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Heterogeneity in the effects of algorithmic and high-frequency traders on institutional transaction costs☆

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Abstract

The net effects of algorithmic and high-frequency traders mask considerable heterogeneity in how they impact institutional transaction costs. Using regulatory data, we analyze the heterogeneity across individual trading accounts. We develop a method to identify subsets of traders causally related to higher institutional transaction costs and estimate that they add ten basis points to the cost of executing large institutional orders. Their effects are counteracted by traders that systematically decrease these costs. We find that fast traders and those with high order-to-trade ratios are no more likely to increase costs than others. Traders that increase costs are more active in small stocks.

JEL classification: G14

Keywords: algorithmic trading, high-frequency trading, liquidity, transaction costs, implementation shortfall, predatory trading

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1. Introduction

Technology has fundamentally transformed how trading occurs on financial markets, but not everyone agrees that it is for the better. There is considerable debate about the effects of algorithmic trading (AT) and high-frequency trading (HFT) on market liquidity and transaction costs. A large number of academic and regulatory studies find that AT/HFT in aggregate is beneficial (e.g., lowering spreads and improving price discovery) or at worst benign. The benefits stem from increased competition in liquidity provision, more efficient intermediation, and ability to incorporate more information and faster when pricing securities.

In contrast, many buy-side institutional investors maintain that finding liquidity for large orders has become more difficult and their transaction costs in contemporary markets are worse than before the technological advancements. For example, “as big institutional buyers and sellers, if we can’t find blocks we have to trade in smaller sizes, across multiple venues using algos ... which leaves us open to being taken advantage of by HFT and other participants”.

One of the main culprits blamed for increased execution costs is predatory algorithmic traders that use order anticipation strategies to front-run or piggy-back (“back-run”) large institutional orders. Such concerns are echoed in financial markets all around the world indicating that it is a pervasive and systematic concern among institutional investors. Furthermore, new trading mechanisms are emerging to address the buy-side concerns about increasing market impact costs. Institutional investors have always been important market participants and are becoming increasingly important with their holdings of US large-cap equities having increased to approximately 80%.

The objective of this paper is to reconcile the contradiction between recent academic/regulatory evidence on the effects on AT/HFT and the concerns voiced by institutional investors. Unlike existing studies that analyze the net effects of AT/HFT, we focus on

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1 Richard Nelson (Head of Australia and Japan Equity Trading at T. Rowe Price) quoted in Global Trading (Nov 21, 2015).
2 Brunnermeier and Pedersen (2005) and Yang and Zhu (2015) provide theoretical evidence of such strategies, and Hirschey (2013) and van Kervel and Menkveld (2015) provide empirical evidence suggesting that some HFTs employ such strategies.
3 Large institutions increasingly rely on block crossing networks, dark pools, and closing auctions where liquidity is consolidated (Norges Bank Investment Management’s “Asset Manager Perspectives Report”, 02/2015). NYSE, LSE and Chi-X Europe have announced the introduction of additional batch auction mechanisms for liquidity consolidation. New trading venues such as Plato in Europe and Luminex in the US specifically claim to shield users from HFTs to lower transaction costs.
4 Based on 13F institutional holding filings, institutions hold more than 80% of the free float of large-cap US equities in 2015, compared to just 50% in the year 2000 (NBIM “Asset Manager Perspectives Report”, 02/2015). Similarly, institutional holdings of Australian equities have increased to above 80% in 2014 (Bradrania, Grant, Westerholm, and Wu, 2015; assuming foreign holdings are predominantly institutional).
heterogeneity across AT/HFT—this is our main contribution. AT/HFT are not monolithic; they comprise a wide range of trading strategies from market making, to arbitrage, directional strategies, and predatory trading. To understand the concerns of institutional investors we analyze whether there are traders that systematically increase institutional execution costs (hereafter “toxic traders”), and if so, how many and how severely they impact institutional transaction costs. We also examine whether these effects are offset by other traders, and what characteristics distinguish traders that increase costs from others. We analyze heterogeneity at the most granular level: individual trading accounts, using regulatory data. To the best of our knowledge, this is the first study to examine the effects of AT/HFT at the trader level. We show that the net effects of AT/HFT mask pockets of higher costs, or toxicity, which we quantify. This evidence helps understand institutional investor concerns despite the evidence that, as a group, AT/HFT are benign or beneficial.

Another unique feature of our study is that we cast our net wider than HFTs and analyze a broad cross-section of traders (which includes, but is not limited to HFT) that could potentially impact institutional transaction costs. We do so because predatory traders are not necessarily HFTs. Speed is not essential to exploit institutional investors that manage orders in the market over horizons of hours or days. Starting from a broader set of traders allows us to ask whether speed is a characteristic of traders that increase costs; the evidence indicates that it is not.

The third unique feature of our study is that it uses accurate and comprehensive measures of institutional transaction costs. Using regulatory data, we reconstruct parent orders from account-level trade sequences. This allows us to measure implementation shortfall, which is the difference between the volume-weighted average price (VWAP) at which the parent order is executed and the price at the time of the first trade of the parent order. Unlike other studies, our measures draw on data from all market participants. Simple liquidity measures such as bid-ask spreads and depth do not adequately capture the cost of executing large parent orders that are broken down into a series of child orders. For such orders, price impact (“slippage”), which is captured by implementation shortfall, can be a considerably larger component of transaction costs than the spread.

We use unique trader-identified regulatory audit trail data covering trading in the 200 largest Australian equities during the 13 month period September 2014 to October 2015. The Australian equity market is similar to the US and other major equity markets with respect to the types of trading platforms, the level of HFT trading activity, the major trading firms that participate in the market and the trading technology that they use, and the level of institutional
holdings. The regulatory data allow us to construct comprehensive estimates of institutional transaction costs and measure the trading activity of individual high-turnover non-directional traders, hereafter “active traders”. The active traders in our sample account for around 50% of turnover, which is roughly twice as much as the narrower set of pure HFTs.

We find that a significant fraction of the active traders systematically increase or systematically decrease institutional transaction costs, i.e., they appear “toxic” or “beneficial”, respectively. Our basic approach involves regressing institutional transaction costs (implementation shortfall of large intuitional orders) on measures of the activity of each of the active trader accounts. This gives “toxicity estimates” for each of the trading accounts with a cross-sectional distribution across traders. We use instrumental variables to pin down causality. The high level of granularity poses additional challenges. Working at the trading account level, our regressions effectively have 187 right-hand side variables (one for each of the active traders). Even if none of these traders have any relation with institutional transaction costs, some will appear toxic (others beneficial) purely by statistical chance. This is analogous to the problem of disentangling skill from luck in the cross-section of fund managers. Consequently, we borrow from the fund management literature and quantify excess toxicity (the amount that exceeds what would be expected by statistical chance alone) using bootstrap simulations. The bootstrap simulations provide strong evidence that the 5% most toxic and 5% most beneficial traders are significantly more toxic/beneficial than would occur by chance under the null of zero toxicity.

The effects of toxic and beneficial traders on institutional transaction costs are economically meaningful. The toxic traders increase institutional execution costs by more than ten basis points, roughly the same magnitude as the effective bid-ask spread and more than half of the average implementation shortfall cost on a large institutional order. This equates to additional transaction costs of around $437 million per annum for large institutional orders in the top 200 stocks. The negative effects of the toxic traders are offset by significant reductions in institutional transaction costs from beneficial traders. Consequently, active traders as a group have little or no net effect on institutional transaction costs.

Our results show that the net effects of active traders, suggesting AT/HFT as a group are benign or beneficial, mask considerable heterogeneity and pockets of toxicity. One implication is that the trading technology and the sophistication with which institutions execute large orders is likely to have a considerable impact on execution costs. Institutions that disproportionately trade against toxic traders are likely to experience higher transaction costs. The magnitudes imply that carelessly managed execution can have a material effect on a fund’s performance. Our findings
assist in understanding the concerns raised by institutional investors. At the same time, our results reconcile those concerns with the evidence that HFT and AT as a group seem to be benign or beneficial—the negative effects of toxic traders are offset by different beneficial traders.

Who are the toxic traders? Given that one of the main determinants of implementation shortfall for large orders is whether others are trading in the same direction as the order or against it (e.g., ASIC, 2015) toxic traders are likely to trade with institutional order flow rather than against it. Such trading patterns could occur from intentionally exploiting institutional order flow, crowding due to the use of common entry/exit signals, or through active participation in the price discovery process during periods of imbalance. Examples include predatory trading strategies (e.g., Brunnermeier and Pedersen, 2005), order anticipation algorithms (e.g., Hirschey, 2013), and strategies that seek to identify and “back-run” large informed orders (e.g., Yang and Zhu, 2015). In contrast, the beneficial traders are likely to be liquidity-providing intermediaries, employing market making strategies that “lean against the wind”, thereby attenuating price pressure that arises from large institutional orders.

We also shed light on the characteristics of the toxic traders. Across a number of characteristics, we consistently find that speed is not associated with toxicity. For example, a trader’s share of turnover is unrelated to their toxicity. Prior studies show that faster traders account for larger shares of turnover and high turnover is even used as the defining characteristic that separates HFTs from other non-directional traders (e.g., Kirilenko, Kyle, Samadi, and Tuzun, 2015). To the extent that HFT trading accounts are likely to have higher turnover than non-HFT trading accounts, our finding indicates that HFT are no more likely than non-HFTs to be toxic and harm institutional transaction costs. Other characteristics corroborate this finding: toxicity is unrelated to the speed of order amendments, the frequency of fast orders, the consistency with which a trader extracts intraday trading profit, and order-to-trade ratios.

We find that the activity of toxic traders tends to have higher cross-sectional standard deviation and lower time-series standard deviation than other traders, suggesting a concentration of their activity within a subset or “preferred habitat” of stocks. These traders tend to be more active in smaller securities. Finally, we find no difference in the relative activity of toxic traders during a period of market stress in which the market fell sharply compared to other times.

Related literature

On a broad level, this paper is related to the literature on the effects of AT and HFT on market quality. For good surveys of this literature see Jones (2013) and Menkveld (2016). Most
of these studies find that AT/HFT in aggregate are beneficial, lowering bid-ask spreads and improving price discovery, or at worst benign (e.g., Hendershott, Jones, and Menkveld, 2011; Hasbrouck and Saar, 2013; Menkveld, 2013; Brogaard, Hendershott, and Riordan, 2014; Boehmer, Fong, and Wu, 2014; Brogaard, Hagströmer, Nordén, and Riordan, 2015; and van Kervel, 2015). Our study differs in that we focus on the heterogeneity across traders, institutional transaction costs rather than simple liquidity measures, and a broader cross-section of traders allowing us to examine the relation between speed and toxicity. Brogaard, Hendershott, Hunt, and Ysusi (2014) find that HFTs as a whole have a negligible effect on institutional transaction costs, consistent with our findings that the effects of toxic traders are offset by a group of beneficial active traders and fast traders are no more toxic than slow traders. Our results highlighting substantial toxicity of a subset of active traders help reconcile the evidence that AT/HFT in aggregate are beneficial or at worst benign with the continued concerns of institutional investors.

Hagströmer and Nordén (2013) separate HFTs in Stockholm into market making and other (which they label “opportunistic”), allowing for some heterogeneity across HFTs. They show that market making HFTs mitigate intraday volatility, but they do not examine the effects of these two types of HFT on institutional transaction costs, nor do they partition HFTs further than the two categories.

Our paper is also related to literature on trading strategies that intentionally exploit institutional investor order flow and thereby increase their transaction costs. In a theoretical model, Brunnermeier and Pedersen (2005) show that strategic traders will often provide liquidity to institutional investors but, at times, will predate on distressed institutions that are forced to liquidate a position. When strategic traders become predatory, they initially trade in the same direction as the institutional investor, amplifying price impact (increasing implementation shortfall), before closing the position. Yang and Zhu (2015) show in a two-period Kyle model framework, that strategic traders engage in “back-running” informed institutional orders, i.e., identifying (with noise) the presence of a large informed institution and then trading in the same direction.

Three recent studies provide empirical evidence consistent with HFTs engaging in order anticipation, predatory, and back-running strategies at different frequencies. Hirschey (2013) finds that on Nasdaq, HFT’s aggressive trades predict non-HFT order flow over the next 30

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5 A similar study by Tong (2015) reaches different conclusions to Brogaard et al. (2015) regarding the effects of HFT as a group on institutional transaction costs.
seconds. Korajczyk and Murphy (2015) examine HFTs in Canada that use predominantly (>80%) passive orders and find that they reduce liquidity provision to (and switch to competing with) large “stressful” institutional trades. Van Kervel and Menkveld (2015) examine HFT trading around the orders of four large institutions in Stockholm and find that HFTs tend to “lean against the wind” initially (provide liquidity to the institutional orders), but then after a few hours, trade “with the wind”, amplifying institutional transaction costs. These studies are complimentary to ours as they illustrate trading patterns that are likely to be responsible for some of the toxicity that we quantify. Our study differs in several ways. First, we examine a broader cross-section of traders and show that it is not only HFTs that impose toxicity on institutional orders and in fact HFTs are no more toxic than non-HFTs. Second, we do not limit the analysis to specific strategies such as order anticipation/predatory/back-running strategies and instead identify all traders that systematically increase institutional transaction costs irrespective of how they do so. Third, we explicitly allow for heterogeneity across active traders and analyze the characteristics that distinguish toxic traders from the rest.

Finally, this paper is also related to the smaller literature on institutional transaction costs more generally. Anand, Irvine, Puckett, and Venkataraman (2012) characterize the heterogeneity across institutional investors and brokers in their trade execution abilities. In contrast, we characterize heterogeneity across active traders and intermediaries that either harm or benefit institutional transaction costs. Anand et al. (2012) find considerable dispersion in trading-desk and broker skill, and show that the trade implementation process is economically important and can contribute to relative portfolio performance. Our findings support the conclusion that the trade implementation process can have first order effects on performance because the increases in costs from disproportionately interacting with (or leaving orders expose to) toxic traders are considerable (same order of magnitude as unconditional mean implementation shortfall).

2. Data, trader types and transaction costs

2.1. Sample and institutional details of the market

Our sample covers trading in the ASX 200 Index constituents (the largest 200 Australian equities) during the 13 month period September 1, 2014 to September 31, 2015 (273 trading days). At the stock-day level, this gives us a panel with 52,873 observations. We use unique trader-identified regulatory audit trail data to construct comprehensive estimates of institutional

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6 Because stocks enter and leave the ASX 200 during the sample period, in total our sample includes 225 stocks, although not all stocks are in the sample at all times.
transaction costs and identify active non-directional traders and measure their trading activity.\textsuperscript{7} The identification of individual traders occurs through the “origin of order” identifiers that the main market regulator, the Australian Securities and Exchange Commission (ASIC), collects within the regulatory data feed that they obtain under the Market Integrity Rules.\textsuperscript{8}

The Australian equities market is in the top-ten largest in the world by market capitalization, with total market capitalization of around $1.6 trillion.\textsuperscript{9} It has two lit trading venues, the Australian Securities Exchange (ASX) and Chi-X Australia, and a number of dark trading venues (an exchange-operated dark pool, Centre Point, and 17 broker-operated dark pools during our sample period). Additionally there is an “upstairs” market for block trades, which are allowed to be negotiated off-market at any price if they exceed size thresholds ($1 million, $0.5 million or $0.2 million, depending on the liquidity category of the stock). The two lit venues operate centralized electronic limit order books, which trade approximately 52% and 8% of total turnover, respectively. Their technical protocol is effectively the same as that used on Nasdaq (it is owned by Nasdaq OMX Group). The ASX opening and closing auctions account for a further 15% of turnover. Block trades account for 15% of turnover and below-block size dark trading accounts for the final 10% of turnover.\textsuperscript{10} Therefore, there is considerable fragmentation of trading in the Australian equity market, comparable to Canada and several European countries (somewhat less extreme than in the US) and the types of trading venues and platforms are similar to those in the US.

Many of the participants in the Australian equity market are major international banks and electronic trading firms, using similar trading technology as they use elsewhere. These include Goldman Sachs, Merrill Lynch, UBS, Bank of America, Citigroup, Deutsche Bank, J.P. Morgan, GETCO, Citadel, and others.

Turnover in Australian equities is around $5.5 billion per day during Q1 2015, or around $25 million per stock per day for the 200 stocks in our sample. Effective bid-ask spreads during the same time period in our sample have a value-weighted average of 11 basis points (bps).\textsuperscript{11}

\textsuperscript{7} ASIC process the audit data and provide only aggregated data that is purged of confidential information.
\textsuperscript{8} Under the Market Integrity Rules, all market participants must provide to ASIC (via market operators) information about each order submitted to and trade executed on a market. Among the fields that must be submitted is an identifier for the “the person on whose instructions the Order is submitted or Transaction was executed”, which allows ASIC to identify all the order and trades originating from each trader irrespective of the broker through which the orders are routed (orders split across several brokers are linked by the identifier).
\textsuperscript{9} Given that trading occurs in Australian dollars (AUD), throughout this paper we use “$” to refer to AUD unless stated otherwise. At the start of our sample, AUD 1.00 is equal to approximately USD 0.93.
ASIC (2015) estimates that institutional brokerage (direct market access) is around 1–5 bps, exchange trading, clearing and settlement fees are around 0.3–0.7 bps.

ASIC estimates that high-frequency trading accounts for around 28% of turnover in our sample of stocks during Q1 2015 (ASIC, 2015), which is comparable to estimates of HFT trading activity in UK equities (27%; Aquilina and Ysusi, 2016), US E-mini S&P 500 futures market before the May 2010 flash crash (34%; Kirilenko et al., 2015), Canadian equities (33%, averaging the 20% estimated by Brogaard, Hendershott, and Riordan (2016) and the 46% estimated by Boehmer, Li, and Saar (2016)), slightly lower than US large-caps (42%; Brogaard et al., 2014) and slightly higher than US small-caps (18%; Brogaard et al., 2014). Slightly over 80% of Australian equity market capitalization is held by institutions (Bradrania et al., 2015), which is comparable to the estimated 80% in US large-caps.

In summary, the Australian equities market is similar in most respects (market structure, trading platforms, fragmentation, level of HFT trading activity, institutional holdings, and market participants) to other major, developed equity markets.

2.2. Classification of trader types

Our study classifies traders in two dimensions as illustrated in Figure 1. The first, directionality, is the tendency for a trader to either buy or sell a given security in a given interval of time, but not both buy and sell. The second is turnover. Directional traders (the left quadrants) are fundamental buyers and fundamental sellers—traders moving into or out of a position that is not quickly reversed. They can be thought of as “investors”. Large directional traders (top left quadrant) are the “institutional investors” that are used in our transaction cost measurement. Small directional traders (bottom left quadrant) are likely to be retail traders and small institutions for which traditional liquidity measures such as the bid-ask spread are likely to closely approximate transaction costs.

In contrast, non-directional traders (those that both buy and sell a given security within a relatively short period of time—right quadrants) comprise intermediaries such as market makers, and traders that use short horizon strategies such as statistical arbitrage, news arbitrage, latency arbitrage, predatory, and order anticipation. Non-directional traders that account for substantial proportions of turnover (top right quadrant) almost certainly are algorithmic traders, with the highest turnover traders likely to be HFTs. We label this group of high-turnover non-directional traders “active traders”; they are the focus of this study as the traders that could systematically increase or decrease institutional transaction costs.
Our focus on high-turnover traders is primarily because for a trader to have a meaningful impact on the transaction costs of large institutional orders (be it positive or negative) they are likely to trade in considerable volume. Our classification of active traders along the dimensions of directionality and turnover has similarities with data-driven definitions of HFT that have been used in prior studies (e.g., Kirilenko et al., 2015; ASIC, 2015; Brogaard et al., 2016), but is not as narrow. An advantage of casting the net wider is it allows us to ask whether speed, order-to-trade ratio, near-zero inventory or other trading characteristics are defining features of toxic traders.

Non-directional traders that account for small shares of turnover (bottom right quadrant) are likely to use strategies similar to those of active traders but on a smaller scale or with less sophistication/automation. This category is likely to involve some retail trading and some opportunistic strategies that only occasionally trade. Traders in this category are therefore unlikely to have a material effect on institutional transaction costs.

We classify as “active traders” those trading accounts that have the highest level of non-directional turnover throughout the sample. We measure non-directional turnover as buying that is accompanied by corresponding selling (and vice versa) of a given security within a period of one week. This definition ensures that fundamental buying and fundamental selling does not contribute to non-directional turnover. After summing non-directional dollar volume for each trading account, we classify as “active traders” those that trade on average at least $8 million of non-directional volume per day. We impose two additional (not particularly restrictive) requirements that ensure the active traders have sufficient breadth and continuity: (i) they are active in at least ten of the weeks in our 13 month sample, and (ii) they trade an average of at least 20 securities per day. This procedure results in 187 “active trader” accounts. Once an account is classified as an active trader that classification stays with the account throughout the sample and is applied to all of the trading activity of that account. The cutoffs that result in 187 active trader accounts are based on regulatory judgement about the types of traders that could have a material effect (good or bad) on institutional transaction costs.

12 The turnover threshold is also likely to act as a filter that removes the slowest and least automated non-directional traders, as automation and speed result in large volumes (e.g., Roşu, 2016; Kirilenko et al., 2015).

13 Our definition of active traders sufficiently separates them from fundamental institutional investors such that the trading of active traders does not result in unidirectional trade packages that are used in estimation of institutional transaction costs.
For each stock-day \( it \), we measure the fraction of that day’s double-counted dollar volume (the dollar volume of the buy side of all trades plus that of the sell side) executed by active trader \( k \) as \( \text{Activity}_{itk} \). We also define the binary variable \( \text{Presence}_{itk} = 1 \) if \( \text{Activity}_{itk} > 0 \) (i.e., trader \( k \) is present in stock-day \( it \)) and 0 otherwise.

Figure 2 shows the 187 active traders’ percentage of turnover in stock quartiles through time (summing \( \text{Activity}_{itk} \) across all 187 active traders and expressing it as a percentage). The participation rates of active traders do not vary substantially across the stock quartiles, ranging from an average of around 46% in the lowest turnover quartile to around 52% in the second highest turnover quartile (these estimates are reported in Table 1). The pattern across quartiles is not monotonic; the highest proportional activity of active traders is in the second highest turnover quartile. There is a slight upward trend through time; active traders account for around 43% of turnover at the start of the sample and around 53% at the end, roughly one year later.

Table 1 indicates that the 187 active traders collectively account for around 48% of turnover, which is close to double the turnover of “pure” HFTs during the sample.\(^\text{14}\) On an average stock-day, 64 of the active traders are present and trading the given stock.

< Figure 2 here >

< Table 1 here >

2.3. Institutional transaction costs

Measuring institutional transaction costs from the regulatory trader-level data involves three steps. First, we reconstruct institutional unidirectional trade packages (“parent orders”) as follows:

a) aggregate all transactions for each trading account within a given stock-day into a single parent order;

b) classify parent orders as unidirectional if all trades are in one direction (all buying or all selling); and

c) classify unidirectional parent orders as institutional if their dollar volume exceeds the median of all unidirectional parent orders traded that stock-day and the parent order is “worked” in the market for at least two hours.

\(^\text{14}\) ASIC (2015) estimate that HFTs (using a data-driven identification procedure involving total turnover, inventory and the tendency to go home flat, order-to-trade ratio, number of fast messages, holding time and sophistication) account for around 28% of turnover in our sample of stocks during Q1 2015.
In the second step we measure the execution costs of the institutional trade packages. For this we use implementation shortfall (Perold, 1988; Anand et al., 2012), which, for trade package $j$ in stock $i$ on day $t$, is calculated as:

$$I_{Shorfall_{itj}} = \left[\frac{VWAP_{itj} - P_{0_{itj}}}{P_{0_{itj}}}\right] D_{itj}$$ (1)

where $VWAP_{itj}$ is the volume-weighted average execution price for the trades in the package, $P_{0_{itj}}$ is the price at the time of the first trade in the package, and $D_{itj}$ is the direction of the trade package (+1 for buys and −1 for sells).

In the third step, we calculate the volume-weighted average implementation shortfall for all trade packages in each stock-day. The resulting measure, $I_{Shorfall_{it}}$, is measured in bps.

Figure 3 Panel A shows the large institutional orders as a percentage of turnover through time and Table 1 provides descriptive statistics on the institutional orders. Overall, the large institutional orders that are the basis of the institutional transaction cost measurement account for approximately 19.3% of turnover. Their share of turnover is not monotonic across the stock size quartiles. Figure 3 Panel B plots the simple average of $I_{Shorfall_{it}}$ in stock turnover quartiles through time. As expected, $I_{Shorfall_{it}}$ is monotonically larger for lower turnover stocks, averaging around ten bps in the highest turnover quartile and around 24 bps in the lowest turnover quartile. Table 1 indicates that the pooled mean of $I_{Shorfall_{it}}$ is around 16 bps, which is very similar to the 17 bps average implementation shortfall for institutional orders in the US, as reported by Anand et al. (2012) for 2007, the most recent non-crisis year of their sample.

< Figure 3 here >

3. Analysis of toxicity

3.1. Measuring toxicity: The general approach

Our general approach to measuring toxicity (which we refine in various ways) involves estimating the following regression:

$$I_{Shorfall_{it}} = \alpha + \sum_{k=1}^{187} \gamma_k Activity_{itk} + \varepsilon_{it}$$ (2)

The estimated coefficients $\gamma_k$ measure the “toxicity” of each trader $k$. Positive (negative) values of $\gamma_k$ indicate that the trader’s activity is associated with an increase (decrease) in institutional transaction costs. Traders that increase (decrease) institutional transaction costs significantly are termed “toxic” (“beneficial”). We double cluster standard errors by stock and by date in all regressions to account for dependencies within the panel data.
We further define gross toxicity of a trader as their estimated toxicity per unit turnover ($\hat{\gamma}_k$) multiplied by their average share of turnover ($\text{Activity}_{ik}$): $GrossToxicity_k = \hat{\gamma}_k \text{Activity}_{ik}$. A trader’s gross toxicity is their estimated average impact on institutional transaction costs.

Visual representation of the results from the general toxicity regression is telling. Figure 4 plots each of the 187 traders in a two dimensional space. The vertical axis measures the trader’s toxicity point estimate, $\hat{\gamma}_k$, (on a log scale) with positive (negative) numbers indicating the trader is associated with increased (decreased) institutional transaction costs. The horizontal axis measures the consistency of the trader’s toxicity (log of the standard error of $\hat{\gamma}_k$) with lower values indicating greater consistency or lower uncertainty about the trader’s toxicity level. The size of the circles indicates the statistical significance of the toxicity estimate, from insignificant at the 10% level (smallest circles) to significant at the 10%, 5%, and 1% levels (largest circles). The figure shows that the 187 active traders cluster fairly distinctly into toxic and beneficial traders. Many traders’ toxicity coefficients are statistically different from zero. To some extent, this is expected by chance under the null that all toxicity coefficients are actually zero. We address this issue later and show the number of statistically significant coefficients is considerably greater than what would be expected by chance alone.

Institutional investors are likely to be concerned not only about an active trader’s toxicity point estimate, but also the consistency with which the trader imposes toxicity, which we measure using the standard error of the toxicity estimate. Therefore, the collection of active traders that have maximum estimated toxicity for a given level of uncertainty about the toxicity estimate, or a minimum level of estimation uncertainty for a given level of toxicity, form what we term the “toxicity frontier”. Figure 4 illustrates the approximate toxicity frontier for our sample.

< Figure 4 here >

We test a few functional form variations on the general approach to measuring toxicity before proceeding to instrumental variables models and bootstrap simulations. First, we add stock fixed effects, then date fixed effects, then both sets of fixed effects. The latter of these models is:

$$I\text{Shorfall}_{it} = \alpha_t + \mu_e + \sum_{k=1}^{107} \gamma_k \text{Activity}_{itk} + \epsilon_{it}$$  

(3)

The fixed effects eliminate many potential confounding effects and subsume most potential control variables. The fixed effects subsume stock characteristics that have mainly cross-sectional variation (e.g., market capitalization, institutional holdings, spread/depth, whether the
stock’s spread is constrained by its tick size causing limit order queuing, percentage of turnover traded in the dark, and so on), and time-series variables including market conditions (e.g., VIX, market-wide realized volatility/turnover/returns, and so on). In addition to subsuming most potential control variables, fixed effects have the additional advantage of mopping up unobservable confounding factors that are either purely time-varying or purely cross-sectional. Fixed effects in our setting also come at a cost, mainly that they also soak up much of the time-series and cross-sectional variation that is useful in identifying traders’ toxicity.

Figure 5 illustrates the results from the toxicity regressions with fixed effects. The distributions of toxicity are qualitatively similar with and without fixed effects, pointing away from the presence of significant confounding factors or omitted variables bias. The levels of statistical significance in the toxicity estimates are also similar with fixed effects. Although the distributions and significance are similar with fixed effects, it is possible that the ordering of traders with respect to their toxicity is different, e.g., a trader estimated to be toxic could swap places with a trader estimated to be beneficial in two different models without changing the distributions of toxicity. To investigate this possibility we compute Pearson parametric correlations and Spearman non-parametric rank correlations for the trader toxicity estimates across the different models (with/without fixed effects). The correlations are all very high (above 0.8) indicating that even the relative ranking of traders on the toxicity scale is not overly affected by the inclusion of fixed effects. Given these results, we proceed with the simpler model with no fixed effects as it places less burden on parameter estimation (important in the bootstrap simulations) and allows us to exploit more dimensions of variance in further tests and instrumental variables models.

We report two further variations on the basic toxicity regression (2) in the Appendix. The first is a model that considers whether an active trader’s presence in the market (trading non-zero volume, \( \text{Presence}_{itk} \)) affects institutional transaction costs, or whether their level of activity (share of turnover, \( \text{Activity}_{itk} \)) affects institutional transaction costs, or both have independent effects. We simultaneously include \( \text{Activity}_{itk} \) and \( \text{Presence}_{itk} \) into a regression similar to (2) and find that while the presence of some active traders has an effect on institutional transaction costs independent of the effect of their activity, presence does not subsume activity in explaining the effects of active traders on execution costs. The statistical significance of the toxicity
estimates derived from measures of active trader activity remain approximately the same when presence is included in the toxicity regressions. The relative ranking of traders on a toxicity scale is also not overly affected, with correlations around 0.8 between the rankings generated by the two approaches.

Second, we transform the bounded activity measures, $Activity_{itk}$, into unbounded variables via a logit transformation and re-estimate the toxicity regression. We find that the transformation compresses the estimated average difference between toxic and beneficial traders, but it does not overly affect inference about toxicity levels, statistical significance of toxic and beneficial traders, or the relative ranking of traders on a toxicity scale (correlations around 0.9 between the rankings).

3.2. Instrumental variables models

To deal with the potential endogeneity of active traders’ activity and pin down their causal effects on institutional transaction costs, we turn to instrumental variables. Given the heterogeneity in our sample of active traders, which is a deliberate result of casting a wider net across traders than most studies (e.g., HFT studies) it is unlikely that exogenous market-wide changes will be useful in identifying the effects of our cross-section of active traders—some traders will be affected, but others almost certainly will not, or will be affected differently to other traders. This rules out the possibility of using market structure changes such as platform upgrades for latency reduction or co-location, which have been used as instruments in studies of narrower groups of traders. Instead, we use exogenous information on the individual traders as instruments, more precisely, their lagged trading activity in a given stock. This approach is similar in spirit to Sarkar and Schwartz (2009) who also use lags of endogenous variables as instruments in a microstructure setting.

We estimate the following two-stage least squares instrumental variables (2SLS IV) model:

$$Activity_{itk} = \mu + \sum_{\tau,k=1}^{5} Activity_{(t-\tau,k)} + \epsilon_{itk} \quad (4)$$

$$I\text{Shorfall}_{it} = \alpha + \sum_{k=1}^{187} \gamma_k Activity_{itk} + \epsilon_{it} \quad (5)$$

In the first stage (4), the trading activity of each active trader $k$ in stock-day $it$ is regressed on that active trader’s activity in the same stock in each of the past five trading days. In the second stage (5), we estimate the same toxicity regression as previously, but replacing the activity variables with their fitted values from the first stage, $\hat{Activity}_{itk}$.
The first requirement of instrumental variables—that they are correlated with the endogenous explanatory variables—is clearly satisfied. The correlations between lagged and current activity of a given trader in a given stock are between 0.54 and 0.62 (depending on the lag) and F-tests of whether the instruments in the first stage are statistically significant produce p-values well below 1%. The second requirement—that the instrumental variables are exogenous with respect to the dependent variable (not correlated with the error term)—is satisfied as a result of the temporal offset between the instrumental variable and the dependent variable. Past activity cannot respond to current market or stock-specific conditions that affect institutional transaction costs. The only possible contamination is through persistence in the conditions that affect institutional transaction costs. We rule out this concern with three additional tests: (i) adding lagged $I_{Sho}rfa_{lt}$ as a control variable in the first and second stages to absorb persistence in institutional transaction costs, (ii) adding time fixed effects to absorb any time-series trends or persistent changes in market conditions, and (iii) omitting the first and second lags in the first-stage regression and using only the third, fourth, and fifth lags as instruments. Our results are largely unchanged in these three additional tests.

Figure 6 illustrates the results from the 2SLS IV toxicity regressions (5). The distributions of toxicity, as previously, indicate that some traders systematically tend to increase (others decrease) institutional transaction costs. In general, fewer traders have a statistically significant relation with institutional transaction costs than in the OLS models, which could be the result of eliminating endogeneity in the estimates, but it could also be due to the decrease in statistical power. The Pearson parametric correlation (Spearman non-parametric rank correlation) of trader gross toxicity estimated via OLS and the 2SLS IV models is 0.70 (0.48) indicating that using instrumental variables somewhat changes inference about individual traders and their relative ranking on a toxicity scale. Given these results, we proceed with the 2SLS IV models in the further analysis of toxicity.

< Figure 6 here >

3.3. **Quantifying toxicity beyond chance**

One of the challenges in analyzing toxicity at the level of individual traders is that if sufficiently many traders are analyzed some will, purely by statistical chance, appear toxic even if there is no true relation between any of the traders and institutional transaction costs. Put differently, with a non-zero Type 1 error rate, the probability of making a certain number of Type
1 errors (or the number of Type 1 errors) increases with the number of tests performed (traders tested for toxicity).

The challenge of disentangling true toxicity from chance at the individual trader level is similar to the problem of disentangling skill from luck in the cross-section of fund managers. Given a sufficiently large number of fund managers, some will purely by chance beat their benchmark over many consecutive periods and thus appear skilled. In neither the fund management context nor the toxic trader context is it sufficient to adjust critical values because the distributions of alpha and toxicity are complex and non-normal. Instead, we borrow the approach from the fund management literature for dealing with this challenge and use bootstrap simulations. The bootstraps allow us to quantify excess toxicity i.e., the amount that exceeds what would be expected by statistical chance alone.

For the bootstraps, we follow the approach of Kosowski. Timmermann, Wermers, and White (2006). The details are in Appendix B. The essence of the procedure is as follows. Estimate the 2SLS IV model second stage and save the residuals (the procedure works the same with the simpler OLS model, but the 2SLS IV models have the advantage of addressing potential endogeneity). Simulate data on implementation shortfall for each observation in the stock-day panel by sampling from the residuals (with replacement) for each stock and imposing the null that none of the active traders have an underlying relation with institutional transaction costs (the “zero-toxicity null”). Estimate the 2SLS IV model on the simulated data saving the toxicity estimates. Repeat the simulate-then-estimate steps many (1,000) times to build distributions of the levels of toxicity and their statistical significance that would be expected purely by chance (under the restriction of no true toxicity). Finally, compare the actual estimated toxicity levels and significance to that which would be expected by chance. Throughout the bootstrap, we estimate double clustered standard errors (clustered by stock and by date).

< Table 2 here >

Table 2 reports the bootstrap results. Panel A reports estimates from the 2SLS IV model using the actual data, i.e., the model estimated previously. The columns min through to max (with P5, P25, P75, P95 being the 5th, 25th, 75th, 95th percentiles) describe the distribution of the 187 toxicity estimate t-statistics (one estimate for each of the 187 active traders in the sample). The median t-statistic is close to zero (−0.08). The 5% most statistically toxic (beneficial) traders have toxicity estimate t-statistics above 2.12 (below –2.37). The minimum and maximum
toxicity t-statistics across the 187 active traders are $-3.61$ and $+4.00$, respectively. The last four columns of the table indicate how many of the 187 active traders have toxicity t-statistics beyond a certain threshold given in the column heading. In the actual data (Panel A), four traders are estimated as toxic with t-statistics above $+3$ and 12 traders with t-statistics above $+2$. Similarly, four and 15 of the active traders are statistically beneficial (tend to lower institutional execution costs) with t-statistics less than $-3$ and $-2$, respectively.

Table 2 Panel B reports an extract of the results using simulated data: simulation iterations 1–6 and 1,000, omitting the iterations in between. Each iteration recreates a panel dataset similar to the actual dataset (but with zero toxicity by design) and on that dataset estimates the same 2SLS IV model and extracts information about the 187 toxicity estimates. The results from an individual iteration (rows of Panel B) by themselves are not overly useful (we report them to give a better understanding of how the bootstrap works); what is useful is the distribution for each of the columns across the 1,000 iterations. Each iteration forms a point in the “bootstrap distribution” for each statistic (column). The last row of Panel B reports means (across the 1,000 iterations) of the number of active traders with toxicity t-statistics beyond a certain threshold.

Having built a bootstrap distribution for what we would expect to see for the toxicity t-statistics purely by chance (Panel B), we can test whether the toxicity t-statistics estimated on the actual data (Panel A) deviate from what is expected by chance. Panel C expresses the toxicity t-statistic estimates using actual data (Panel A) in terms of percentiles in the bootstrap distribution. For example, for the column min, the 52 in Panel C indicates that the minimum toxicity t-statistic of $-3.61$ in the actual data (Panel A) corresponds to the 52nd percentile of the minimum t-statistics in the 1,000 simulated datasets (Panel B). Thus, the most negative t-statistic (most statistically beneficial trader) in the actual data is no more extreme than would be expected by chance. Put differently, in 52% of the simulated datasets in which the zero-toxicity null is imposed by design, the most negative t-statistic across the 187 traders is more negative (larger absolute value) than the most negative t-statistic in the actual data. Similarly, the largest positive t-statistic in the actual data is no more extreme than would be expected by chance (it is in the 50th percentile of the bootstrap distribution). This suggests the actual data do not contain extreme individual outliers. Also, the median active trader is no different in their estimated toxicity to what would be expected under the zero-toxicity null.

The 5th and 25th percentiles of the toxicity t-statistics in the actual data (the 5% and 25% most beneficial traders), however, are more beneficial than would be expected under the zero-toxicity null. The toxicity t-statistics for those groups of traders are in the 0th percentile (the 0–
1% segment of the bootstrap distribution). Similarly, the 5% most toxic traders in the actual data are also more toxic than would be expected by chance; their toxicity t-statistics are in the 99th percentile (the 99–100% segment of the bootstrap distribution). These results indicate that it is very unlikely (less than 1% probability) that one would find the levels of toxicity estimated for the 5% most beneficial and 5% most toxic traders by chance. Thus the bootstrap results reject the zero-toxicity null hypothesis.

The last four columns of Table 2 provide an additional way of quantifying toxicity beyond statistical chance. The Mean row in Panel B indicates that under the zero-toxicity null, we would expect by chance 5.55 of the 187 active traders to appear to be statistically toxic at 95% confidence (toxicity t-statistic > +2) and 1.20 to be statistically toxic at 99.5% confidence (toxicity t-statistic > +3). In the actual data (Panel A) we observe that in fact 12 (rather than 5.55) of the active traders are statistically toxic at 95% confidence, and four (rather than 1.20) are statistically toxic at 99.5% confidence, i.e., considerably more than would be expected under the zero-toxicity null. In fact, Panel C indicates that the probability of observing that many statistically toxic traders at the 95% and 99.5% confidence levels is less than 1% and less than 2%, respectively. Similarly for the beneficial traders, Panel B indicates that we would expect by chance 6.87 of the 187 active traders to appear to be statistically beneficial at 95% confidence (t-statistic < –2) and 1.24 to be statistically beneficial at 99.5% confidence (t-statistic < –3). In the actual data (Panel A) we observe that in fact 15 of the active traders are statistically beneficial at 95% confidence, and four are statistically beneficial at 99.5% confidence, with the probabilities of observing that many beneficial traders by chance being less than 1% and less than 2%, respectively (Panel C).

Repeating the bootstrap analysis for GrossToxicity_k rather than the t-statistics of the toxicity estimates leads to similar conclusions, namely, that the level of toxicity in the 5% most toxic and most beneficial traders is beyond what would be expected by chance.

3.4. Net toxicity?

The bootstrap analysis, building on the 2SLS IV model, indicates that there are groups of traders in the data that have a causal effect on institutional transaction costs (both positive and negative) beyond what would be expect by chance. We now turn to quantifying the economic significance of their impacts on institutional execution costs. We also compute their net effects by aggregating across the toxic and beneficial traders.
In terms of economic significance, what matters is the ultimate impact on institutional transaction costs. This is best measured by $\text{GrossToxicity}_k$, which is an estimate of each trader’s effect on the implementation shortfall of large institutional orders in bps (the product of their estimated toxicity per unit turnover and their average share of turnover). Aggregating $\text{GrossToxicity}_k$ across groups of traders involves summing their $\text{GrossToxicity}_k$ estimates. Accounting for what would be expected by chance is done by subtracting, for each trader, their expected $\text{GrossToxicity}_k$ estimated from the bootstrap distribution under the zero-toxicity null ($\mathbb{E} [\text{Toxicity}_k]$). This process effectively integrates the difference between actual and expected $\text{GrossToxicity}_k$ across segments of the $\text{GrossToxicity}_k$ distribution (or across the whole distribution). Continuing the analogy with skill in the cross-section of funds managers, calculating the excess gross toxicity for a group of traders is like quantifying the net alpha generated by a group of fund managers accounting for the alpha that is the result of chance (luck).

First we analyze how active traders that have statistically significant toxicity estimates ($\gamma_k \hat{t}$), positive or negative, affect $\text{IShall} or \text{fa} l l_{it}$, beyond what is expected by chance (under the zero-toxicity null):

\[
\begin{align*}
\text{ExcessGrossToxicity}_{\text{ToxicTraders}} &= \sum_k (\text{GrossToxicity}_k - \mathbb{E} [\text{Toxicity}_k]) \mathbf{1}_{(t_k > 2)} \tag{6} \\
\text{ExcessGrossToxicity}_{\text{BeneficialTraders}} &= \sum_k (\text{GrossToxicity}_k - \mathbb{E} [\text{Toxicity}_k]) \mathbf{1}_{(t_k < -2)} \tag{7}
\end{align*}
\]

where $\mathbf{1}_{(t_k > 2)}$ and $\mathbf{1}_{(t_k < -2)}$ are indicator functions for whether trader $k$ is estimated to be significantly toxic ($\gamma_k \hat{t}$-statistic > +2) and significantly beneficial ($\gamma_k \hat{t}$-statistic < −2), respectively.

We find that the 12 significantly toxic traders increase the average implementation shortfall for large institutional orders by 10.3 bps beyond what is expected by chance ($\text{ExcessGrossToxicity}_{\text{ToxicTraders}} = 10.3$). That is an economically meaningful impact compared to the pooled sample unconditional mean implementation shortfall of 16.4 bps (Table 1), and the value-weighted average effective bid-ask spread of around 11 bps. In dollar terms, large institutional orders account for around 19% of turnover, and turnover is approximately $25 million per stock per day during our sample.\(^{15}\) All up, that implies that a 10.3 bps increase in $\text{IShall} or \text{fa} l l_{it}$ as a result of the toxic traders equates to increased execution costs of around $437 million across all large institutional orders in the ASX 200 stocks during a one-year period (assuming 220 trading days). At the same time, the 15 significantly beneficial active traders decrease the average implementation shortfall for large institutional orders by 8.9 bps beyond

\(^{15}\) With large institutional orders accounting for 19% of turnover, their dollar value is $2 \times 19\% \times $25mil to account for both the buying and selling sides of turnover.
what is expected by chance \((\text{ExcessGrossToxicity}_{\text{BeneficialTraders}} = -8.9)\). This effect is also economically meaningful compared to average implementation shortfall and is similar in magnitude to the increase in implementation shortfall caused by the significantly toxic traders. The estimated impact in dollar terms from the significantly beneficial active traders is a reduction in institutional execution costs of around $375 million across all large institutional orders in the ASX 200 stocks during a one-year period. These dollar estimates represent a lower bound for two reasons: (i) they only capture the largest institutional trades, not medium trades, which are also likely to be affected to some extent, and (ii) they cover the top 200 stocks and not others.

Netting the effects of the significantly toxic and significantly beneficial active traders, implies a small net effect: around +1.4 bps or an increase in annual costs of around $62 million across all large institutional orders. Thus, while toxic and beneficial traders individually have large effects on institutional transaction costs (same order of magnitude as average institutional execution costs, their net effect is close to zero.

We also measure the net effects across all active traders whether they have statistically significant toxicity estimates or not, again accounting for what is expected by chance. The absence of statistical significance does not rule the possibility that a trader has a true impact on institutional transaction costs, so it is worth assessing the impact of such traders. On the other hand, incorrectly including traders in the aggregation that have no effect on institutional transaction costs will not bias the net toxicity estimate, merely add noise. Net excess toxicity across all active traders is estimated as:

\[
\text{NetExcessToxicity} = \sum_k (\text{GrossToxicity}_k - \mathbb{E}[\text{Toxicity}_k])
\]  

We find that net excess toxicity across all active traders is near zero: –0.79 bps. The sign of the point estimate implies net benefits from the active traders as a whole in terms of reducing implementation shortfall on large institutional orders by around $33 million per annum in the ASX 200. However, this estimate is not statistically distinguishable from zero using parametric or non-parametric tests, at the 5% level.

The estimates of toxicity among the toxic traders and the net effects when aggregating across all active traders help understand why there are significant concerns about traders that increase institutional transaction costs (including predatory traders and order anticipation algorithms), despite several studies finding that AT/HFT as a whole are beneficial to markets or benign. Toxic traders have an economically meaningful detrimental effect on institutional transaction costs, which explains the concerns about these types of traders and the costs spent on sophisticated trading technology to minimize the ability for toxic traders to harm execution
quality. But at the same time, the net effect of active traders is close to zero. This occurs because an important group of active traders significantly reduces institutional transaction costs, offsetting the effects of toxic traders.

Given the heterogeneity in the cross-section of active traders, it is also not surprising that studies of AT/HFT that use different exogenous events as instruments often arrive at different conclusions about the net effects of this group of traders. An event that disproportionately encourages the trading activity of the group of beneficial traders or gives them an advantage will tend to improve transaction cost dimensions of market quality. The opposite is true for events that benefit or encourage the group of toxic traders. Brogaard et al. (2015) for example, find that the introduction of co-location at Nasdaq OMX Stockholm improves market quality, implying that this event disproportionately encouraged the activity of beneficial active traders.

3.5. Characteristics of toxic traders

Having estimated the toxicity of each active trader account, we now ask what characteristics distinguish the toxic traders from the beneficial ones? The toxic traders are likely to use different trading strategies compared to the beneficial traders. Given that one of the main determinants of implementation shortfall for large orders is whether others are trading in the same direction as the order or against it (e.g., ASIC, 2015) toxic traders are likely to trade with institutional order flow (in the same direction as institutional orders) rather than against it. Such trading patterns could occur from intentionally exploiting institutional order flow or unintentionally trading with institutional flow due to common entry/exit signals. For example, some of the toxic traders might employ predatory trading strategies (e.g., Brunnermeier and Pedersen, 2005), order anticipation algorithms (e.g., Hirschey, 2013), or strategies that seek to identify and “back-run” large informed orders (e.g., Yang and Zhu, 2015). Other toxic traders might unintentionally amplify institutional execution costs by using strategies that tend to trade in the same direction as large intuitional orders. In contrast, the beneficial traders are likely to be liquidity-providing intermediaries, employing market making strategies that “lean against the wind”, thereby attenuating price pressure that arises from large institutional orders. The differences in trading strategies imply that some trading characteristics and patterns in activity should be different for toxic and beneficial traders. We first explore the characteristics of trading activity (how much, when and where toxic traders trade) and then the speed, sophistication and order placement characteristics.
Our approach to estimating the characteristics of toxic traders is to use regressions of the form:

\[ Toxicity_k = \alpha + \sum_c \beta_c Characteristic_{c,k} + \epsilon_k \]  

(9)

where the toxicity estimates for each active trader \( k \) (\( Toxicity_k \)) are either estimated toxicity per unit activity (\( \hat{y}_k \)), estimated gross toxicity of each trader (\( GrossToxicity_k \)), estimated excess gross toxicity (\( GrossToxicity_k - E[Toxicity_k] \)), or the statistical significance of the trader’s toxicity estimate (t-statistic of \( \hat{y}_k \)), all derived from the 2SLS IV toxicity regressions. The set of \( c \) trader-level characteristics involve measures of how much, when and where toxic traders trade as well as the trader’s speed, sophistication and order placement characteristics.

Table 3 reports the results of the regression in (9) using excess gross toxicity as the dependent variable (the results are similar using the other toxicity estimates) and characteristics of trading activity as the independent variables. The first characteristic we test is average activity measured as each trader’s equal-weighted average share of turnover across all stock-days. Higher turnover traders are likely to be more sophisticated, but importantly also faster—several papers show, both theoretically and empirically, that relative speed has a large impact on a trader’s turnover (e.g., Roșu, 2016). Models 1 and 2 in Table 3 show that turnover is not significantly related to toxicity. To the extent that turnover is a proxy for speed, this finding suggests that speed is not a distinguishing characteristic of toxic traders—a finding that we confirm below with other measures of speed. On one hand, this conclusion seems reasonable in light of the evidence on the timing of predatory or back-running strategies. For example, van Kervel and Menkveld (2015) show that HFTs initially trade against institutional parent orders and only seem to be able to detect (and then exploit) them several hours after the start of the parent order. Speed is not necessary for predatory trading or back-running orders. Yet, on the other hand, this evidence suggests that concerns voiced by institutional investors about HFTs being the culprits responsible for increased transaction costs might be misdirected. While some HFTs may be predatory traders, to the extent that HFT accounts are likely to have higher turnover than non-HFT accounts, it seems HFTs are no more predatory than other slower traders.

The next characteristic we examine is the consistency of a trader’s presence. Rather than simply computing the standard deviation of the trader’s activity across all stock-days, we separately compute the cross-sectional standard deviation of their activity and the time-series
standard deviation. Model 3 in Table 3 shows that toxic traders tend to have higher cross-sectional standard deviation and lower time-series standard deviation than other traders (although the latter is only marginally statistically significant). The high cross-sectional standard deviation of active traders’ activity suggests that, on any given day, toxic traders tend to concentrate their activity in a subset of stocks rather than trading equally across the market portfolio. The low time-series standard deviation suggests toxic traders tend to be more consistently present day-to-day in the stocks in which they concentrate their trading activity. Thus, they appear to have a preferred habitat of stocks.

Next we examine what is the preferred habitat of toxic traders. We measure each trader’s share of turnover in large (top quartile) medium (second quartile) and small (bottom two quartiles) stocks, as well as expressing their activity in small stocks relative to their overall activity. Models 4 and 5 in Table 3 show that toxic traders are more active in small stocks and less active in large stocks.

We also examine whether toxic traders are more active in times of market stress by measuring each trader’s relative activity during a period in which the market fell sharply and exhibited high volatility (August 5–24, 2015). Models 6 and 7 in Table 3 indicate that there is no statistical difference in the activity of toxic traders (relative to other traders) during the period of market stress compared to other times. This is consistent with their relatively low time-series standard deviation. It is worth noting that institutional orders as a share of turnover also slightly decline during this period (Figure 2).

Model 8 of Table 3 combines all of the activity characteristics in one regression. The characteristics that are individually significant remain significant after controlling for other characteristics. The R-squared reaches a maximum of 7% in Model 8, suggesting that there are many factors (which could be predominantly unobservable) beyond those included in our regression models that explain variation in toxicity. Additionally, measurement error in the toxicity estimates is also likely to contribute to the low R-squared.

< Table 4 here >

Table 4 continues the analysis with other measures of speed, sophistication and order placement characteristics. The first of these is the average holding time of long or short positions
that are closed within a day.\textsuperscript{16} \textit{Holding Time} is not significantly related to toxicity and if anything, the point estimate suggests toxic traders have \textit{longer} holding times. To the extent that HFTs have short holding times, this evidence supports our conclusion that HFTs are no more toxic than non-HFTs. We define fast orders as order amendments sent within 500 milliseconds of the order placement and use such orders to construct two related measures: the number of fast orders (\textit{Number Fast}), and the average speed of fast orders (\textit{Order Amendment Time}). \textit{Number Fast} indicates how active a trader is in “managing” submitted orders. \textit{Order Amendment Time} is a proxy for the speed of the trader’s technology. Model 2 shows that neither of these characteristics is significantly related to toxicity, consistent with the conclusion that fast traders are not more toxic on average. The point estimate on the number of fast orders is positive in Model 2 but becomes negative when we control for the total number of orders (Model 7).

We measure each trader’s efficiency in generating intraday margin from trading stock as the Sharpe ratio of daily trading profit (counting only those positions that are closed within the day). This Sharpe ratio of trading profit is a measure of sophistication—sophisticated active traders consistently make money on their trading. We find that toxic traders are not more efficient in generating intraday margin than others (statistically insignificant coefficient in Model 3), in fact, the insignificant point estimate goes the other way.

Model 4 shows that toxic traders on average close a larger percentage of their positions by the end of the day, i.e., they hold fewer positions overnight. Across all 187 active traders, around 22\% of their turnover on average is intra-day round-trip trades, with a standard deviation of around 27\%. The effect size (coefficient of \textit{Percentage Traded}) is economically meaningful and larger in magnitude once we control for other characteristics (Model 7).\textsuperscript{17} If electronic market makers tend to “go home flat” (some of the earlier literature on electronic market making suggests they do) then it might seem surprising that \textit{Percentage Traded} is positively related to toxicity. However, several recent studies that track inventory of electronic market makers (e.g., Malinova and Park, 2016) show that they do not go home flat in individual securities and in fact hold large inventory positions overnight. Rather than going home flat in individual securities, electronic market makers often try to go home flat in terms of risk (either netting beta-adjusted positions across stocks, beta hedging their net inventory, or multi-factor hedging their inventory).

\begin{footnotesize}
\textsuperscript{16} For a given trader in a given stock-day we construct first-in-first-out (FIFO) “pipes” for long and short positions and measure the average time a position spends in the pipe. Positions held overnight do not contribute to this measure.

\textsuperscript{17} The coefficient estimate in Model 4 implies that a one-standard deviation (27\%) increase in the percentage of turnover made up by intraday round-trip trades for the 12 significantly toxic traders would increase their detrimental effect on institutional implementation shortfall by around one bp in total.
\end{footnotesize}
In contrast, order anticipation strategies might hold little to no inventory overnight and therefore have a high percentage of their positions closed by the end of each day.

Models 5 and 6 show that a trader’s order-to-trade ratio, which measures the degree of strategic order submission and active order management, is not significantly related to toxicity. Model 5 tests the relation between a trader’s toxicity and their average number of submitted orders, holding their turnover fixed, and Model 6 tests the order-to-trade ratio directly (we find similar results expressing the order to trade ratio in value terms). Although not statistically significant, the point estimates are consistent with the notion that toxicity is positively related to excessive quoting. The average order-to-trade ratio across all active traders is around 22. Consistent with our previous results, Model 5 shows that turnover is not significantly related to toxicity. Models 7 and 8 include all the speed, sophistication, and order placement characteristics together as well as the cross-sectional and time-series standard deviations of activity from before. Our main conclusions hold when the characteristics are tested together.

The main findings in this subsection concur with the results of Hagströmer and Nordén (2013) who do not examine toxic traders per se, but characterize market making HFTs compared to other HFTs, which they label “opportunistic”. They find that market making HFTs have lower latency and higher order-to-trade ratios than other HFTs, who in turn have latency and order-to-trade ratios on par with non-HFTs.

In summary, many of the characteristics associated with HFT are unrelated to toxicity, including turnover, speed of order amendments, frequency of fast orders, consistency with which they extract intraday trading profit, and order-to-trade ratios. The evidence consistently points to the conclusion that HFTs are not more toxic than non-HFTs. Toxic traders differ from non-toxic traders in a few regards—they tend to concentrate their activity in a subset of stocks, are more active in smaller stocks, and are more likely to close positions before the end of the day.

3.6. Robustness tests

We find qualitatively similar results across a number of robustness tests, including: (i) subperiod tests, omitting a period of one month in which the market fell sharply (August 2015); (ii) stock and/or time fixed effects in the toxicity regressions; (iii) logit transformations of the toxic trader activity measures to give unbounded variables; (iii) controlling for the presence of active traders in the toxicity regressions (in addition to their activity); (iv) using different toxicity estimates (toxicity per unit activity, gross toxicity of each trader, and the t-statistic of the trader’s toxicity estimate) in the bootstrap analysis and analysis of trader characteristics. The results of
some of these robustness tests are mentioned above in the corresponding section of the paper, others are omitted for conciseness.

4. Conclusions

We find strong evidence that some active traders systematically increase institutional transaction costs while others decrease these costs, i.e., some appear “toxic” from the perspective of an institutional investor while others appear “beneficial”. The effects of these two groups on institutional transaction costs are economically meaningful. Toxic traders increase institutional execution costs by more than ten bps, roughly the same magnitude as the effective bid-ask spread and more than half of the average implementation shortfall cost on a large institutional order. In dollar terms this translates to additional transaction costs of around $437 million per annum for large institutional orders in the top 200 stocks. The effects of the toxic traders are offset by a group of beneficial traders that significantly decrease those costs. Consequently, active traders as a group have little or no net effect on institutional transaction costs.

The net effects of active traders, while consistent with evidence that AT/HFT as a group are benign or beneficial, mask the considerable heterogeneity uncovered by our analysis. An implication of our findings, in particular the pockets of toxicity within subsets of the active trader population, is that the trading technology used by institutions is likely to have an impact on their execution costs. Institutions that disproportionately trade against toxic traders are likely to experience higher transaction costs. The magnitudes imply that carelessly managed execution that unnecessarily exposes large orders to toxicity can have a material effect on a fund’s performance. These findings help understand the concerns raised by institutional investors. At the same time, our results reconcile these concerns with the evidence that HFT and AT as a group seem to be benign or beneficial—the negative effects of toxic traders are offset by significantly beneficial active traders.

Who are the toxic traders? Toxic traders are likely to trade with institutional order flow rather than against it. Such trading patterns could occur from intentionally exploiting institutional order flow (e.g., predatory, order anticipation, or back-running strategies), from unintentionally trading with institutional flow by trading on common entry/exit signals, or through active participation in price discovery in the presence of flow imbalances. In contrast, the beneficial traders are likely to be liquidity-providing intermediaries, employing market making strategies that “lean against the wind”, thereby attenuating price pressure that arises from large institutional orders.
We shed light on the characteristics of toxic traders. We consistently find that speed is not associated with toxicity. For example, a trader’s share of turnover is unrelated to their toxicity. Prior studies show that faster traders account for larger shares of turnover and high turnover is even used as the defining characteristic that separates HFTs from other non-directional traders (e.g., Kirilenko et al., 2015). To the extent that HFT trading accounts are likely to have higher turnover than non-HFT trading accounts, our finding indicates that HFT are no more likely than non-HFTs to be toxic and harm institutional transaction costs. Other characteristics corroborate this finding: toxicity is unrelated to the speed of order amendments, the frequency of fast orders, the consistency with which a trader extracts intraday trading profit, and order-to-trade ratios.

We find that toxic traders tend to concentrate their activity in a subset of stocks and are consistently active in their “preferred habitat”. We find that the preferred habitat tends to be smaller stocks. Finally, we find no difference in the relative activity of toxic traders during a period of market stress in which the market fell sharply compared to other times.

The focus of this paper has been on the diversity of the active traders. Future work might explore the diversity of institutions in contemporary markets. Our finding that the effects of toxic and beneficial traders are substantial in magnitude suggests that the extent to which an institution interacts with these two types of traders or the sophistication with which a large order is executed can have a considerable impact on the cost of executing the order. This raises questions such as do some institutions systematically get exploited? If so which ones and why? To what extent are naïve or unsophisticated execution algorithms to blame? Even in markets before the proliferation of AT and HFT, an unsophisticated execution strategy would result in higher execution costs. Is the institutional investor concern about AT/HFT anything more than this age old issue re-cast in the new high-tech environment?
Appendix A: Further tests of the toxicity functional form

We test the independent effects of presence and activity by estimating the following regression:

\[
I_{\text{Shorfall}}_{it} = \alpha + \sum_{k=1}^{187} \beta_k \text{Presence}_{ltk} + \sum_{k=1}^{187} \gamma_k \text{Activity}_{ltk} + \epsilon_{it}
\]  \hspace{1cm} (A.1)

giving two measures of toxicity for each active trader, \(\hat{\beta}_k\) and \(\hat{\gamma}_k\). The results are shown in Figures A.1 and A.2 below:

Panel A: Toxicity of active trader activity, measured by \(\hat{\gamma}_k\)

Panel B: Toxicity of active trader presence, measured by \(\hat{\beta}_k\)

Fig. A.1. Independent effects of active trader activity and presence.

We test the sensitivity of the toxicity estimation procedure to transformation of the activity measures from bounded variables to continuous ones via logit transformations:
\[
\text{LogitActivity}_{itk} = \ln \left( \frac{\text{Activity}_{itk} + 0.01}{1 - \text{Activity}_{itk} + 0.01} \right)
\]  
(A.2)

and estimating the following regression:

\[
I\text{Shorfall}_{it} = \alpha + \sum_{k=1}^{187} \gamma_k \text{LogitActivity}_{itk} + \epsilon_{it}
\]  
(A.3)

The results are shown below in Figure A.2.

Fig. A.2. Toxicity, estimated using a continuous measure of active trader activity.
Appendix B: Bootstrap procedure

The bootstrap procedure is as follows:

1. Estimate the 2SLS IV models saving the residuals and 187 t-statistics.
2. For each stock $i$, draw with replacement from its residuals to create a pseudo-time-series of resampled residuals in such a way that re-orders the original time-series. Retain the original values of $Activity_{itk}$ in their original chronological order (relaxed in robustness tests).
3. Construct the pseudo-values of $IShorfall_{it}$ using the resampled residuals, imposing the null hypothesis of zero toxicity, i.e., $\gamma_k = 0 \ \forall k$.
4. Estimate the second stage of the IV models saving the 187 t-statistics.
5. Repeat steps 2–4 many (1,000) times to build a bootstrap distribution of the t-statistics for the toxicity estimates $\gamma_k$.
6. Compare the mean, median, quartiles, min, and max of the cross-sectional 187 t-statistics from step 1 against the bootstrap distributions for each of these measures. For example, the bootstrap distribution for the max t-statistic across traders is constructed as the distribution of the maximum t-statistic generated in each of the 1,000 iterations of the bootstrap.
References
Boehmer, E., D. Li, G. Saar, 2016, Correlated high-frequency trading, Working paper.
Jones, C.M., 2013, What do we know about high-frequency trading?, Working paper.
Korajczyk, R., and D. Murphy, 2015, High frequency market making to large institutional trades, Working Paper.
Tong, L., 2015, A blessing or a curse? The impact of high frequency trading on institutional investors, Working Paper.
Table 1
Descriptive statistics

This table reports descriptive statistics for a number of variables calculated at the stock-day level (stock $i$ on day $t$). $\text{Turnover}_{it}$ is the dollar volume of trades per stock-day, $\text{TotalActivity}_{it}$ is the active traders’ share of turnover (“active traders” are the 187 highest non-direction turnover traders), $\text{TotalPresence}_{it}$ is the number of active traders trading a given stock on a given day, $\text{InstoTurnover}_{it}$ is the large institutional order share of turnover (large institutional orders are unidirectional parent orders that are worked in the market for at least two hours and exceed the stock-day’s median unidirectional parent order value), and $\text{IShorfall}_{it}$ is implementation shortfall for large institutional orders. Quartiles are by turnover, with 1 (4) being the highest (lowest) turnover stocks.

<table>
<thead>
<tr>
<th>Quartile Statistic</th>
<th>$\text{Turnover}_{it}$ ($\text{mil}$)</th>
<th>$\text{TotalActivity}_{it}$ (%)</th>
<th>$\text{TotalPresence}_{it}$ (# of stocks)</th>
<th>$\text{InstoTurnover}_{it}$ (%)</th>
<th>$\text{IShorfall}_{it}$ (bps)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Panel A: Pooled sample</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>22.3</td>
<td>48.4%</td>
<td>63.9</td>
<td>19.3%</td>
<td>16.4</td>
</tr>
<tr>
<td>Std.dev.</td>
<td>43.2</td>
<td>13.1%</td>
<td>16.6</td>
<td>10.2%</td>
<td>57.8</td>
</tr>
<tr>
<td>25th percentile</td>
<td>3.1</td>
<td>40.3%</td>
<td>52.0</td>
<td>11.8%</td>
<td>8.7</td>
</tr>
<tr>
<td>median</td>
<td>7.9</td>
<td>49.3%</td>
<td>63.0</td>
<td>18.3%</td>
<td>32.4</td>
</tr>
<tr>
<td>75th percentile</td>
<td>22.1</td>
<td>57.5%</td>
<td>76.0</td>
<td>25.5%</td>
<td>8.7</td>
</tr>
<tr>
<td>Observations</td>
<td>52,873</td>
<td>52,873</td>
<td>52,873</td>
<td>52,873</td>
<td>52,873</td>
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<tr>
<td><strong>Panel B: By quartile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 Mean</td>
<td>67.7</td>
<td>48.1%</td>
<td>82.0</td>
<td>17.9%</td>
<td>10.4</td>
</tr>
<tr>
<td>2 Mean</td>
<td>15.4</td>
<td>51.5%</td>
<td>70.4</td>
<td>20.0%</td>
<td>14.2</td>
</tr>
<tr>
<td>3 Mean</td>
<td>6.3</td>
<td>48.7%</td>
<td>58.9</td>
<td>20.9%</td>
<td>16.4</td>
</tr>
<tr>
<td>4 Mean</td>
<td>2.6</td>
<td>45.6%</td>
<td>46.7</td>
<td>18.4%</td>
<td>23.6</td>
</tr>
</tbody>
</table>
Table 2

**Bootstrap results**

This table reports results from bootstrap simulations that quantify toxicity beyond that which is expected by statistical chance (the bootstrap procedure is described in Appendix B). Panel A reports results from estimating the 2SLS IV model to estimate toxicity using the actual data. The columns min through to max (P=“percentile”) describe the distribution of the 187 toxicity estimate t-statistics (one t-statistic for each of the 187 active traders in the sample). The last four columns indicate how many of the 187 active traders have toxicity t-statistics beyond a certain threshold given in the column heading (e.g., the column with heading \( t < -3 \) displays the number of active traders with toxicity t-statistics less than \(-3\)). Panel B reports examples of the results using simulated data (simulation iterations 1–6 and 1,000). Each simulation iteration recreates a panel dataset similar to the actual dataset (with 187 active traders and institutional transaction costs measured each stock-day) but with the restriction that none of the active traders have a true relation with institutional transaction costs. In each simulation iteration we estimate the same 2SLS IV model and report the results in the same format as for the actual data. Additionally, the last row of Panel B reports means (across the 1,000 simulation iterations) of the number of active traders with toxicity t-statistics beyond a certain threshold. Panel C reports where each of the results using actual data would sit in the distribution generated by the 1,000 simulation iterations in terms of a percentile. Percentiles are recorded as the starting point of the range, i.e., 0 is the 0–1% bucket, 99 is the 99–100% bucket. For example, for the column min, the 52 indicates that the minimum t-statistic of \(-3.61\) in the actual data corresponds to the 52nd percentile of the minimum t-statistics in the 1,000 simulated datasets.

<table>
<thead>
<tr>
<th>Iteration</th>
<th>Distribution of t-values for the 187 active trader toxicity estimates</th>
<th>Number of active traders with toxicity t-values beyond various significance thresholds</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>min</td>
<td>P5</td>
</tr>
<tr>
<td>Panel A: Actual data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>–3.61</td>
<td>–2.37</td>
<td>–1.10</td>
</tr>
<tr>
<td>Panel B: Simulated data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>–2.58</td>
<td>–1.75</td>
</tr>
<tr>
<td>2</td>
<td>–3.09</td>
<td>–1.87</td>
</tr>
<tr>
<td>3</td>
<td>–2.69</td>
<td>–1.73</td>
</tr>
<tr>
<td>4</td>
<td>–3.79</td>
<td>–1.75</td>
</tr>
<tr>
<td>5</td>
<td>–3.04</td>
<td>–1.91</td>
</tr>
<tr>
<td>6</td>
<td>–3.00</td>
<td>–1.88</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>…</td>
</tr>
<tr>
<td>1000</td>
<td>–3.28</td>
<td>–1.85</td>
</tr>
<tr>
<td>Mean</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel C: Actual data in terms of percentiles of the bootstrap distributions

|          | 52 | 0 | 0 | 27 | 31 | 99 | 50 | 98 | 99 | 99 | 98 |
Table 3
Characteristics of toxic trader activity

This table reports results from regressions of trader-level toxicity estimates on characteristics of trader-level activity:

\[ \text{Toxicity}_k = \alpha + \sum c \beta_c \text{ActivityCharacteristic}_{c,k} + \epsilon_k \]

where the dependent variable is estimated gross toxicity in excess of expected toxicity. The \( c \) trader-level activity characteristics are as follows. \( \text{Average Activity} \) is the trader’s average share of turnover averaged across all stock-days. \( \text{Average Stocks} \) is the average number of stocks in which the trader is active per day. \( \text{Cross-sectional StdDev} \) for a trader is calculated by taking their daily cross-sectional standard deviation of the trader’s activity (share of turnover) and then averaging those daily cross-sectional standard deviations. \( \text{Time-series StdDev} \) for a trader is calculated by taking, for each stock, the time-series standard deviation of the trader’s activity (share of turnover) and then averaging those time-series standard deviations. \( \text{Activity in Medium} \) and \( \text{Activity in Small} \) are the trader’s average share of turnover in medium stocks (second quartile) and in small stocks (bottom two quartiles), with \( \% \text{ Activity in Small} \) being a measure of activity in small stocks relative to the trader’s overall activity. \( \text{Activity In Falling} \) is similarly defined as the trader’s average share of turnover during a period when the market fell sharply (August 5–24, 2015), with \( \% \text{ Activity In Falling} \) being the trader’s activity during that period relative to their average activity overall. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>−0.01 (−0.17)</td>
<td>−0.03 (−0.80)</td>
<td>−0.02 (0.04)</td>
<td>−0.27 (−4.32)</td>
<td>−0.01 (−0.18)</td>
<td>−0.03 (−0.65)</td>
<td>−0.27 (−3.86)</td>
<td></td>
</tr>
<tr>
<td>Average Activity</td>
<td>1.24 (0.11)</td>
<td>−1.53 (−0.11)</td>
<td>−304.28 (−2.04)</td>
<td></td>
<td>−22.08 (−0.77)</td>
<td></td>
<td>−8.24 (−0.62)</td>
<td></td>
</tr>
<tr>
<td>Average Stocks</td>
<td>0.10 (0.51)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cross-sectional StdDev</td>
<td></td>
<td>32.27 (2.00)**</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>44.03 (2.27)**</td>
</tr>
<tr>
<td>Time-series StdDev</td>
<td></td>
<td>−32.23 (−1.68)*</td>
<td></td>
<td></td>
<td>−39.33 (−1.97)*</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Activity In Medium</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>87.76 (1.15)</td>
</tr>
<tr>
<td>Activity In Small</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>222.6 (2.89)**</td>
</tr>
<tr>
<td>% Activity In Small</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.83 (3.81)**</td>
<td></td>
<td></td>
<td>0.90 (3.93)**</td>
</tr>
<tr>
<td>Activity In Falling</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>21.43 (0.95)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% Activity In Falling</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.06 (0.65)</td>
<td>−0.02 (−0.19)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.02%</td>
<td>0.20%</td>
<td>1.87%</td>
<td>5.56%</td>
<td>4.19%</td>
<td>0.51%</td>
<td>0.08%</td>
<td>7.00%</td>
</tr>
</tbody>
</table>
Table 4
Characteristics of toxic traders

This table reports results from regressions of trader-level toxicity estimates on trader-level characteristics:

\[ Toxicity_k = \alpha + \sum \beta_c Characteristic_{c,k} + \epsilon_k \]

where the dependent variable is estimated gross toxicity in excess of expected toxicity. The \( c \) trader-level characteristics are as follows. **Holding Time** is the average holding time (in ‘000 seconds) of long or short positions that are closed within a day. **Number Fast** is the number of order amendments (in millions) sent within 500ms of the order submission. **Order Amendment Time** is the average time (in seconds) between an order submission and its amendment for amendments sent within 500ms of the order submission. **Sophistication** is a measure of each trader’s efficiency in generating intraday margin from traded stock (Sharpe ratio of daily trading profit). **Percentage Traded** is the average percentage of the trader’s turnover that is in the form of intraday round-trip trades (i.e., both buying and selling a stock within a day). For a given trader, this percentage is calculated each stock-day, then averaged across stocks (with turnover weighting) and across days (equal weighting). **Turnover** is the natural log of the trader’s average daily turnover. **Number of Orders** is the natural log of the trader’s average daily number of orders submitted. **Order-to-trade Ratio** is the average of the number orders submitted divided by the number of trades executed by the trader in each stock-day. **Cross-sectional StdDev** for a trader is calculated by taking their daily cross-sectional standard deviation of the trader’s activity (share of turnover) and then averaging those daily cross-sectional standard deviations. **Time-series StdDev** for a trader is calculated by taking, for each stock, the time-series standard deviation of the trader’s activity (share of turnover) and then averaging those time-series standard deviations. T-statistics are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10% levels, respectively.

<table>
<thead>
<tr>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
<th>Model 5</th>
<th>Model 6</th>
<th>Model 7</th>
<th>Model 8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>−0.03</td>
<td>−0.01</td>
<td>0.01</td>
<td>−0.06</td>
<td>0.35</td>
<td>0.20</td>
<td>0.99*</td>
</tr>
<tr>
<td></td>
<td>(−0.55)</td>
<td>(0.12)</td>
<td>(0.24)</td>
<td>(−1.31)</td>
<td>(0.78)</td>
<td>(0.46)</td>
<td>(1.95)</td>
</tr>
<tr>
<td>Holding Time</td>
<td>0.01</td>
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<td>0.008</td>
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<td></td>
<td>(0.71)</td>
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<tr>
<td></td>
<td></td>
<td>(0.99)</td>
<td></td>
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<td></td>
<td>(−0.27)</td>
<td>(−0.57)</td>
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<tr>
<td>Order Amendment Time</td>
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<td></td>
<td>−0.13</td>
<td>−0.10</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(−0.30)</td>
<td></td>
<td></td>
<td></td>
<td>(−0.37)</td>
<td>(−0.27)</td>
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<tr>
<td>Sophistication</td>
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<td>−0.05</td>
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<td>−0.09</td>
<td>−0.09</td>
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<tr>
<td></td>
<td></td>
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<td>(−0.80)</td>
<td></td>
<td></td>
<td>(−1.22)</td>
<td>(−1.26)</td>
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<tr>
<td>Percentage Traded</td>
<td></td>
<td></td>
<td></td>
<td>0.25**</td>
<td></td>
<td>0.40**</td>
<td>0.34**</td>
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<td></td>
<td></td>
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<td></td>
<td>(2.07)</td>
<td></td>
<td>(2.53)</td>
<td>(2.12)</td>
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<tr>
<td>Turnover</td>
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<td>−0.04</td>
<td>−0.01</td>
<td>−0.08**</td>
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<td></td>
<td>(−1.20)</td>
<td>(−0.49)</td>
<td>(−2.24)</td>
</tr>
<tr>
<td>Number of Orders</td>
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<td>(1.58)</td>
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<td>(1.36)</td>
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<td>Order-to-trade Ratio</td>
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<td>(1.21)</td>
<td>(1.61)</td>
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<td>Cross-sectional StdDev</td>
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<td>(−1.17)</td>
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<td>Time-series StdDev</td>
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</tr>
<tr>
<td>R-Squared</td>
<td>0.28%</td>
<td>0.67%</td>
<td>0.36%</td>
<td>2.34%</td>
<td>0.39%</td>
<td>0.93%</td>
<td>6.24%</td>
</tr>
<tr>
<td>High turnover</td>
<td>Directional trading</td>
<td>Non-directional trading</td>
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<td>“Institutional investors”</td>
<td>Large fundamental buyers or sellers</td>
<td>“Active traders”</td>
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<td>Low turnover</td>
<td>“Retail and small institutional investors”</td>
<td>“Other”</td>
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<td>Small fundamental buyers or sellers</td>
<td>Algorithmic market making and short holding horizon strategies including various arbitrage algorithms and predatory trading</td>
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<td>Non-algorithmic intermediation, small short holding horizon traders, opportunistic traders</td>
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**Fig. 1. Classification of traders in two dimensions.** This figure shows qualitatively how the two main groups of traders that we analyze are classified (“Institutional investors”, top left quadrant, and “Active traders”, top right quadrant).
Fig. 2. **Active trader share of turnover in stock quartiles through time.** Active traders are the 187 traders with the highest non-directional turnover (buys that are accompanied by sells in the same security within a week and vice versa) throughout the sample period. Their share of turnover is measured each stock-day as the dollar volume of their buys and their sells normalized by the total dollar volume of all buys and all sells. We then compute equal-weighted averages of their share of turnover in quartiles of stocks each month.
Fig. 3. Large institutional orders and their transaction costs for turnover quartiles through time. This figure shows large institutional orders as a percentage of turnover (Panel A) and their average implementation shortfall in bps (Panel B). Large institutional orders are unidirectional parent orders that are worked in the market for at least two hours and exceed the median size of unidirectional parent orders that stock-day. We calculate value-weighted average implementation shortfall for each stock-day and then take the equal-weighted average across stocks in a given turnover quartile each month.
Fig. 4. Toxicity of active traders using the baseline OLS approach. Each point on this figure represents one of the 187 active traders. The vertical axis measures the trader’s toxicity estimate (expressed in log terms) with positive (negative) numbers indicating the trader is associated with increased (decreased) institutional transaction costs. Toxicity estimates are derived from an OLS regression of institution transaction costs each stock-day on each of the trader’s share of turnover that stock-day. The horizontal axis measures the consistency of the trader’s toxicity (log of the standard error of the toxicity estimate) with lower values indicating greater consistency or lower uncertainty about the trader’s toxicity level. The superimposed curve is the approximate “toxicity frontier”, i.e., the collection of active traders that have maximum estimated toxicity for a given level of uncertainty about the toxicity estimate or a minimum level of estimation uncertainty for a given level of toxicity. The size of the circles indicates the statistical significance of the toxicity estimate, from insignificant at the 10% level (smallest circles) to significant at the 10%, 5%, and 1% levels (largest circles). Numbers next to the largest circles are masked (anonymized) trader identifiers.
Panel A: Model with stock fixed effects

Panel B: Model with date fixed effects

Panel C: Model with both stock and date fixed effects

Fig. 5. Toxicity of active traders using OLS approach and fixed effects. Each point on this figure represents one of the 187 active traders. The vertical axis measures the trader’s toxicity point estimate (expressed in log terms) with positive (negative) numbers indicating the trader is associated with increased (decreased) institutional transaction costs. The horizontal axis measures the consistency of the trader’s toxicity (log of the standard error of the toxicity point estimate). Toxicity estimates are derived from an OLS regression of institution transaction costs each stock-day on each of the trader’s share of turnover that same stock-day, similar to Figure 4, but with stock fixed effects (Panel A), date fixed effects (Panel B), and both stock and date fixed effects (Panel C).
Fig. 6. **Toxicity of active traders using 2SLS IV regressions.** Each point on this figure represents one of the 187 active traders. The vertical axis measures the trader’s toxicity point estimate (expressed in log terms) with positive (negative) numbers indicating the trader is associated with increased (decreased) institutional transaction costs. Toxicity estimates are derived from two-stage least squares instrumental variables regressions in which active trader activity is instrumented with lags of their activity in the same stock. The horizontal axis measures the consistency of the trader’s toxicity (log of the standard error of the toxicity point estimate) with lower values indicating greater consistency or lower uncertainty about the trader’s toxicity level. The size of the circles indicates the statistical significance of the toxicity estimate, from insignificant at the 10% level (smallest circles) to significant at the 10%, 5%, and 1% levels (largest circles). Numbers next to the largest circles are masked (anonymized) trader identifiers.