit by IDT rather than their profit ratio because total profit captures their activity as well as profitability. Panel C of Figure 2 shows the time series of 5-day moving averages IDT Profit and BA Spread. While the relationship looks noisy visually, we examine it more rigorously in Section 4.4.

IDT Activity and BA Spread could move in the opposite direction due to reverse causality. In times of lower bid ask spread, more IDT may find it lucrative to enter the market, as theorized by Admati and Pfleiderer (1988), and hence their activity would be greater in liquid markets. Similarly, a positive relationship between IDT Profit and BA Spread could be driven by reverse causality. A higher BA Spread means IDT earn more compensation for their liquidity provision, and hence their profit is greater. To get around this issue and establish that it is IDT Activity / Profit that influences BA Spread, we use an instrumental variable approach. In the next section, we explore potential instruments for IDT Activity.

4.3 What Explains IDT Activity and Profit?

We conjecture that when more IDT had a profitable day, that information will encourage greater IDT participation in the market the next day. Based on this conjecture, we use IDT Winners, the number of IDT with positive profit the previous trading day, as our first explanatory variable. One question may arise as to the mechanism through which IDT Winners influence IDT Activity. There are two possibilities. One is that IDT who make a profit are more likely to participate in the market/trade aggressively the next day. Indeed, in untabulated results, we do see a positive association between a particular IDT's profit and the volume traded by her the next day. The other possible channel, supported by anecdotal evidence, is that IDT within the same social group (residential areas, friend circles) talk to each other and the information about IDT Winners seeps to the broader IDT category.

If IDT are distracted or engaged otherwise, we expect their stock market activity to be lower. In India, cricket is hugely popular, attracting more than

90% sports viewership.[25] In cricketing nations, which include India, losses in international cricket matches are followed by negative abnormal stock market returns (see Edmans, Garcia, and Norli (2007)), highlighting that cricket is emotionally important to stock market participants. Based on the importance of cricket to Indians, we define Cricket Match as one on the days the Indian men's national team plays a One-Day-International cricket match with the national team of another country.[26] If IDT are distracted because they follow cricket matches, we expect this variable to be negatively related to IDT Activity. IDT may also be less attentive on festival days. Thus, we define the variable Festival to be one on festival days on which the stock market is open and days before the festival days on which the stock market is closed.

We use the same three variables to explain IDT Profit. If greater IDT Winners attracts more unsophisticated IDT to the market, we expect IDT Winners to have a negative relationship with IDT Profit. If IDT are more distracted by cricket matches and festivals but continue to participate in the market, the variables Cricket Match and Festival are likely to have a negative relationship with IDT Profit.

All three explanatory variables are potential instruments for IDT Activity and Profit. Cricket Match and Festival are exogenous to the stock market. The number of IDT winners does depend on the stock market conditions of the previous trading day of IDT Activity. However, once we control for other variables affecting BA Spread, including its lagged value,

[25] "Cricket draws 93% of sports viewers in India: BARC', Business Standard, June 4, 2019. https://www.business-standard.com/article/news-ians/cricket-draws-93-of-sports-viewers-in-india-barc-119060400786_1.html, accessed on November 14, 2022.

[26] We collect the dates of One Day Internationals from www.espncricinfo.com. Following Edmans, Garcia, and Norli (2007), we do not use cricket matches, such as test matches, played over multiple days.

IDT Winners will affect BA Spread only through IDT Activity/Profit, satisfying the exclusion restriction.

Table 5 shows the results of the regressions of IDT Activity and IDT Profit on the three explanatory variables. We include stock fixed effects and cluster standard errors at the day level. As expected, the variable IDT Winners has a significant positive relationship with IDT Activity and a significant negative one with IDT Profit. Thus more IDT Winners the previous day in a particular stock, there is greater IDT Activity the next day in that stock and greater total loss, i.e., more negative IDT Profit. Cricket Match and Festival have no significant association with IDT Activity. Thus, unlike overall individual investors, whose activity goes down during distracting events (See, Peress and Schmidt (2020)), the activity of individual *day traders* does not seem to decrease during the events that compete for their attention. IDT Profit is not different on cricket match days but significantly lower on festival days. Since IDT Activity, IDT Profit, and IDT Winners all have trends, we also use a time trend as control, and our conclusions remain the same.

Since IDT Winners has a strong relationship in the expected direction with both IDT Activity and IDT Profit, we use it as our instrument. We formally test its strength in the analysis in the following subsection.

4.4 Effect of IDT on BA Spread

We run the instrumental variable regressions of $BA\ Spread_{s,d}$ using a stock-day panel, where IDT Activity, IDT Profit, and IDT Winners are measured for stock s on the day d. The control variables include: i) Stock Volatility, the annualized standard deviation of the daily return for stock s over the trailing 22 trading days, ii) Lagged Stock Return, and iii) Lagged BA Spread.

Table 6 provides descriptive statistics for all these variables. The mean for BA Spread is 8.8 basis points with a standard deviation of around five basis points. To get a sense of the magnitude of IDT losses relative to the bid ask spread, we repeat the analysis in Table 2 for the BA Spread Sample (June 2009 to Dec 2011, see Section 2.3 for details) in Table A.2 in the Online Appendix. Even in this subsample, IDT lose while trading with PDT, XDT, and LT. IDT's loss while transacting with LT of 2.53 basis points is around 29% of the mean BA Spread or 58% of the half-spread, substantial fractions. IDT's loss to PDT comes to around 6.5 basis points, 148% of the half-spread.

Table 7 presents the results for the IV regressions. IDT Activity, IDT Profit, and IDT Winners are scaled to have a unit standard deviation. We include stock fixed effects and cluster the standard errors at the day level to account for correlation across stocks on the same day. Further, the variables show a statistically significant trend in our sample. To control for that, we also add Date fixed effects. The results are similar in magnitude and significance if we include a trend instead of adding Date fixed effects. The first two columns show the impact of IDT Activity on BA Spread. IDT Winners is a very strong instrument with the lowest first stage F-statistic being more than 800. The coefficient of IDT Winners in the first-stage regression is positive, as expected from Table 5.

IDT Activity has a substantial and statistically significant negative effect on BA Spread. One-standard-deviation higher IDT Activity reduces BA spread by around one basis point, which is 20% of the standard deviation of the bid ask spread, a big effect. This result shows that the experimental evidence in Bloomfield, O'hara, and Saar (2009) that noise trading reduces bid ask spread carries over to the real world. It also complements the findings in Peress and Schmidt (2020) that on days when noise traders are distracted, market liquidity is worse, particularly in stocks owned by individual investors.

The last column of Table 7 shows IV regressions with IDT Profit as the main explanatory variable. In this case, the first stage F-statistic is 14.32, indicating a moderately strong instrument.[27] IDT Winners has a negative relationship with IDT Profit in the first stage, in line with the results in Table 5.

IDT Profit has a significant, positive effect on BA Spread, further supporting the hypothesis that IDT activities subsidize the cost of intraday liquidity provision: the lower the profit of IDT, the lower the BA Spread. A one-standard-deviation increase in IDT Profit results in a 0.35 standard deviation increase in the BA Spread, i.e., a rise of 1.5 basis points.

Given that IDT Activity reduces BA spread, it is likely to have an impact on the overall volume and volatility as well as spillover effects on the other market participants. We investigate this next.

5 IDT: Volume, Volatility, and Spillover Effects

In this section, we examine how variation in IDT Activity affects overall volume, trading of proprietary day traders, and volatility. We use the same methodology as in the previous section (Table 7) with IDT Winners as an instrument for IDT Activity. We use Log IDT Volume as the measure of IDT Activity. The results using Log IDT Number are very similar.

[27]We use the generalization by Olea and Pflueger (2013) of the weak instrument test of Stock, Yogo, and Andrews (2005), implemented by Pflueger and Wang (2015). The F-statistics, in this case, is higher than 12.34, the cut-off for worse bias of 20% at 10% statistical significance.

5.1 Volume

We expect overall volume to be increasing in the extent of noise trader activity. This is pretty much mechanical - increasing the number of active traders is unlikely to cause less trading. The only way it could go the other way is if the noise traders' presence drives out other traders. We do not expect this since they appear, at least on average, to be willing to suffer losses.

Column (1) of Table 8 presents the impact of IDT Activity on Log Volume. As expected, IDT Activity increases the total volume traded in a stock. Bloomfield, O'hara, and Saar (2009) provide experimental evidence that noise trading reduces bid-ask spreads and increases volume. Our results in the previous section and this subsection are in line with their findings and support the interpretation that IDT are noise traders.

In this section, we also investigate the impact of IDT Activity on the volume traded by PDT (Proprietary Day Traders). Studies have documented proprietary traders to be liquidity providers in the market (for example, see Biais, Declerck, and Moinas (2017), and Bergman et al. (2020)). PDT are professional traders focused on intraday trading and can be considered sophisticated intraday liquidity providers. Thus, any reduction in the bid-ask spread is likely associated with their activity and profitability.

The implications for the spillover effects of IDT Activity on volume traded by PDT with various counterparties are less clear than those for overall volume. We measure IDT Activity based on transactions between IDT and LT. If it is a substitute for trading between IDT and PDT, we would expect a negative relationship between IDT Activity, as defined by us, and the extent of trading between PDT and IDT. On the other hand, if IDT Activity reflects overall IDT trading, it is likely to increase PDT trading with IDT. We measure PDT Volume with IDT as the total volume in INR of PDT in their trades with IDT. Column (2) of Table 8 shows that the higher the IDT Activity (with LT), the higher the log PDT Volume with IDT.

Since PDT, on average, make money from their trades with IDT, changes in their volume with IDT will likely have spillover effects for their trades with LT. Examining the effect of IDT Activity on PDT trading with LT also allows us to rule out the possibility that Columns (1) and (2) of Table 8 simply capture a mechanical relationship. We repeat the analysis in Column (2) with Log Volume PDT and LT defined analogously. Column (3) of Table 8 finds a positive effect of IDT Activity on PDT-LT volume as well. Not surprisingly, the results extend to the overall volume traded by PDT (reported in Table A.3 in the Online Appendix).

5.2 PDT Profit and Competition

What spillover effect does IDT Activity have on PDT profit? IDT Activity increases PDT Volume in trades with IDT and LT, and PDT realize a profit, on average, when trading with both these groups (Table 2). Thus we expect the total INR profit of PDT to go up with IDT Activity. We measure Profit of PDT with IDT as the total profit in INR made by PDT in their trades with IDT. Profit of PDT with LT is defined analogously. When we run instrumental variable regression of these two variables on IDT Activity, we get a positive and significant relationship, as expected (Columns (1) and (2) Table 9).

While the total profit of PDT, as a group, goes up with IDT Activity, what can we expect about PDT profitability? With competitive liquidity suppliers (implicit assumption of models in Glosten and Milgrom (1985) and

Kyle (1985)), we expect their profitability to remain unchanged with changes in IDT Activity. We define Profit Ratio of PDT with IDT as Profit of PDT with IDT divided by PDT Volume with IDT. Profit Ratio of PDT with LT is calculated in a similar manner. In line with the prediction of competition among PDT, IDT Activity has no significant effect on either of these profit ratios, as shown in the last two columns of Table 9. These results do not change materially if we replace the dependent variables in Tables 8 and 9 with Log PDT Volume, Profit PDT and Profit Ratio PDT, i.e., variables based on PDT's all trading (Table A.3 in the Online Appendix).

Increased competition among PDT in response to greater noise trader activity can happen along the intensive margin – the same number of PDT trade more per capita volume – or the extensive margin – more PDT become active or both. Table 10 shows the regression of Log PDT Number in Trades with IDT and LT on IDT Activity.[28] We see the extensive margin at play from the positive and statistically significant coefficient for IDT Activity.

Based on the overall pattern in Tables 8-10, we interpret that PDT trade more in response to higher IDT Activity. Further, while PDT's total profit goes up, competition among them leaves their proportionate profit unchanged. Even with lower bid-ask spreads, they are able to maintain the same profitability due to increased volume of trades with IDT.

5.3 Intraday Volatility

Finally, we study the effect of IDT Activity on the intraday volatility of the stock. Theory does not provide unambiguous predictions on the effect of noise trading on volatility in the presence of informed trading but without inventory risk concerns. For example, the Kyle model predicts that the

[28] PDT Number in Trades with IDT (LT) is the number of PDT that participated in the trades with IDT (LT).

information of the informed is revealed in prices gradually over time and independent of the level of noise trade. In that model, the volatility of price changes is precisely the volatility of updated expectations. Thus, the volatility of price changes during the day is the variance of the information held by the informed trader divided by the number of transactions during the day, independent of the variance of the noise trader trades.

The Glosten-Milgrom model with long-lived information does not provide much of a prediction except to say that early volatility will be higher than later volatility as the information of the informed is impounded in prices. Simulations of the model reveal that with high noise trader participation, initial volatility is small but persistent. In contrast, with low noise trader participation, initial volatility is high but subsequently quite low as prices come to reflect the informed traders' information. Since we plan to examine intraday volatility, the implications for initial volatility are the relevant ones.

When market makers are risk-averse, inventory risk considerations play an important role. In such a setting, increased noise trading does lead to increased price volatility. Peress and Schmidt (2020) show that an extension of the model in Kyle (1985) incorporating inventory risk delivers these predictions. Thus, with greater noise trading, whether short-term volatility increases, stays the same, or reduces, depends on the information structure and the risk-aversion of the market-makers. Empirically, Foucault, Sraer, and Thesmar (2011) find that reduced retail trading activity lowers the volatility of stock returns. Peress and Schmidt (2020) document that on days with distracting news unrelated to the stock market, stocks owned predominantly by individual investors display less volatility.

To examine the effect of IDT Activity on volatility, we measure intraday volatility as the square root of average squared half-hour returns following Andersen, Bollerslev, Diebold, and Ebens (2001). The results are in Table 11. IDT Activity increases intraday volatility even after controlling for lagged volatility of daily returns. This result supports the presence of inventory risk. It complements the findings in Foucault, Sraer, and Thesmar (2011) and Peress and Schmidt (2020).

6 Robustness

We have measured IDT Activity and IDT Profit based on IDT's trades with LT because we want to examine spillover effects on PDT trades. However, in this section, we use volume and profit from all IDT trades as a robustness test. Using the same approach as in Table 7, we run an instrumental variable regression of BA Spread on All IDT Activity/Profit. All IDT Activity is measured as Log All IDT Volume, log of INR volume of IDT. All IDT Profit is IDT's total profit from all their trades. We present the results in Table 12 and find that they are very similar to those in Table 7.

In the analysis so far, we have used panel regressions which impose the condition that the coefficient of any particular variable, including the control variables, is the same across the 33 stocks. In this section, we relax this assumption by running a separate IV regression for each stock for BA Spread as the dependent variable. IDT Activity/Profit is the explanatory variable of interest, instrumented by IDT Winners. The control variables are Stock Volatility, Lagged Stock Return, lagged dependent variable, and a trend. We average the coefficients in the second stage from stock-by-stock regressions by regressing them on a constant using weighted least squares with the inverse of the square of standard error as weights. The second column of Table 13 presents this average IDT Activity/Profit coefficient with corresponding t-statistics in parentheses. The first column of the table shows the estimates from panel regressions from Table 7 for easy comparison. Our conclusion that IDT Activity lowers BA Spread goes through using stock-by-stock regressions, although the relationship between IDT Profit and BA Spread loses statistical significance.

We repeat both these robustness tests for our analyses in Tables 8-11 and A.3. IDT Activity/All IDT Activity is the primary explanatory variable, and IDT Winners its instrument. The control variables are Stock Volatility, Lagged Stock Return, and lagged dependent variable. The second column of Table 14 shows the coefficients for All IDT Activity using a panel regression with stock and date fixed effects. The third column shows the average coefficients of IDT Activity from stock-by-stock regressions, as described in the previous paragraph. The first column of the table shows the estimates from panel regressions from Tables 8-11 and A.3 for a quick reference. We see that the results reported using panel regressions are generally robust to the change in methodology, and our conclusions go through.

7 Conclusion

There is an ongoing debate among academics and policymakers about the effect of individual day traders, whom some view as adding noise to the market, on the liquidity and informational efficiency of the stock market. The behavioral finance literature highlights their negative impact on the stock market by making arbitrage activities costly, which slows the reaction of stock prices to new information. Bloomfield, O'hara, and Saar (2009), through experiments in a laboratory setting, find that while noise traders reduce informational efficiency, they also improve market liquidity by reducing bid ask spreads. Recent empirical evidence (Peress and Schmidt (2020), Eaton et al. (2022)) complements these results by providing empirical evidence about the effect of noise traders on market liquidity.

We augment this literature by highlighting that individual *day traders* fit the definition of pure noise traders more closely. Using detailed transaction data with masked trader ids from the Bombay Stock Exchange, we identify individual day traders and show that their activity reduces the bid ask spread and increases volatility. Further, we show that this activity has spillover effects of increasing proprietary day traders' volume, total profit and competition, underscoring the impact of their presence in lubricating financial markets.

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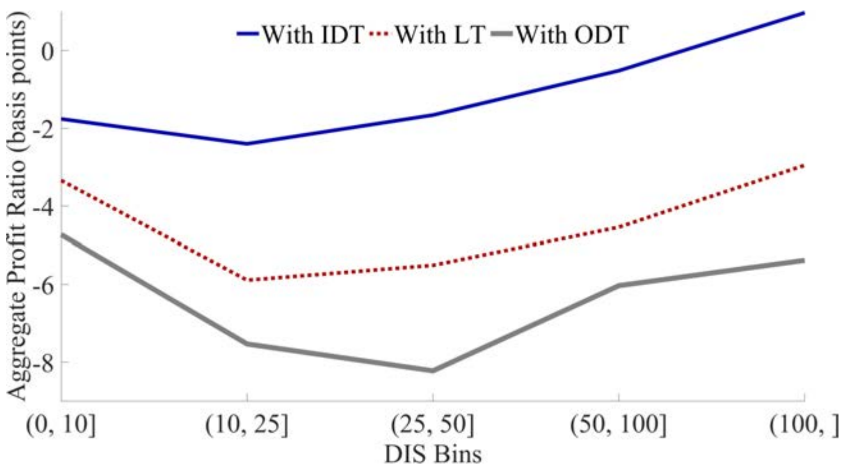
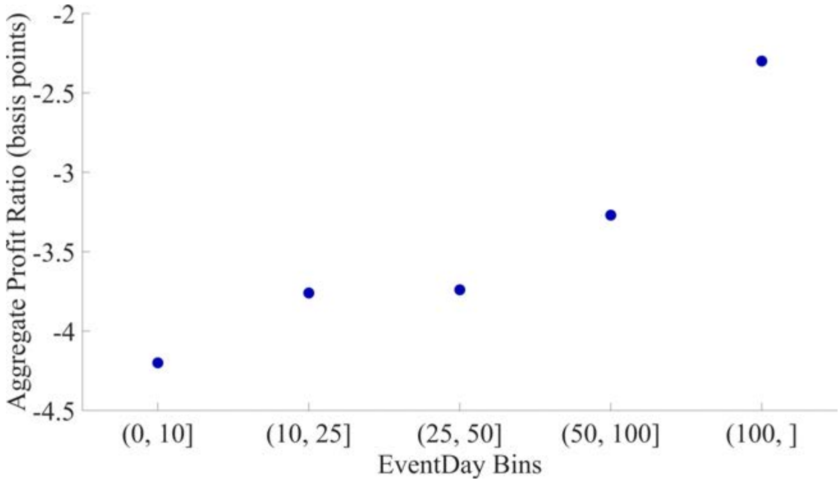
Figure 1: **IDT Profitability**

This figure presents the profitability patterns of individual day traders (IDT). Aggregate Trading Profit is the profit made by IDT in a particular group till the end of the day. We define Aggregate Profit Ratio as Aggregate Trading Profit divided by Aggregate Volume. Panel A shows the profitability of IDT by different bins based on their Days in Sample (DIS), the number of days they have traded. We plot the Aggregate Profit Ratio separately for trades of IDT in each bin with other IDT, LT, i.e., longer-term traders, and ODT (PDT, i.e., proprietary day traders and XDT, i.e., day traders excluding IDT and PDT). We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). XDT are day traders among institutional investors and corporations. See Section 2 and Table 1 for the details about the classification. Panel B plots the evolution of profitability of IDT who continue to trade beyond 100 days (DIS > 100) over their EventDays. EventDay 1 for each trader is her first trading day, and her remaining trading days are numbered sequentially. Panel C depicts IDT Profitability by ActiveRatio for IDT with DIS > 10. ActiveRatio for a trader, a variable between 0 and 1, is defined as DIS/(Total market trading days between (including) first and last days of the trader). The sample period is from January 1, 2005, to December 31, 2011.

Panel A: IDT Profitability by DIS



Panel B: Evolution of profitability of IDT with DIS>100



Panel C: Profitability by ActiveRatio of IDT with DIS>10

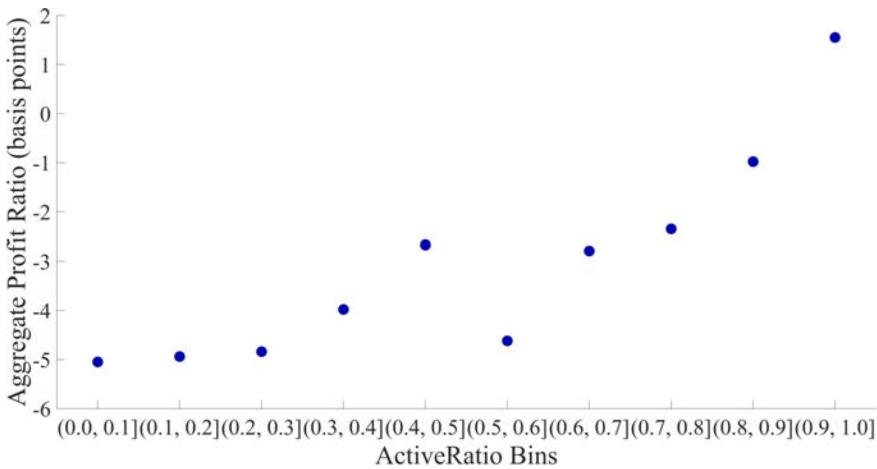
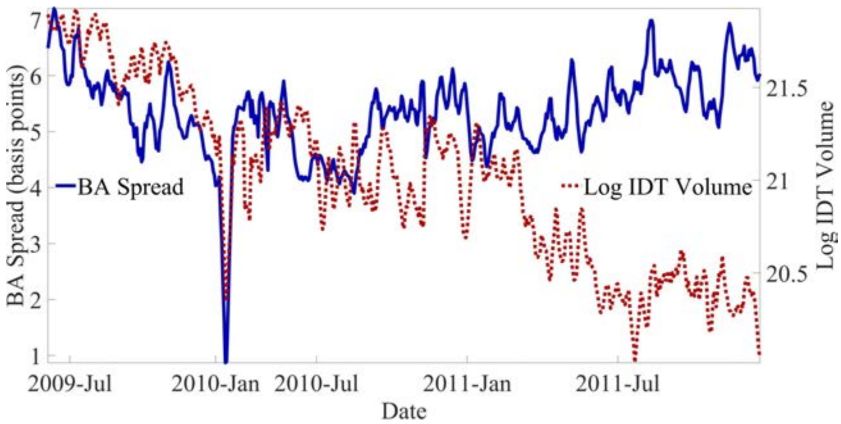


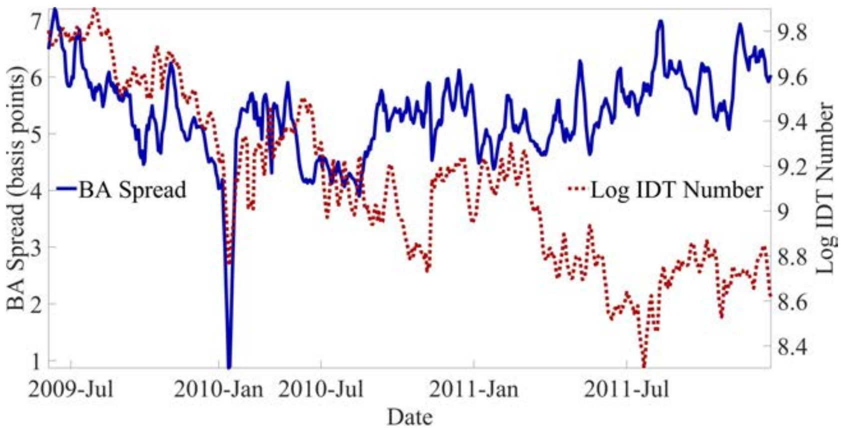
Figure 2: **BA Spread and IDT Activity/Profit**

This figure presents time-series plots of BA Spread and IDT Activity or Profit. BA Spread for a day is measured as the volume-weighted average across stocks of BA Spread for each stock. BA Spread for a stock is the proportionate bid-ask spread for each order book snapshot averaged during that day. IDT Activity is either Log IDT Volume (Panel A) or Log IDT Number (Panel B). IDT Volume is the total INR volume of IDT for their trades with LT aggregated across stocks on a day. IDT Number is the number of IDT in trades with LT across all stocks. IDT Profit is the profit in INR of IDT from their trades with LT aggregated across stocks. The plots show 5-day moving averages. The sample period is from June 1, 2009, to Dec 31, 2011, during which BA Spread data are available.

Panel A: BA Spread and Log IDT Volume



Panel B: BA Spread and Log IDT Number



Panel C: BA Spread and IDT Profit

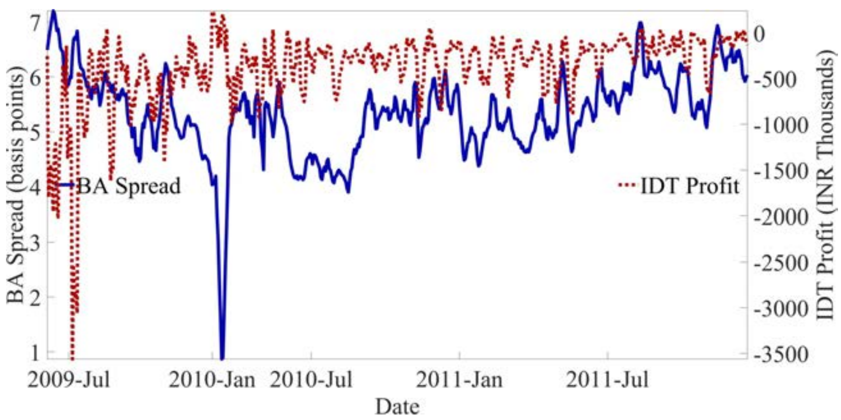


Table 1: **Trader Categories**

This table shows the trader classification scheme and the corresponding day trader classification used in our analysis. The first column shows finer trader categories provided by the BSE. Additionally, we create the category Proprietary Traders, where a broker trades on her own account. We group categories other than Corporations, Foreign Institutional Investors, Mutual Funds, Individuals, and Proprietary Traders into Others. We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). The second column shows the broad categories combining the groups of the finer categories, with DT/LT classification in the third column. In the last column, we divide DT into Individual Day Traders (IDT) proprietary day traders (PDT), day traders excluding IDT and PDT (XDT) and LT into Individual Longer-term Traders (ILT) and Other (non-individual) Longer-term Traders (OLT). The sample period is from January 1, 2005, to December 31, 2011.

Finer Categories	Broad Category	DT/LT	IDT/PDT/XDT/ ILT/OLT
Individuals	IND_DT	DT	IDT
Proprietary Traders	PDT	DT	PDT
Corporations, Mutual Funds, and Foreign Institutional Investors	CO_MF_DT	DT	XDT
Others	OTHERS_DT	DT	XDT
Individuals	IND	LT	ILT
Proprietary Traders	PROP	LT	OLT
Corporations	CO	LT	OLT
Mutual Funds	MF	LT	OLT
Foreign Institutional Investors	FII	LT	OLT
Others	OTHERS	LT	OLT

Table 2: **Trading between IDT and Others**

This table presents the summary for trading between individual day traders (IDT), proprietary day traders (PDT), day traders excluding IDT and PDT (XDT), and longer-term traders (LT). We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). XDT are day traders among institutional investors and corporations. See Section 2 and Table 1 for the details about the classification. Category indicates the category of the first party in a trade. "Other Party: Category" is the category of the counterparty. Aggregate Trading Profit is the profit made by the first party till the end of the day. Aggregate Profit Ratio is Aggregate Trading Profit divided by Aggregate Volume. The sample period is from January 1, 2005, to December 31, 2011.

Category	Other Party Category	Aggregate Trading Profit (INR Millions)	Aggregate Volume (INR Billions)	Aggregate Volume (% of total)	Aggregate Profit Ratio (bps)
IDT	IDT	0.00	396.55	1.2%	0.00
IDT	PDT	-210.48	322.09	0.9%	-6.53
IDT	XDT	-30.30	86.92	0.3%	-3.49
IDT	LT	-951.63	2,531.45	7.4%	-3.76
PDT	IDT	210.48	322.09	0.9%	6.53
PDT	PDT	0.00	170.91	0.5%	0.00
PDT	XDT	29.71	76.49	0.2%	3.88
PDT	LT	703.82	1,832.08	5.4%	3.84
XDT	IDT	30.30	86.92	0.3%	3.49
XDT	PDT	-29.71	76.49	0.2%	-3.88
XDT	XDT	0.00	59.36	0.2%	0.00
XDT	LT	107.04	575.91	1.7%	1.86
LT	IDT	951.63	2,531.45	7.4%	3.76
LT	PDT	-703.82	1,832.08	5.4%	-3.84
LT	XDT	-107.04	575.91	1.7%	-1.86
LT	LT	0.00	22,529.72	66.3%	0.00
Total		0.00	34,006.41	100.0%	0.00

Table 3: **Trading between IDT and Others: Marketable and Non-marketable Orders**

This table presents the summary for trading between individual day traders (IDT), proprietary day traders (PDT), day traders excluding IDT and PDT (XDT), and longer-term traders (LT) using marketable and non-marketable orders. We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). XDT are day traders among institutional investors and corporations. See Section 2 and Table 1 for further details about the classification. Category indicates the category of the first party in a trade. "Other Party: Category" is the category of the counterparty. In a trade, marketable order is the one that is placed later of the two and triggers the trade. Non-marketable order is the other order placed earlier. % of Aggregate Volume from marketable (non-marketable) orders is the percentage of aggregate volume where the first party has placed a marketable (non-marketable) order. Trading Profit is the profit made by the first party till the end of the day. Profit Ratio is Trading Profit divided by Aggregate Volume, calculated separately for makertable and non-marketable orders. The sample period is from January 1, 2005, to December 31, 2011.

Category	Other Party Category	% of Aggregate Volume		Profit Ratio (bps)	
		Marketable Orders	Non-marketable Orders	Marketable Orders	Non-marketable Orders
IDT	PDT	42.83%	57.17%	-6.25	-6.75
IDT	XDT	52.42%	47.58%	-2.61	-4.49
IDT	LT	53.01%	46.99%	-4.21	-3.26
PDT	IDT	57.17%	42.83%	6.75	6.25
PDT	XDT	54.30%	45.70%	4.28	3.40
PDT	LT	59.56%	40.44%	3.30	4.64

Table 4: **Trading between ILT, OLT, and Others**

This table presents the summary numbers for trading between individual day traders (IDT), proprietary day traders (PDT), day traders excluding IDT and PDT (XDT), individual longer-term traders (ILT), and other longer-term traders (OLT). We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). XDT are day traders among institutional investors and corporations. OLT are longer-term traders among the proprietary traders, institutional investors, and corporations. See Section 2 and Table 1 for further details about the classification. Category indicates the category of the first party in a trade. "Other Party: Category" is the category of the counterparty. Aggregate Trading Profit is the profit made by the first party till the end of the day. Aggregate Profit Ratio is Aggregate Trading Profit divided by Aggregate Volume. Rows, where a party and counterparty belong to the same group, are not shown. The sample period is from January 1, 2005, to December 31, 2011.

Category	Other Party: Category	Aggregate Trading Profit (INR Millions)	Aggregate Volume (INR Billions)	Aggregate Volume (% of total)	Aggregate Profit Ratio (bps)
IDT	ILT	327.32	1,100.99	3.2%	2.97
IDT	OLT	-1,278.95	1,430.47	4.2%	-8.94
PDT	ILT	1,008.96	1,012.48	3.0%	9.97
PDT	OLT	-305.14	819.60	2.4%	-3.72
XDT	ILT	226.24	264.70	0.8%	8.55
XDT	OLT	-119.20	311.20	0.9%	-3.83
ILT	OLT	-6,505.33	4,832.61	14.2%	-13.46

Table 5: **IDT Activity and Profit**

This table presents the results of the regression of BA Spread on IDT Activity and IDT Profit. IDT Activity is measured as Log IDT Volume or Log IDT Number as described in the last row. IDT Volume is the total INR volume of IDT for their trades with LT aggregated across stocks on a day. IDT Number is the number of IDT in trades with LT across all stocks. IDT Profit is the profit in INR of IDT from their trades with LT. IDT Winners is the number of IDT with positive profit the previous trading day in the same stock. Cricket Match is an indicator equal to one on days when the Indian men's national team is playing in a One Day International cricket match and zero otherwise. Festival is an indicator set to one on festival days on which the stock market is open and the day before the festival days on which the stock market is closed and zero otherwise. IDT Activity, IDT Profit, and IDT Winners are scaled to have a unit standard deviation. The regressions include stock fixed effects. t-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to Dec 31, 2011, during which BA Spread data is available.

	Dependent Variable		
	IDT Activity		IDT Profit
	(1)	(2)	(3)
IDT Winners	0.406***	0.40***	-0.177***
	(51.00)	(54.42)	(-4.48)
Cricket Match	-0.026	-0.01	0.023
	(-0.66)	(-0.31)	(1.07)
Festival	0.002	0.00	-0.105**
	(0.05)	(0.14)	(-2.52)
Observations	19,639	19,639	19,639
R-squared	0.741	0.804	0.048
IDT Activity Definition	Log IDT Volume	Log IDT Number	-

Table 6: **Descriptive Statistics**

This table presents the descriptive statistics of dependent, main independent, control, and instrumental variables in regressions in Table 7 for the stock-day panel data. BA Spread for a stock is the proportionate bid-ask spread for each order book snapshot averaged during that day. See Section 2.3 for further details. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Number is the number of IDT in trades with LT. IDT Profit is the profit in INR of IDT from their trades with LT. IDT Winners is the number of IDT with positive profit the previous trading day in the same stock. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return is for the previous trading day. Sample period: June 1, 2009, to Dec 31, 2011, during which BA Spread data is available.

Variable	Units	Obs	Mean	SD	Median	25th %tile	75th %tile
BA Spread	Basis Points	19,640	8.80	4.97	7.88	5.42	10.96
Log IDT Volume	Log	19,640	16.65	1.50	16.65	15.59	17.73
Log IDT Number	Log	19,640	5.04	1.19	5.02	4.11	5.92
IDT Profit	INR ('000)	19,640	-11.89	92.14	-0.83	-11.96	4.78
Stock Volatility	%	19,619	37.98	49.40	29.99	23.56	39.18
Lagged Stock Return	Basis Points	19,639	-6.1	388.4	-0.9	-118.8	119.5
IDT Winners	Number	19,639	169	228	80	32	206

Table 7: **BA Spread and IDT Activity/Profit**

This table presents the results of instrumental variable regression of BA Spread on IDT Activity and IDT Profit. BA Spread for a stock is the proportionate bid-ask spread for each order book snapshot averaged during that day. See Section 2.3 for details. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Number is the number of IDT in trades with LT. IDT Profit is the profit in INR of IDT from their trades with LT. IDT Winners is the number of IDT with positive profit the previous trading day in the same stock. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged BA Spread are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data is available.

	Dependent Variable		
	(1) BA Spread	(2) BA Spread	(3) BA Spread
IDT Activity	-1.104***	-0.963***	-
	(-6.84)	(-6.81)	-
IDT Profit	-	-	1.509***
	-	-	(3.73)
Stock Volatility	0.000	0.000	0.000
	(-0.46)	(1.03)	(-0.76)
Lagged Stock Return	0.000	0.000	0.000
	(0.38)	(0.42)	(0.33)
Lagged BA Spread	0.677***	0.687***	0.735***
	(21.37)	(22.30)	(27.68)
Observations	18,908	18,908	18,908
R-squared	0.886	0.883	0.803
First stage F-statistic	898.10	1,081.44	14.32
IDT Activity Definition	Log IDT Volume	Log IDT Number	-
First Stage Regression			
Dependent variable	IDT Activity	IDT Activity	IDT Profit
Instrument	IDT Winners	IDT Winners	IDT Winners
Coefficient			
IDT Winners	0.183***	0.210***	-0.134***
	(29.97)	(32.89)	(-3.78)

Table 8: **Volume**

This table presents the results of instrumental variable regression of overall volume, PDT Volume with IDT, and PDT Volume with LT on IDT Activity. Volume is the total two-sided volume in INR. PDT Volume with IDT is the total volume in INR of PDT in their trades with IDT. PDT Volume with LT is the total volume in INR of PDT in their trades with LT. IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity and IDT Winners are scaled to have a unit standard deviation. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged Dependent Variable are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

	Dependent Variable		
	(1) Log Volume	(2) Log PDT Volume with IDT	(3) Log PDT Volume with LT
IDT Activity	1.526***	1.219***	0.903***
	(25.78)	(17.90)	(13.60)
Stock Volatility	0.000	0.000	0.000**
	(-0.10)	(-0.11)	(2.39)
Lagged Stock Return	0.000	0.000	0.000
	(-0.74)	(1.01)	(-1.16)
Lagged Dependent variable	-0.046*	0.382***	0.470***
	(-1.81)	(21.55)	(24.89)
Observations	19,101	18,466	18,732
R-squared	0.880	0.836	0.809
First stage F-statistic	230.59	565.93	695.33

Table 9: **PDT Profit**

This table presents the results of instrumental variable regression of PDT profit with IDT and LT on IDT Activity. Profit of PDT with IDT is the total profit in INR made by PDT in their trades with IDT. PDT Volume with IDT is the total volume in INR of PDT in their trades with IDT. Profit Ratio of PDT with IDT is Profit of PDT with IDT divided by PDT Volume with IDT. PDT variables with LT are defined in a similar mannter. IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity and IDT Winners are scaled to have a unit standard deviation. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged Dependent Variable are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

	Dependent Variable			
	(1)	(2)	(3)	(4)
	Profit of PDT with IDT	Profit of PDT with LT	Profit Ratio of PDT with IDT	Profit Ratio of PDT with LT
IDT Activity	28,483***	69,887***	-0.681	0.523
	(6.29)	(6.37)	(-0.58)	(1.00)
Stock Volatility	-3.34	-8.73	0.003	0.003**
	(-1.17)	(-1.07)	(0.71)	(2.00)
Lagged Stock Return	-0.70	-0.31	-0.001	-0.001**
	(-0.82)	(-0.20)	(-0.87)	(-2.51)
Lagged Dependent variable	0.05**	0.01	0.010	-0.018
	(2.51)	(0.55)	(0.64)	(-1.01)
Observations	18,466	18,732	18,466	18,732
R-squared	0.076	0.069	0.050	0.077
First stage F-statistic	1,278.98	1,213.93	1,342.17	1,369.45

Table 10: **Number of PDT**

This table presents the results of instrumental variable regression of PDT number on IDT Activity. PDT Number in Trades with IDT (LT) is the number of PDT that participated in the trades with IDT (LT). IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity and IDT Winners are scaled to have a unit standard deviation. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged Dependent Variable are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

	Dependent Variable	
	(1)	(2)
	Log PDT Number in Traders with IDT	Log PDT Number in Traders with LT
IDT Activity	0.467***	0.388***
	(20.67)	(19.36)
Stock Volatility	0.000***	0.000***
	(4.53)	(5.29)
Lagged Stock Return	0.000	0.000**
	(-1.23)	(-2.00)
Lagged Dependent variable	0.309***	0.367***
	(24.81)	(30.50)
Observations	18,466	18,732
R-squared	0.734	0.740
First stage F-statistic	788.23	811.96

Table 11: **Intraday Volatility**

This table presents the results of instrumental variable regression of intraday volatility on IDT Activity. Intraday volatility is the annualized square root of average squared half-hour returns. IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity and IDT Winners are scaled to have a unit standard deviation. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged Dependent Variable are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

	Dependent Variable
	Intraday Volatility
IDT Activity	3.866***
	(3.97)
Stock Volatility	0.010***
	(6.02)
Lagged Stock Return	0.000
	(0.27)
Lagged Dependent variable	0.130***
	(5.24)
Observations	19,101
R-squared	0.444
First stage F-statistic	1,208.17

Table 12: **BA Spread and All IDT Activity/Profit**

This table presents the results of instrumental variable regression of BA Spread on IDT Activity and IDT Profit from all their trades. BA Spread for a stock is the proportionate bid-ask spread for each order book snapshot averaged during that day. See Section 2.3 for further details. All IDT Volume is the total INR volume of IDT. All IDT Profit is the profit in INR of IDT from all their trades. IDT Winners is the number of IDT with positive profit the previous trading day in the same stock. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged BA Spread are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data is available.

	Dependent Variable	
	(1)	(2)
	BA Spread	BA Spread
All IDT Activity	-1.029***	-
	(-6.81)	-
All IDT Profit	-	1.155***
	-	(4.62)
Stock Volatility	0.000	0.000
	(-0.64)	(-0.76)
Lagged Stock Return	0.000	0.000
	(0.47)	(0.25)
Lagged BA Spread	0.681***	0.736***
	(21.85)	(27.85)
Observations	18,908	18,908
R-squared	0.884	0.833
First stage F-statistic	1,000.97	25.02
IDT Activity Definition	Log All IDT Volume	-
First Stage Regression		
Dependent variable	All IDT Activity	All IDT Profit
Instrument: IDT Winners		
Coefficient		
IDT Winners	0.197***	-0.175***
	(31.64)	(-5.00)

Table 13: **BA Spread and IDT Activity/Profit: Robustness**

This table presents the results of instrumental variable regression of BA Spread on IDT Activity and Profit. BA Spread for a stock is the proportionate bid-ask spread for each order book snapshot averaged during that day. See Section 2.3 for details. IDT Activity is measured as Log IDT Volume or Log IDT Number. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Number is the number of IDT in trades with LT. IDT Profit is the profit in INR of IDT from their trades with LT. IDT Activity and Profit are instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity, IDT Profit and IDT Winners are scaled to have a unit standard deviation. Stock Volatility, Lagged Stock Return, and lagged dependent variable are the controls. The first column presents the coefficients of IDT Activity/Profit in the second stage of a panel regression with stock and date fixed effects (Table 7). z-statistics based on standard errors clustered at the day level are in parentheses. We also run an instrumental variable regression for each stock with a trend as an additional control. Using weighted least squares with the inverse of the square of standard error as weights, we average the coefficients in the second stage from stock-by-stock regressions. The second column of this table presents this average IDT Activity/Profit coefficient with corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data is available.

	Dependent Variable: BA Spread	
	(1)	(2)
Independent Variable	Panel Regression	Stock-by-stock regressions
IDT Activity: Log IDT Volume	-1.104***	-0.328***
	(-6.84)	(-3.35)
IDT Activity: Log IDT Number	-0.963***	-0.295***
	(-6.81)	(-3.37)
IDT Profit	1.509***	-0.07
	(3.73)	(-1.07)

Table 14: **Volume, PDT Profit, Volatility: Robustness Tests**

This table presents the results of instrumental variable regression of various dependent variables on IDT Activity or All IDT Activity. Volume is the total two-sided volume in INR. PDT Volume with IDT is the total volume in INR of PDT in their trades with IDT. Profit of PDT with IDT is the total profit in INR made by PDT in their trades with IDT. Profit Ratio of PDT with IDT is Profit of PDT with IDT divided by PDT Volume with IDT. PDT Number in Trades with IDT is the number of PDT that participated in the trades with IDT. PDT variables with LT are defined analogously. PDT Volume is the total volume in INR of PDT. Profit of PDT is the total profit in INR made by PDT. Profit Ratio of PDTis Profit of PDT divided by PDT Volume. Intraday volatility is the annualized square root of average squared half-hour returns. IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. All IDT Activity is measured as Log All IDT Volume. All IDT Volume is the total INR volume of IDT from all their trades. IDT Activity/All IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity, All IDT Activity, and IDT Winners are scaled to have a unit standard deviation. Stock Volatility, Lagged Stock Return, and lagged dependent variable are the controls. The first column presents the coefficients of IDT Activity in the second stage of a panel regression with stock and date fixed effects. The second column presents the coefficients of All IDT Activity in the second stage of a panel regression with stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. We also run an instrumental variable regression for each stock with a trend as an additional control. Using weighted least squares with the inverse of the square of standard error as weights, we average the coefficients in the second stage from stock-by-stock regressions. The third column of this table presents this average IDT Activity coefficient with corresponding t-statistics in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

Dependent Variable	Panel Regressions		Stock-by -stock Regressions
	(1) IDT Activity	(2) All IDT Activity	(3) IDT Activity
Log Volume	1.526***	1.322***	0.925***
	(25.78)	(26.72)	(20.82)
Log PDT Volume with IDT	1.219***	1.204***	0.445***
	(17.9)	(18.68)	(4.47)
Log PDT Volume with LT	0.903***	0.882***	0.188**
	(13.60)	(13.75)	(2.72)
Profit of PDT with IDT	28,483***	27,231***	1,747**
	(6.29)	(6.29)	(2.46)
Profit of PDT with LT	69,887***	66,723***	4,804**
	(6.37)	(6.38)	(2.05)
Profit Ratio of PDT with IDT	-0.681	-0.651	1.532
	(-0.58)	(-0.58)	(1.44)
Profit Ratio of PDT with LT	0.523	0.499	0.807*
	(1.00)	(1.00)	(1.85)
Log PDT Number in Trades with IDT	0.467***	0.449***	0.28***
	(20.67)	(21.04)	(9.42)
Log PDT Number in Trade swith LT	0.388***	0.373***	0.224***
	(19.36)	(19.53)	(9.17)
Log PDT Volume	0.929***	0.913***	0.155*
	(13.37)	(13.58)	(2.02)
Profit of PDT	95,945***	91,599***	8,100***
	(7.64)	(7.65)	(3.18)
Profit Ratio of PDT	0.259	0.247	0.541
	(0.57)	(0.57)	(1.46)
Intraday Volatility	3.866***	3.698***	0.485
	(3.97)	(3.97)	(0.66)

Online Appendix

Table A.1: **U.S. Equity Markets and the BSE**

This table presents the descriptive statistics for 33 stocks that were part of BSE SENSEX (Panel A) and 35 stocks that were included in the Dow Jones Industrial Average (Panel B) at any point during the sample period, from January 2005 to December 2011. Return is the daily return, excluding dividend. Volume is two-sided volume, as explained in Section 2.2. Market cap and volume for the SENSEX stocks in USD are calculated using the exchange rate on the respective day. For all rows except the last of each panel, we first calculate the average / Std Dev of a characteristic for each stock and then present cross-sectional descriptive statistics. For the last row in each panel, we show the descriptive statistics of the daily return of an equal-weighted portfolio of all the stocks.

Panel A: BSE SENSEX Stocks

	Obs	Mean	Median	Std Dev
Average Daily Return (%)	33	-0.01	-0.01	0.06
Average Daily Market Cap (INR Million)	33	648,952	382,531	607,668
Average Daily Volume (INR Million)	33	648	392	634
Std Dev of Daily Return (%)	33	3.77	3.65	1.29
Average Daily Market Cap (USD Million)	33	14,441	8,596	13,465
Average Daily Volume (USD Million)	33	14	9	14
Equal-Weighted Portfolio				
Daily Return (%)	1,732	-0.01	0.12	1.81

Panel B: DJIA Stocks

	Obs	Mean	Median	Std Dev
Average Daily Return (%)	35	0.01	0.02	0.05
Average Daily Market Cap (USD Million)	35	113,961	96,153	81,711
Average Daily Volume (USD Million)	35	1,450	1,032	987
Std Dev of Daily Return (%)	35	2.16	1.93	1.16
Equal-Weighted Portfolio				
Daily Return (%)	1,764	0.02	0.07	1.54

Table A.2: **Trading between IDT and Others: BA Spread Sample**

This table presents the summary for trading between individual day traders (IDT), proprietary day traders (PDT), day traders excluding IDT and PDT (XDT), and longer-term traders (LT). We classify a given trader as a day trader (DT) if they carry 0% of the quantity traded during the day as inventory, at least 50% or more days in each of the stocks they trade over the entire sample period. The traders who do not satisfy this condition are Longer-term Traders (LT). XDT are day traders among institutional investors and corporations. See Section 2 and Table 1 for the details about the classification. Category indicates the category of the first party in a trade. "Other Party: Category" is the category of the counterparty. Aggregate Trading Profit is the profit made by the first party till the end of the day. Aggregate Profit Ratio is Aggregate Trading Profit divided by Aggregate Volume. The sample is the period from June 1, 2009 to Dec 31, 2011, during which BA Spread data are available.

Category	Other Party Category	Aggregate Trading Profit (INR Millions)	Aggregate Volume (INR Billions)	Aggregate Volume (% of total)	Aggregate Profit Ratio (bps)
IDT	IDT	0.00	154.58	1.2%	0.00
IDT	PDT	-117.93	183.62	1.5%	-6.53
IDT	XDT	-20.59	53.22	0.4%	-3.49
IDT	LT	-232.17	917.93	7.4%	-3.76
PDT	IDT	117.93	183.62	1.5%	6.53
PDT	PDT	0.00	101.67	0.8%	0.00
PDT	XDT	20.56	59.60	0.5%	3.88
PDT	LT	442.59	1,010.98	8.1%	3.84
XDT	IDT	20.59	53.22	0.4%	3.49
XDT	PDT	-20.56	59.60	0.5%	-3.88
XDT	XDT	0.00	51.30	0.4%	0.00
XDT	LT	69.08	336.15	2.7%	1.86
LT	IDT	232.17	917.93	7.4%	3.76
LT	PDT	-442.59	1,010.98	8.1%	-3.84
LT	XDT	-69.08	336.15	2.7%	-1.86
LT	LT	0.00	7,054.68	56.5%	0.00
Total		0.00	12,485.22	100.0%	0.00

Table A.3: **PDT Volume and Profit**

This table presents the results of instrumental variable regression of PDT volume and profit on IDT Activity. PDT Volume is the total volume in INR of PDT. Profit of PDT is the total profit in INR made by PDT. Profit Ratio of PDT is Profit of PDT divided by PDT Volume. IDT Activity is measured as Log IDT Volume. IDT Volume is the total INR volume of IDT for their trades with LT. IDT Activity is instrumented by IDT Winners, the number of IDT with positive profit the previous trading day in the same stock. IDT Activity and IDT Winners are scaled to have a unit standard deviation. Stock Volatility is annualized standard deviation of daily return over the trailing 22 trading days. Lagged Stock Return and Lagged Dependent Variable are for the previous trading day. The regressions include stock and date fixed effects. z-statistics based on standard errors clustered at the day level are in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% respectively. Sample period: June 1, 2009, to December 31, 2011, during which BA Spread data are available.

	Dependent Variable		
	(1)	(2)	(3)
	Log PDT Volume	Profit of PDT	Profit Ratio of PDT
IDT Activity	0.929***	95,945***	0.259
	(13.37)	(7.64)	(0.57)
Stock Volatility	0.000**	-9.76	0.004***
	(2.25)	(-0.97)	(2.60)
Lagged Stock Return	0.000	-1.36	0.000**
	(-0.93)	(-0.66)	(-2.14)
Lagged Dependent variable	0.468***	0.01	-0.021
	(23.97)	(0.80)	(-0.96)
Observations	18,737	18,737	18,737
R-squared	0.818	0.092	0.092
First stage F-statistic	669.89	1,073.70	1,368.60