Short-term trading skill: An analysis of investor heterogeneity and execution quality*

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Abstract

We examine short-horizon return predictability using a novel data set of institutional trades on large-cap U.S. stocks. We estimate investor-specific short-term trading skill and find that there is pronounced heterogeneity in predicting short-term returns among institutional investors. Incorporating short-term predictive ability, our model explains much higher fraction of variation in asset returns. Ignoring the heterogeneity in short-term trading skill can have major implications in modeling price impact. We uncover several stylized trading patterns of skilled trading: skilled investors choose larger trade sizes, avoid dark pools, and trade fewer stocks on any given day, but they do not time high-liquidity periods.

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1. Introduction

Institutional investors engage in costly information acquisition to generate trading strategies that can lead to high risk-adjusted returns. Consider a portfolio manager who has information about a particular stock at a particular time. Her private signal suggests that the stock price may appreciate by up to 1% by the end of the trading day. If she has enough capital, she may want to build a large long position in this stock. To execute this large trade, she sends a large buy order to her broker. The broker will then execute this large parent order in small child orders and each executed child order may gradually increase the future transaction prices based on the strength of the broker's algorithm and short-term supply/demand dynamics in the market. If the portfolio manager's information is correct, the stock price will also increase gradually in the absence of her large order. In these circumstances, it is very difficult to estimate the price impact of the large order due to the portfolio manager's trade initiation. Using a novel data set with intraday timestamps, we propose an empirical estimation methodology to overcome this challenge by decomposing the total price impact realized during a large order execution into two components: (1) an investor-specific "trading skill" component, which captures the timing of the decision to trade relative to favorable or unfavorable short-term price movements; and (2) a market impact or price impact component, which measures investor-independent execution costs.

In a typical algorithmic trading situation, where an investor executes a large order through a broker's algorithm, the investor rarely communicates their short-term price views directly to this broker. Instead, investors might implicitly express their signals by choosing the asset, direction, and start- and end-time. By not accounting for short-term trading skill, any subsequent transaction cost analysis may misestimate the price impact associated with the investor's trades.

Empirically, documenting the trading skill of the investor is very difficult. For example, using an informative signal, a short-term skilled investor may initiate a large order with her broker at 2:05 pm and request an expected completion by the market close at 4:00 pm. Typical public databases, like the Trade and Quote (TAQ) database, would not allow the researcher to identify the series of child orders originating from the parent order. Similarly, proprietary databases utilized in the literature, like the data compiled by Ancerno Ltd. (formerly the Abel/Noser Corp.), would not have high-frequency timestamps that provide the exact initiation time of the large order and do not have any information about its subsequent child order executions.[1] In this paper, we utilize a distinctive data set with millisecond timestamps of order initiation times to uncover the heterogeneity of investors' short-term trading skill. We jointly estimate an investor-dependent short-term trading skill and an investor-independent measure of execution costs by considering short-term trading skill as an investor characteristic. Besides the usual price impact factors such as the relative size of the order, speed and volatility, the model introduces the investor's short-term predictive ability in the form of a risk-adjusted performance metric as in the typical usage with Sharpe ratio. The risk-adjusted measure of short-term trading performance allows our model to capture the dependence of future price movements when an investor wants to trade an asset at a specific point in time.

We apply our proposed model on a unique and proprietary data set consisting of masked investor identifiers and their intraday U.S. equity transaction data from 2011 and 2012 on large-cap stocks. Our estimation results point to the presence of skilled short-term investors in the data. They are the ones who systematically buy (sell) an asset during a period when the asset return is positive (negative). In addition, we find strong evidence for the presence of unskilled investors in our data. They systematically decide to buy (sell) the asset during a trading interval when the asset return is negative (positive) on average. We use the terms, skilled and unskilled, to highlight the timing ability of the investor as the prices move in the same direction as his trading.

Since we have access to masked client identifiers along with granular execution-level statistics, our estimated skill coefficients can be examined to answer various questions debated in the microstructure literature. For example, we can study whether measures of illiquidity capture the short-term information asymmetry reflected in the skill estimates. Similarly, we can test whether various trading decisions differ across skilled and unskilled investors. For example, do skilled investors select larger order sizes? Do unskilled investors prefer round order sizes? Do skilled investors prefer lit exchanges? Our data set and estimation results allow us to study all of these questions in an out-of-sample data set.

Accurate estimation of price impact is an important concern for portfolio managers. They rebalance their portfolios according to their investment views and will determine an optimal trading amount based on their return forecasts and cost of trading (e.g., Gârleanu and Pedersen, 2013). We show empirically that short-term trading skill nuances across investors may bias the price impact

[1]For example, Anand et al. (2012) and Edelen and Kadlec (2012) utilize Ancerno's data.

estimates. Addressing this bias is an important concern, as price impact coefficients are routinely used to evaluate various policy issues. For example, one significant issue in modern markets is whether dark pools have better execution quality compared to traditional lit exchanges. There is evidence from both theoretical and empirical literature that heterogeneity in trading skill may affect the choice of selecting different venues for trading needs. Zhu (2014) and Iyer et al. (2015) argue that informed traders strategically choose the lit markets for their execution needs, whereas dark pools are relatively more attractive to uninformed traders. Consequently, a naïve execution cost analysis that does not take this into account may systematically suggest that (assuming all else is equal) dark pools have better execution quality.

Heterogeneity in short-term trading skill has important implications for measures of execution costs, such as the implementation shortfall (IS), introduced by Perold (1988). Since skilled traders typically predict short-run future returns, the cost of their trades appears high when compared to the trades of a benchmark noise trader. Similarly, because unskilled traders make trading decisions that are systematically opposite to short-term returns, the execution costs of their trades appear low when compared to a noise trader. As a result, measured execution costs may not be an unbiased estimate of the true cost of trading, which has been the crucial measure of transaction costs in the literature.[2]

In summary, our empirical analysis yields the following main findings:

1. There is strong evidence for investor heterogeneity in short-term trading skill. We find that approximately one-third of the investors are systematically skilled or unskilled relative to the rest. In other words, an ability to predict short-term price changes may be a significant motivation for many investors in our sample to trade an asset at a specific point in time. We provide a supplementary analysis on bootstrapped samples to provide evidence that the numbers of skilled and unskilled investors are abnormally high.

2. Short-term trading skill significantly increases the power of the model in explaining the variation of returns relative to arrival price. In fact, including investor-specific skill variables improves the R^2 of the model relative to a model that only considers the price impact of or-

[2]For example, Brogaard et al. (2014) and Tong (2015) examine the impact of high-frequency trading on the executions costs of institutional investors using IS. Similarly, Korajczyk and Murphy (forthcoming) and van Kervel and Menkveld (forthcoming) use IS to study the interaction between high-frequency liquidity provision and large order institutional executions.

ders by an order of magnitude, from 0.5% to 10%. In other words, the identity of an investor who wishes to trade is highly predictive of future price movements relative to considering only the orders the investor places. Moreover, ignoring investor identity may result in systematic misestimation of the price impact of trades. Our results are robust to alternative model specifications and execution cost measures. We can predict out-of-sample returns using skill coefficients estimated from in-sample data.

3. We examine the correlation between short-term trading skill and ex ante stock-level characteristics and our findings largely imply that skilled trading prevails in stocks that have weak information environments. We then use a simple measure of information-based trading based on permanent price changes and show that our skill estimates are correlated with this measure using out-of-sample data. In other words, our classification of skilled and unskilled traders is consistent with their ability to predict future returns in the short-term. We find evidence that skilled traders are better at following momentum-based trading strategies compared to unskilled traders. These findings do not directly imply that unskilled investors are losing money in the long-run. These investors are possibly long-term investors who are ignoring short-term predictable patterns.

4. We analyze the trading decisions of skilled and unskilled investors using an out-of-sample data set and provide several stylized trading patterns. First, we find that skilled investors do not have liquidity timing ability. Instead, several measures of illiquidity seem to be positively correlated with skilled trading, suggesting that these measures capture the information asymmetry. Second, skilled traders differ significantly from unskilled investors by trading (relatively) larger orders and trading more in lit markets. Third, unskilled traders are more likely to trade large sets of stocks on a single day. Finally, we find that the use of round order sizes or clustering around round prices is not correlated with the skill level of the investor.

We demonstrate that short-term predictive ability is very heterogeneous among an institutional investor base. This is consistent with theoretical agent-based microstructure models where information asymmetry provides a major motivation to trade (e.g., Easley et al., 2002). Moreover, while informed and uninformed investors are the focus in the literature, our results reveal the presence of another type of investor who systematically places orders in the opposite direction of short-term future returns.

From a policymaker perspective, our results illustrate that mere comparison of execution costs cannot be a standalone measure of execution quality. Venues populated either with skilled or unskilled traders may have misestimated measures of execution quality if the heterogeneity in short-term trading skill is ignored. Consequently, these biased estimates may not lead to an optimal policy recommendation. Our methodology could be utilized in the study of the Consolidated Audit Trail (CAT) that will be updated significantly in November 2018 (Michaels, 2016). Thus, we expect that the regulators may soon be able to run price impact models using a data set with trader identities.

From a practical perspective, our methodology and findings have broad applications where trader identities are readily available. First, from the perspective of a single institutional investor who seeks to estimate price impact in order to better understand and account for transaction costs, our results suggest that price impact should be measured only on the investor's own historical trades. Second, from the perspective of large institutional investors who aggregate executions across distinct internal strategies (e.g., a multi-strategy hedge fund), our work suggests that the estimation of price impact should account for the origination of each order. Finally, brokers who algorithmically execute large orders on an agency basis for clients can improve decision-making throughout the trading process by accounting for the short-term trading skill of the investor.

The rest of the paper is organized as follows: In Section 2, we present a brief literature review and highlight our contributions relative to these studies. In Section 3, we review the relevant theoretical models that guide our empirical framework. In Section 4, we set up the underlying statistical model. We describe our experimental study in Section 5, while Section 6 contains our model estimation and analysis. In Section 7, we examine the robustness of our results and provide strong evidence for our interpretations with investor heterogeneity in short-term trading skill. In Section 8, we present empirical analysis on the determinants of short-term trading skill. We discuss the differences in the trading decisions of skilled and unskilled investors in Section 9. Finally, we conclude in Section 10.

2. Literature review

Our paper is mainly related to the empirical microstructure literature studying the granular transaction data of institutional investors. We first review this strand of the literature and highlight our contributions.

Using the transactions of 37 money managers, Chan and Lakonishok (1995) find that growth-oriented strategies incur higher transaction costs due to differences in their demands for immediacy. Using equity executions from 21 institutional traders, Keim and Madhavan (1997) find that total trading costs for a technical-style investment strategy is higher compared with a value-style investment strategy. Intuitively, they relate this finding to the differences in aggressiveness as value investors trade patiently via worked orders. These authors mainly study the variation in execution skill across institutional investors. Controlling for differences in trading schedules or demands for immediacy, we complement these studies by focusing on a fundamentally different theme. In our model, heterogeneity across investors does not stem from better trading schedules as this is ultimately controlled by the same algorithm of the broker used by all of the investors in our data set. In our context, investors differ with regards to their success in timing favorable short-term price changes.

In this literature, the most closely related paper to ours is Anand et al. (2012). They document that institutional trading desks have persistent trading costs – institutions that have low trading costs continue to have low trading costs over time at the aggregate quintile level. They use institutional transaction data from Ancerno and regress IS on institutional fixed effects, along with other determinants of execution costs. They consider skill in the context of minimizing execution costs via choosing brokers, algorithms or specific trade instructions (e.g., using limit orders with a particular price). Instead, we examine trading skill in the context of the timing ability of the investor (i.e., initiating a trade due to a particular view about expected price changes). The trades are executed by a single broker with two known algorithms, thus we can capture and focus on the timing ability of the investors instead.

More importantly, the Ancerno data set is reported not to provide reliable intraday timestamps (e.g., Brogaard et al., 2014) so in these data, it is only possible to know the start- or end-time of an execution at the stock-day level, whereas in our data set the start- and end-time is timestamped to the millisecond. Therefore, with Ancerno data set, an investor's timing ability cannot be measured accurately as the price of the asset may change significantly intraday. Further, this data set would not allow the researchers to compute price impact measures based on the participation rate, the ratio of order size to the interval volume, as it is not possible to compute the exact volume realized during the execution period. Almgren et al. (2005) document that participation rate is the primary driver of price impact, thus we complement Anand et al. (2012) by utilizing a more granular and informative data set.[3] Our data also include additional information on the executed child orders, which allows us to study the sensitivity of the trading skill with regards to trading in dark pools or lit venues, which has not been examined in the literature. Finally, to our knowledge, our paper is the first to document the substantial increase in explaining the variation in asset returns when client identifiers are estimated in a risk-adjusted setting.

A large literature on institutional trading activity addresses the question of whether institutional investors are informed. Yan and Zhang (2009) argue that this relationship is driven by short-horizon institutions. Using intra-quarter data, Puckett and Yan (2011) find that institutional investors are skilled even after accounting for trading costs. In a more recent study using news analytics, Hendershott et al. (2015) find that institutional investors are informed and their trading direction can predict the sentiment of the future news. Di Mascio et al. (2017) also find that sophisticated fund managers are highly successful at forecasting risk-adjusted returns at the short- or medium-term horizon. We complement these studies by finding empirical evidence for the presence of both skilled and unskilled investors in regards to predicting short-run returns.

The relationship between trading activity and asset prices in financial markets has been an important question in the economic microstructure literature for several decades. The theoretical origins of price impact arise from the presence of informed traders as, for example, in the celebrated models of Glosten and Milgrom (1985) or Kyle (1985). As a result, a line of literature has emerged focusing on the empirical analysis of the impact of trades on prices, motivated by the economic question of understanding the role of information asymmetry in markets. This work is nicely summarized by Hasbrouck (2007) and it is still actively pursued (see Easley et al., 2012).

More recently, however, with the rise of electronic and algorithmic trading, a new line of literature has emerged. Motivated by the concerns of practitioners, this literature focuses on the decision problem faced by an investor seeking to algorithmically spread his trades out over time, in order to minimize execution costs. A key ingredient in such algorithmic trading is the estimation of the

[3]Anand et al. (2012) instead control for the ratio between order size and the past 30-day volume.

effect of a sequence of child orders placed by an algorithm executing an investor's parent order on the asset price across future time horizons. The most notable early works here are those of Bertsimas and Lo (1998) and Almgren et al. (2005). More broadly, Bouchaud et al. (2008) provide a summary of theoretical and empirical results on models that predict the impact of trades on prices, bid-ask spreads, and other market dynamics over time. They theorize that much of these dynamics can be explained by the presence of algorithmic traders strategically spreading their orders across time. Edelen and Kadlec (2012) provide a theoretical model to examine the agency conflicts arising from the trading arrangements between the portfolio manager and the trading desk executing the trades. The model implies that the trading desk implicitly prefers to execute orders contrary to the information flow (i.e., execute sell orders as prices increase and execute buy orders as prices decrease). Using Ancerno data, they find empirical support for the model by finding institutional trades executed contrary to the market returns. We complement this paper by providing empirical evidence of heterogeneous short-term trading skill across investors with regards to their timing ability.

A closely related question is the estimation of overall transaction costs for large block trades (e.g., Keim and Madhavan, 1996; Almgren, 2010). These cost functions play an important role in portfolio optimization and other pre-trade analysis. Obizhaeva (2009) estimates such trading cost functions using a data set of large portfolio transitions. Kyle and Obizhaeva (2016) provide a theoretical model that seeks to explain the cross-sectional variation of trading costs across a universe of stocks. Hendershott et al. (2013) propose an approach for measuring the temporary component of the total trading cost of a large execution. Our work extends this line of inquiry by explicitly including investor identity as a predictive factor of order execution costs.

3. Theoretical background

In this section, we briefly review the relevant theoretical models that guide our empirical work. Specifically, we summarize potential theories regarding the short-term price movements around large order executions.

In a survey of market microstructure, Biais et al. (2005) summarize two main competing theories for price formation, which is also applicable for executions of large orders: inventory (liquidity) and information (adverse selection) paradigms. In the inventory paradigm (e.g., Ho and Stoll, 1981), uninformed investors trade with risk-averse market makers who can control the order flow by changing their quotes. For example, when an uninformed investor buys (sells) a large number of shares for liquidity needs, market makers are forced to a net short (long) position deviating from their preferred inventory positions. In this case, they raise (lower) their bid and ask quotes to bring their inventory back to their preferred position, which leads to increase (decrease) in mid-quote prices. In the information-based trading paradigm (e.g., Glosten and Milgrom, 1985; Kyle, 1985), an investor trades a large order due to his private information about the fundamental value of the asset and thus the market maker accounts for the information content of the order and sets his quotes accordingly. In this framework, prices are formed according to the expectations of the value of the asset conditioned on the realized order flow and consequently buy (sell) orders imply higher (lower) valuation and increase (decrease) equilibrium prices. Another difference between these theories is their different implication on the transitory or permanence of the price impact. Liquidity-based trading causes a temporary price impact, whereas information-based trading moves the prices permanently. Thus, if skilled trading arises from superior predictive ability (based on short-term information), then skilled trading should also be correlated with the informational content of the large order.

The literature mostly focuses on two types of traders, informed and liquidity. However, information based-trading models can be generalized to accommodate investors with differing beliefs. For example, Easley et al. (2002) propose an information-based theoretical model in which there is investor heterogeneity with regards to their beliefs of expected returns and the correctness of these priors. Therefore, it is also possible to observe unskilled investors who are systematically deciding to buy (sell) the asset during a trading interval when the asset return is negative (positive) on average due to heterogeneous beliefs. Their trades can be profitable in the long-term but they can be subject to short-term losses.

Another reason for unskilled trading can emerge from behavioral biases in decision-making. Based on findings of prospect theory, Shefrin and Statman (1985) document the investor's tendency to sell winners too early and ride losers too long. They refer to this behavior as "the disposition effect." Empirical evidence suggests that this behavior is more pronounced for individual investors. This theory suggests that a liquidity trader prone to the disposition effect will suboptimally sell (buy) a stock if it has recently realized large positive (negative) returns and as the asset value continues to increase (decrease), the liquidity trader will be subject to short-term losses.

These theories suggest that there may be investor-specific short-term trading skill originating from information-based trading (correct beliefs) or insensitivity to behavioral biases. Furthermore, considering the inventory paradigm, there is also an investor-independent measure of price impact that serves as the market maker's compensation for inventory risk. Thus, it is an empirical question to determine the most important drivers of short-term price movements during a large execution among these potential factors of price impact.

4. The model

We consider a population of J investors sending a total of N orders to an executing broker. The mapping $i \xrightarrow{c} j$ identifies order i, $i = 1 \ldots N$ as belonging to investor $j = c(i)$, with $j = 1 \ldots J$. Each order is for a quantity of Q_i shares of an asset, with $Q_i > 0$ ($Q_i < 0$) for buy (sell) orders, respectively. Each order also has an execution duration of T_i, measured as a fraction of the trading day. We define the participation rate as $\rho_i \triangleq |Q_i|/V_i$, where V_i is the total market volume traded within the interval T_i. The arrival price $P_{i,0}$ is the last traded price prior to the order's arrival and the terminal price is the last execution price P_{i,T_i}. In our model, given order i, we consider the expected return of the asset over the execution interval T_i, that is, $\log(P_{i,T_i}/P_{i,0})$. We posit that this return is driven by two predictable effects. The first effect is short-term trading skill. Some investors will be able to predict short-term asset returns using models of return predictability or correct beliefs. Thus, we expect this impact to be persistent in the short-term. Conditional on the arrival of a buy (sell) order i, we expect a return in the asset price of $\alpha_{c(i)}\sigma_i\sqrt{T_i}$ over the execution interval T_i. Here, the coefficient $\alpha_{c(i)}$ represents the short-term predictive ability of investor $c(i)$ and σ_i is the daily volatility of the mid-quote of the asset price, typically estimated as an average of daily volatilities over the prior month. $\alpha_{c(i)}$ can be positive, zero, or negative, which can be interpreted as skilled, unidentified or unskilled, respectively. Note that this predictive ability is parameterized in a risk-adjusted fashion, i.e. we assume that each particular investor has a constant short-term Sharpe ratio or information ratio over all of the trades.[4]

[4]Here, we ignore the role of a benchmark risk-free return in the definition of a Sharpe ratio, i.e., we do not consider excess returns. This is reasonable since the risk-free return is effectively zero over the intraday time horizons

The second effect is price impact, or, the direct effect of the trades placed on behalf of the investor. The price impact for order i is given by $\lambda\sigma_i\sqrt{T_i}h(\rho_i)$. Here, λ is a (broker-specific) price impact coefficient. We normalize the price impact component with the volatility of the asset during an execution horizon captured by $\sigma_i\sqrt{T_i}$, so that we represent the impact as a fraction of the typical movement of the stock return. Transaction cost models sometimes include a bid-offer spread term to incorporate stock-specific liquidity costs. However, since we are modeling returns over the execution horizon as opposed to the average cost, we did not include spreads in our baseline specification. In Subsection 7.1, we include various controls and stock fixed effects in the price impact specification and our findings remain largely unchanged. Our price-impact assumption is consistent with the literature (e.g., Almgren et al. (2005)). On theoretical front, Keim and Madhavan (1996) derive price impact as a concave function of the trade size. Similarly, Chacko et al. (2008) also find that the expected price impact is proportional to the volatility and empirically validates this claim.

The price impact function $h(\cdot)$ captures the effect of the participation rate (or trading speed) on price. The idea here is that orders executed with a higher participation rate will have a larger price impact. In order to illustrate the robustness of our results with respect to our price impact formulation, we will consider two explicit forms for the price impact function: a linear price impact function, i.e.,

$$h(\rho_i) \triangleq \rho_i,$$

or a square root price impact function, i.e.,

$$h(\rho_i) \triangleq \rho_i^{1/2}.$$

The choice of sublinear price impact has been extensively studied both theoretically and empirically. There is a long line of literature supporting the choice for a square root price impact law. For example, Chacko et al. (2008) provide empirical evidence that the expected price impact is proportional to the square root of the quantity traded. Using a large sample of equity trades in the United States, Almgren et al. (2005) also estimate the exponent to be very close to 0.5. This

of interest. Further, note that we do not scale Sharpe ratio with the square root of the investment horizon (as typically done with longer horizons in asset management). In Subsection 7.4, we explore an alternative specification where we define $\alpha_{c(i)}$ to be a daily Sharpe ratio that is scaled by the square root of the length of the execution horizon, and find that both models provide very similar findings.

exponent is also consistent with the well-known Barra model™ for market impact costs outlined in Torre and Ferrari (1998).

Putting everything together, we assume that the sign-adjusted log-return of an order relative to the arrival price and over the execution horizon can be expressed as an additive model of the form:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \alpha_{c(i)}\sigma_i\sqrt{T_i} + \lambda\sigma_i\sqrt{T_i}h(\rho_i) + \epsilon_i\,, \tag{1}$$

with ϵ_i having a mean of zero and variance of ν_i^2.

Explicit forms of the impact function $h(\cdot)$ fully specify the model as a linear regression of the risk-normalized interval return against short-term trading skill and broker impact. For example, with a linear price impact function we obtain:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i + \epsilon_i\,, \tag{2}$$

with $\mathbb{I}$ the indicator function. Likewise, a square root impact function leads to the following model:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i^{1/2} + \epsilon_i\,. \tag{3}$$

When fitted on a historical sample of short-term execution returns, the models in equations (2) and (3) identify the short-term trading of each investor j, along with the impact coefficient.[5] We present our data set and model estimation results in Section 6.

5. Data

We use novel proprietary execution data from the historical order databases of a large U.S. investment bank ("the Bank"), which is one of the top five electronic trading brokers in the U.S. by market share. The orders originate from a diverse pool of investors, such as institutional portfolio

[5]The models in equations (2) and (3) could also be expressed in terms of the arrival slippage $\log\left(\bar{P}_i/P_{i,0}\right)$ instead of the interval return $\log\left(P_{i,T_i}/P_{i,0}\right)$, where $\bar{P}_i$ is the average execution price of the i-th order. This would lead to an approximate rescaling of the coefficients $\alpha_{c(i)}$ and λ by a factor of 1/2. The execution algorithms considered here trade at a constant participation rate. Therefore, the execution price $\bar{P}_i$ is close to the realized interval VWAP, and for a price path with a constant drift, the VWAP return is half of the interval return.

managers, quantitative investment funds, internal trading desks, and other brokers who aggregate their retail order flow.[6] For ease of reference, we refer to our investor universe as "institutional investors."

Our data set consists of the two most widely used algorithmic execution strategies: volume-weighted average price (VWAP) and percentage of volume (POV). These algorithms collectively constitute roughly 75% of all execution strategies employed by the Bank. The VWAP algorithm aims to achieve an average execution price that is as close as possible to the volume-weighted average price over the execution horizon. The main objective of the POV algorithm is to have a constant participation rate in the market within the execution interval. VWAP and POV have relatively small discretion on opportunistically speeding up or slowing down the execution. Execution aggressiveness is mainly controlled by the investor choosing a particular time horizon for VWAP, or a target participation rate for POV. With VWAP and POV algorithms, we eliminate any potential broker-specific effects, such as the usage of short-term order book imbalance, price action signals, or market events that drive more opportunistic algorithms. Recall that the trading skill is based on the investor's timing ability but not on the execution skill. Thus, if we were to have more sophisticated algorithms in our data set, one might argue that skilled traders may actually be just better in choosing algorithms. However, with VWAP or POV, an investor can only have superior short-term trading skill by starting the execution at a particular time.[7]

Although these two algorithms constitute the majority of the execution volume, we ultimately employ a subset of each investor's trading volume targeted to this specific Bank and its two algorithms leading to a potential selection bias. Investors may also use different brokers and trading algorithms during this period; thus, we estimate their skill corresponding to the specific subset at hand.

Our data set provides a rich set of attributes. For each order i, we have access to the following: investor identity tag,[8] $c(i)$, ticker of the traded stock, order size, Q_i, order side (buy/sell), $\operatorname{sgn}(Q_i)$, execution duration, T_i, participation rate, ρ_i, average volatility of the stock over the last 20 trading days, σ_i, the percentage return over the execution interval, $P_{i,T_i}/P_{i,0} - 1$. These data allow us to

[6] The data set only reports the masked identity for the broker so there is no information at the retail investor level.

[7] The delay between the submission of the order to the broker and the execution start time is on the order of milliseconds if the order is sent during market hours.

[8] Investors are identified by numerical aliases to protect anonymity.

fully estimate the model of Section 4. In addition, our data include the daily, average (i.e., over the last 20 trading days[9]) and interval (i.e., during the execution horizon) proportional bid-ask spread, mid-quote volatility, and traded volume for each stock.

We filter the execution data with similar selection criteria employed by the Bank for its development of price impact models. Specifically, the following filters are used:

- The trading period is from January 2011 to June 2012, inclusive.
- The asset universe consists of the S&P 500 stocks. We focus on highly liquid stocks to focus on the differences in short-term predictive ability as a result of following a certain set of strategies. For this set of stocks, it is hard to have an investor trading with insider information.
- Orders come from active investors only: an investor is considered active if he has at least 100 and at most 500 orders within the period of study. Clients with small number of executions (<100) are eliminated as their estimated skill terms may not be reliable with fewer observations. Clients with high number of executions (>500) are filtered out to have a balanced data set across clients and prevent any specific investor from fully driving our estimation results.
- All orders have been fully filled during regular market hours or in the opening and closing auctions. We do not allow intermediate replacements or cancellations. This is to avoid investors that seek manual micro-management of the algorithmic execution.
- The execution duration is greater than 5 minutes but no longer than a full trading day. We exclude executions that last less than 5 minutes to avoid any short-term effects from market orders. We also limit the execution horizon to one trading day, primarily because broker systems are configured to operate on a daily basis. Identification of individual client orders is reliable within a trading day. Across days, orders are subject to overnight quantity revisions by clients and order identities are not linked.

Using the above criteria, our final sample consists of 63,379 executions coming from 30,438 buy and 32,941 sell orders.[10] The trading algorithms used are 41,339 VWAP and 22,040 POV.

[9]Throughout the analysis, we refer to this measure as the average over the past month for conciseness as there are 21 trading days in each month on average.

[10]On average, each parent order has approximately 120 child-order executions, so the total number of trades is roughly 10 million.

The orders came from a set of 293 active investors, with 216.3 parent orders per investor and 168 orders per trading day, on average. The highest number of executions on a single stock is 454, which corresponds to 0.71% of all executions. Table 1 provides additional summary statistics for our sample.

[Insert Table 1 here]

The average percentage return realized during the execution interval is 0.3 bps. We observe that bid-ask spread and volatility lay in a tight range. More than half of the executions have a bid-ask spread between 2 bps and 5 bps and a mid-quote annualized volatility between 15% and 27%. The mean duration of the executions is a little less than 2.5 hours. Finally, we have a wide range of participation rates across executions, with an average (median) of 6.44% (1.59%).

Our data set has a number of advantages but it also has a few shortcomings. Compared to the frequently used institutional trading data set by Ancerno, our data set has the exact identification of the execution start- and end-time (i.e., order duration), the interval volume during the execution (i.e., participation rate), the algorithm type (i.e., VWAP or POV), and interval return. Further, we have information on the executed child orders (e.g., the price, quantity, and execution venue of the child order). On the negative side, as highlighted earlier, our data set only includes a subset of each investor's trading. Investors may also use different brokers during this period, thus, we are measuring their skill corresponding to the particular subset we observe. Second, our data come from the active universe of this broker's clientele, so our analysis might actually understate the true heterogeneity in short-term trading skill, relative to the overall broader universe of investors who are active in this market.

6. Model estimation results

We analyze the execution data using our full model with two price impact specifications: linear price impact as in (2) and square root price impact as in (3). We also fit a reduced model to the data by ignoring trading skill terms, i.e., $\alpha_j = 0$,

$$\operatorname{sgn}(Q_i) \log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \lambda^{\mathsf{base}} \sigma_i \sqrt{T_i} \rho_i^{\gamma} + \epsilon_i \,, \tag{4}$$

where $\gamma = 1$ for the linear model and $\gamma = \frac{1}{2}$ for the square root model. We use a superscript, base, to emphasize the difference between the reduced and full models. We are concerned with heteroscedasticity, contemporaneous correlation across stocks, and auto-correlation within each stock and adjust our standard errors by clustering on calendar day and stock throughout the analysis, as suggested by Petersen (2009).

In this section, we first present the differences between the reduced and the full model with respect to the price impact coefficient and adjusted R^2. Then, we illustrate the cross-sectional distribution of short-term trading skill across investors.[11]

6.1. Price impact coefficients and R^2

In Table 2, we summarize the regression results from the full and the reduced model. These results lead to a number of interesting observations. First, consider the price impact parameter, λ. In all cases, the estimate of λ is statistically significant. The square root model in the absence of trading skill corresponds to the well-known Barra market impact model™, as outlined in Torre and Ferrari (1998). Here, our estimate of λ is of order unity, which is consistent with the literature. Yet, we observe that without accounting for investor's short-term trading skill level, price impact by itself has a very low explanatory power with the maximum adjusted R^2 of 0.52% from both models. The linear price impact model has a relatively better fit than the square root price impact model, even though the difference is negligible. However, the inclusion of the short-term trading skill term substantially increases the goodness-of-fit, leading to an adjusted R^2 of approximately 10%. This significant difference illustrates that the variation in short-term returns can be explained much better when the systematic short-term trading skill of the investor is acknowledged.[12] Consistent with these results, a reduced model excluding the price impact term provides an adjusted R^2 of 9.9%, but this reduced model is rejected with an F–test when compared to the full model with the price impact term.

[Insert Table 2 here]

[11] In Appendix A, we use bootstrap analyses to examine the statistical significance of the biased price impact coefficient in the reduced model, as well as the presence of short-term trading skill.

[12] To highlight the economic significance of this increase, it is worth noting that 500 stock dummies and various controls move the adjusted R^2 by a mere 0.3% as reported in our analysis in Subsection 7.1.

Moreover, if we ignore the predictive abilities of the investors, we observe that price impact is misestimated. If the price impact is linear in the participation rate, then accounting for the timing ability of the investors reduces the price impact coefficient by approximately 20%. This is also observed for the square root model, but to a lesser degree.[13]

In summary, we observe that accounting for investor heterogeneity in short-term trading skill explains much higher variation of asset returns during an execution. We observe that the usual practice of ignoring the investor-specific view may introduce a systematic bias in price impact estimates. We further investigate this implication in the context of execution costs in Subsection 7.3, and find that the standard measure of execution cost, implementation shortfall, also depends on short-term predictive ability with statistical significance.[14] However, we would like to acknowledge that computing the exact bias in price impact estimates is empirically very challenging as trading decisions and resulting price movements are determined in equilibrium and there may be further omitted variables correlated with them. Therefore, our findings should be interpreted with caution and taken as an evidence that the bias is theoretically possible.

6.2. Heterogeneity in short-term trading skill

We also observe that there is significant investor heterogeneity in predicting short-term returns. We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and statistically significant under the 10% level. We label the remaining investors as unidentified. Table 2 reports that with the linear price impact model, 49 out of 293 investors are skilled, while 48 investors are unskilled and 196 investors are unidentified. With the square root price impact model, the alpha estimates slightly drop as the square root model puts more weight on the price impact unilaterally. Figure 3 illustrates this drop in Sharpe ratio estimates graphically. In this case, we find that 36 investors are skilled and 63 are unskilled. In both models, approximately one-third of our investor universe is skilled or unskilled.[15]

[13]The standard errors do not allow us to conclude that the difference between $\hat{\lambda}$ and $\hat{\lambda}^{\mathsf{base}}$ is statistically different. For this reason, we use a bootstrapping analysis in Appendix A to compute the empirical probability that $\hat{\lambda}$ is less than $\hat{\lambda}^{\mathsf{base}}$.

[14]In unreported results, we have also re-run our models using the interval VWAP as the benchmark price (instead of the arrival price) when computing the interval price change and confirmed that our findings are qualitatively very similar.

[15]Evaluating short-term trading skill for a large number of investors can be viewed as a multiple hypothesis testing problem. By random chance, some investors may appear to have significant α coefficients. Consequently, the number of skilled or unskilled investors may not be statistically significant in our data set as we do not know the true

[Insert Figure 1, Figure 2, and Figure 3 here]

We now discuss the magnitudes of the estimated short-term predictive abilities. Figure 1 shows histograms of investor skill estimates both for the linear and the square root price impact model specifications, including statistically insignificant estimates. Figure 2 shows the histograms of the alpha estimates that are statistically significant. We observe that estimates which are small in absolute value are likely to be insignificant. We report the investor short-term trading skill estimates as annualized Sharpe ratios. In the linear model, the range of the estimated Sharpe ratios is between -27.7 and 14.3. The sample mean (median) of the Sharpe ratios is -0.59 (-0.40). We find that the distribution of skill estimates have negative skew and large kurtosis, suggesting that the distributions of the skill estimates are asymmetric and non-normal. The Sharpe ratio estimates arising from our models are much larger than typical Sharpe ratios observed in the traditional asset management industry. However, the empirical literature reports similar Sharpe ratio estimates over short, intraday investment horizons (e.g., for high-frequency traders (HFTs)). For example, Clark-Joseph (2013) estimates that annualized Sharpe ratios of HFTs are in the neighborhood of 10 to 11. Baron et al. (forthcoming) report that high-performing HFTs achieve Sharpe ratios that are greater than 10.

Our findings suggest that, at the individual investor level, there is substantial variation in short-term predictive ability. Roughly, one-third of the investors have statistically significant Sharpe ratio estimates. On the other hand, we observe that half of these investors make systematically wrong bets in the short-term. In the next section, we study the robustness of our findings by separately examining buy versus sell orders.

6.3. Buy versus sell orders

There are many empirical studies that document asymmetry between the cost of buy and sell orders. In the earliest example, Kraus and Stoll (1972) find that block purchases have a larger permanent price impact than block sales. Saar (2001) provides a review of this literature and develops a theoretical model to explain this asymmetry. The model relates the asymmetric effect to the historical price performance of the stock. After a long period of price run-ups, the model

distribution of these statistics under the null hypothesis. Therefore, we employ a bootstrap analysis in Appendix A to formally test the statistical significance of the number of skilled or unskilled investors.

predicts a smaller asymmetry between buys and sells. Chiyachantana et al. (2004) document that the asymmetry depends on the contemporaneous market condition and report that sells (buys) have a larger price impact than buys (sells) in bear (bull) markets. Since our data set exactly identifies the direction of the large order execution, we can study the potential asymmetry of investor skill between buys versus sells by estimating our models separately for each direction.

[Insert Table 3 here]

Table 3 reports the summary of estimated model coefficients and skill terms for the linear price impact model given in (2). The findings are qualitatively very similar in the case of the square root price impact model. Overall, our earlier conclusions from Table 2 using the aggregate data remain the same when we use buy and sell order data separately. For example, for both buy and sell orders, R^2 values are significantly higher if the skill terms are included. Similarly, we find that the λ coefficients increase substantially in the absence of skill terms, implying the importance of the skill terms. Further, we observe that the numbers of skilled and unskilled investors across buy and sell executions are very similar. There are 46 and 47 skilled (48 and 45 unskilled) investors in the buy and sell data sets, respectively. Consistent with these statistics, the mean difference of α estimates across buys and sells is also statistically insignificant. Overall, our findings do not point to a significant difference in short-term trading skill between buy versus sell orders.

7. Robustness tests

In this section, we assess the robustness of our results in several ways. First, we consider various control variables that may be correlated with interval returns. Second, in order to control for the possibility of over-fitting, we assess the robustness of our model predictions on out-of-sample data. Using our estimated model in-sample, we predict out-of-sample short-term returns over an execution. Third, we illustrate that widely-used measures of execution costs are also positively correlated with short-term trading skill. Finally, we explore a different alpha specification that scales with the square root of the execution horizon.

7.1. Incorporating control variables

We can also generalize our regression framework by incorporating various control variables that may be correlated with price movements during the execution. We include proportional bid-offer spread, logarithm of average daily volume, logarithm of market capitalization, logarithm of price level, and dummies for listing venue (NASDAQ or NYSE), trading algorithm (VWAP or POV) and stocks. Formally, we run:

$$\begin{aligned} \operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) &= \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \sum_{c=1}^{C}\delta_c \mathit{ControlVariables}_{c,i} \\ &+ \sum_{k=1}^{S}\beta_k\mathbb{I}_{\{s(i)=k\}} + \epsilon_i\,, \end{aligned} \tag{5}$$

where we use the mapping $i \xrightarrow{s} k$ to identify the executed stock k, $k = 1 \ldots S$.

[Insert Table 4 here]

We summarize our findings in Table 4. First, we still find that there is significant heterogeneity in the numbers of skilled and unskilled investors. Second, the estimated coefficients of price impact seem to depend crucially on including the skill coefficients. Finally, we find that including 500 stock dummies and 6 additional execution-level control variables moves the adjusted R^2 by mere 0.2%–0.3%. This negligible increase contrasts with the substantial explanatory power of 293 investor skill coefficients, which resulted in a 10% increase.

Second, we examine whether our price impact and skill estimates are sensitive to controlling for dark pool executions. Clients of the broker may opt out of dark pool executions by marking a check box in their order submission instructions. To check whether this selection can explain the heterogeneity in skill terms, we use a subset of the full data for which we have information about the execution venue of the child orders. This portion of the data set includes 12,890 parent-order executions, accounting for roughly 20% of the full data set. In this subset, we have 118 unique investors. First, we re-run our model with this subsample and check whether the findings are robust to controlling for dark pool executions.

[Insert Table 5 here]

We summarize our findings in Table 5. First, in this very different subsample, we observe qualitatively very similar takeaways. Roughly one-third of the investors are again skilled or unskilled. In the absence of skill terms, the price impact coefficient increases considerably. We then control for the desire to trade in dark pools with a binary variable, *HasDP*, which takes a value of 1 if there is a dark pool execution and 0 otherwise. The numbers of skilled and unskilled investors remain the same and the price impact coefficients are largely unchanged. These findings highlight the robustness of our results to potential trade instructions involving dark pool executions.

7.2. Out-of-sample predictions

Our model specifications in equations (2) and (3) contain a number of parameters, namely, one for each investor. In order to eliminate the possibility of over-fitting, we consider a cross-validation experiment that illustrates the ability of our model to predict out-of-sample execution returns.

First, we divide the full data set into two parts: in-sample data and out-of-sample data. We perform this by randomly allocating half of each investor's executions into the in-sample data set and the remaining ones into the out-of-sample data set. If a client has odd number of executions, the extra execution is randomly assigned to the in-sample or out-of-sample data set. We then estimate the model parameters by running the regressions specified in equations (2) and (3) using only the in-sample data.

[Insert Table 6 and Figure 4 here]

Table 6 illustrates the regression results for the in-sample data set. The estimated regression coefficients for price impact are very similar to those obtained using all the data. For example, using the linear price impact specification, the price impact estimate, $\hat{\lambda}$, is 1.79, whereas using the complete data, the estimate is 1.81. Similarly, we observe that investor skill estimates are also very stable. Figure 4 shows the skill estimates between the in-sample and the complete data sets. In both price impact models, these are very close to each other, implying the robustness of the estimates. Formally, we find that the correlation between the skill estimates is 77% in both price impact models.

[Insert Table 7 here]

Using the skill and price impact estimates obtained from the in-sample data, we first compute the predicted execution returns implied by in-sample model estimates. We then compare the predicted values with the actual out-of-sample execution returns. Table 7 illustrates the root mean squared prediction error (rMSPE) and out-of-sample R^2 values between the predicted and actual returns. The in-sample and out-of-sample mean-squared errors are very close to each other. Similarly, we obtain an out-of-sample R^2 of more than 8.1% in both price impact models, suggesting that our regression model does not suffer from over-fitting. Both of these findings emphasize that our model has out-of-sample predictive power. These findings suggest that the broker may estimate the execution return in the pre-trade phase by using the client's short-term trading skill estimated from the past execution data.

7.3. Out-of-sample execution costs

Our main analysis illustrates that the price impact coefficients may be biased if investor's short-term trading skill is ignored. Our model implies that traditional measures of execution cost will also suffer from the same bias in the presence of systematic short-term predictive ability. Controlling for execution characteristics, our model predicts that execution costs of skilled (unskilled) short-term investors will be higher (lower).

In order to explore this hypothesis, we use implementation shortfall (IS) and VWAP slippage (VS). Both of these measures have been frequently employed in the literature to proxy institutional trading cost. IS is computed as the normalized difference between the average execution price and the price of the asset prior to the start of the execution. Similarly, VS is computed as the normalized difference between the average execution price and the market VWAP realized during the execution. Formally, the IS and VS of ith execution in our data are given by:

$$IS_i = \operatorname{sgn}(Q_i)\,\frac{P_i^{\mathrm{avg}} - P_{i,0}}{P_{i,0}}, \qquad VS_i = \operatorname{sgn}(Q_i)\,\frac{P_i^{\mathrm{avg}} - VWAP_i}{VWAP_i}, \tag{6}$$

where P_i^{avg} is the volume-weighted execution price of the parent order and $VWAP_i$ is the market VWAP realized during the ith execution.

We fit the following regression model with stock fixed effects and control variables to formally test whether out-of-sample execution costs have statistical dependence on the investor's short-term skill:

$$Cost_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i. \tag{7}$$

where *Cost* is either IS or VS. We consider execution-level control variables including participation rate, bid-offer spread, mid-quote volatility, and turnover during the execution horizon.

[Insert Table 8 here]

Table 8 reports the estimated coefficients of the models with both cost metrics. In each column, we observe that the coefficient on α is positive and highly significant. These results imply that typical institutional trading cost proxies are strongly correlated with short-term trading skill.

7.4. Robustness in alpha specification

Sharpe ratio is typically defined over a reference time horizon, and is often scaled with the square root of the investment horizon when it is projected across different horizons. In our model, however, we assumed that the Sharpe ratio is held constant, independent of the execution horizon. We can also consider the alternative model. In this specification, investor j has an expected return of $\sigma_i \alpha_j T_i$ when he trades ith stock during the trading horizon, T_i. Consequently, our skill estimation models are given by:

$$\operatorname{sgn}(Q_i) \log \left(\frac{P_{i,T_i}}{P_{i,0}} \right) = \sigma_i T_i \sum_{j=1}^{J} \mathbb{I}_{\{c(i)=j\}} \alpha_{c(i)} + \lambda \sigma_i \sqrt{T_i} \rho_i^{\gamma} + \epsilon_i \,, \tag{8}$$

where $\gamma = 1$ for the linear model and $\gamma = \frac{1}{2}$ for the square root model.

[Insert Table 9 here]

Table 9 provides the regression results for the model presented in equation 8. The estimated regression coefficients for price impact are very similar to those obtained in the original model. For example, using the linear price impact specification, the price impact estimate, $\hat{\lambda}$, is 1.875, whereas in our original specification, the estimate is 1.811. Similarly, we find that the sets of skilled and unskilled investors from both models are very similar. For example, we find that the exact same set of 40 (46) investors are identified as skilled (unskilled) in both models. Collectively, this common group nearly constitutes 90% of the original set of the identified traders, suggesting that our results are robust to the choice of alpha specification.

8. The determinants of short-term trading skill

In this section, we examine the sources of skilled and unskilled trading. In the following analyses, we do not claim causality but we are interested in identifying associations in the out-of-sample data. We use the procedure outlined in Subsection 7.2 to generate the in-sample and out-of-sample data sets. Using the in-sample data, we first estimate the investor's skill coefficient by estimating our full model. We then run all of our analyses regarding the determinants of short-term trading skill using only the out-of-sample data. Thus, our empirical design allows us to cleanly determine some drivers of skilled or unskilled trading.

8.1. Alpha and stock characteristics

In this subsection, we examine the potential sources of alpha by directly studying the correlation between it and stock-level characteristics that are in the information set of the investor at the time of the trading decision. For example, skilled or unskilled traders may prefer to trade stocks with certain characteristics, which can ultimately explain the heterogeneity in the short-term trading skill. To uncover such characteristics, we regress the estimated skill terms of each investor on various stock-level measures in the out-of-sample data that are available to the investor at the time of the trading decision. These measures include the average proportional spread, volatility, turnover, and Amihud illiquidity measure (*ILLIQ*) estimated from the prior month. We complement these measures by the logarithm of the number of analyst recommendations from the previous month and the percentage of shares held by index and active funds as of the most recent quarter-end.[16]

[Insert Table 10 here]

Table 10 reports the regression results. In univariate regressions, we find that alpha estimates are positively correlated with the prior monthly *ILLIQ* and index fund ownership and alpha is negatively correlated with the number of analyst recommendations. In the multivariate regression,

[16] Analyst recommendation data are obtained from I/B/E/S and fund ownership data are downloaded from CRSP.

the ownership ratio of index funds remains positive and significant. Overall, these findings imply that skilled trading can be prevalent in stocks with weak information environments. In the next section, we build on these findings and investigate weather skilled trading potentially emerges from information-based trading.

8.2. Does alpha measure skill?

Our estimation methodology allowed us to identify skilled and unskilled traders qualified by a short-term Sharpe ratio over the interval of execution. If skilled trading arises from superior predictive ability (based on short-term information), as is our interpretation, then skilled trading should also be correlated with the informational content of the large order. Motivated by the standard spread decomposition into realized spread (transitory) and adverse selection (permanent), van Kervel and Menkveld (forthcoming) propose a simple proxy for the permanent price impact (*PPI*) of a large order. In this setting, they compute the (*PPI*) of an execution by comparing the arrival mid-quote to the close price of the stock at the end of next trading day. Here, the intuition is that at least one full day elapses to observe what the permanent price impact is.

Formally, we define the *PPI* of ith execution as follows:

$$PPI_i = \operatorname{sgn}(Q_i) \frac{X_{m(i),d(i)+1} - P_{i,0}}{P_{i,0}}, \tag{9}$$

where the mapping $i \overset{d}{\to} u$ is used to identify the date of the execution and $X_{j,u}$ is the close price of the asset j on day u. If there is information-based trading, we would expect that estimated skill coefficients would be positively correlated with *PPI*.

To have a clean identification, we again use the estimated α coefficients from the in-sample data and analyze the sensitivity of these skill terms to *PPI* in the out-of-sample data. This analysis would point to the persistence of our skill estimates and reinforce the interpretation of skilled trading if *PPI* loads positively on alpha.

We fit the following regression model with stock fixed effects and control variables to formally test whether out-of-sample *PPI* exhibits statistical dependence on the investor's short-term skill:

$$PPI_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i. \tag{10}$$

We consider execution-level control variables including participation rate, daily volatility, previous monthly and yearly returns. Table 11 reports the estimated coefficients of the model. We observe that the coefficient on α is positive and highly significant. These results imply that estimates of short-term trading skill indeed capture information-based trading.

[Insert Table 11 here]

8.3. Value and momentum trading

The empirical asset pricing literature illustrates significant return premia with regards to value (an asset's ratio of its long-run value relative to its market value) and momentum (an asset's recent return performance). Asness et al. (2013) document the existence of these premia across eight diverse markets and asset classes. One reason for the skilled trading could be due to following these strategies. Similarly, unskilled trading could emerge if these traders systematically trade against these well-known anomalies.

In order to explore this hypothesis, we first compute the measures of value and momentum signals. One frequently used proxy for value is the book-to-market ratio. Stocks with a higher book-to-market ratio tend to exhibit higher returns when compared to low book-to-market stocks. Following Gârleanu and Pedersen (2013), we compute a measure for medium-term momentum using the past year's average return divided by the past year's standard deviation. Similarly, stocks with a high-momentum signal tend to have higher returns when compared to low-momentum stocks.

At the execution-level, we define the binary variable, *Buy*, that equals 1 if the order is given to purchase shares. We fit the following logistic regression model with interaction terms with skill coefficients to formally test whether short-term trading skill emerges by following these two well-known anomalies.

$$
\begin{aligned}
Buy_i = c_0 + \delta_1 \alpha_i + \delta_2\, Value_i + \delta_3 Momentum_i + \delta_4(\alpha_i \times \, Value_i) + \delta_5(\alpha_i \times Momentum_i) \qquad (11)\\
+ \sum_j c_j\, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i,
\end{aligned}
$$

where $Value_i$ denotes the book-to-market ratio of the executed stock and $Momentum_i$ denotes the executed stock's average return divided by the standard deviation over the past year. Table 12 reports the estimated coefficients of the models. We find that the coefficient on $\alpha \times Momentum$ is positive and significant, suggesting that as the skill level of the investor decreases, the probability of buying a low-momentum stock increases. We do not see a similar effect in exploiting value signals. Overall, this finding indirectly aligns with our earlier conjecture that some investors may be trading against well-known predictability patterns and may serve as a channel for the presence of unskilled trading. However, we would like to acknowledge that a complete explanation of the presence of unskilled traders is beyond the scope of our paper.

[Insert Table 12 here]

9. The impact of skill on trading decisions

In this section, we examine how short-term trading skill can affect important trading decisions, such as timing liquid periods, choosing lit or dark markets, number of shares to trade, and sensitivity to round sizes or prices. In each analysis, we again do not claim causality but we use out-of-sample data as employed in Section 8 to identify robust relationships between short-term trading skill and trading decisions.

9.1. Timing liquidity

There are a few theoretical studies that show that investors who are informed about the (long-term) fundamental value of an asset may choose to trade during high episodes of liquidity (e.g., Admati and Pfleiderer, 1988; Collin-Dufresne and Fos, 2016). We test whether investors with short-term trading skill in our data set strategically trade in high liquidity periods. Using different liquidity measures, L_i, we run the following regression model with control variables and stock fixed effects to formally test whether out-of-sample liquidity measures are correlated with short-term trading skill:

$$L_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i, \tag{12}$$

where α_i denotes the estimated α of the investor who submitted the ith execution.

Our liquidity measures include quoted spread (QS), logarithm of share volume, turnover, Amihud illiquidity measure (*ILLIQ*), effective spreads (ES), and depth realized during the execution period.[17] Higher values of QS, ES, and *ILLIQ* indicate lower liquidity, whereas higher share volume, turnover, and depth tend to be correlated with higher liquidity.

[Insert Table 13 and Table 14 here]

We summarize the estimated models in Table 13. Overall, we find that the alpha coefficients are negatively correlated with proxies of liquidity. We also find that the alpha coefficients are significant at the 5% level for the spread-based measures, suggesting that these proxies reflect the information asymmetry. The signs of the coefficients also consistently point to the negative correlation between α and measures of liquidity. Our findings support that various liquidity measures can detect informed trading activity.

For robustness, we also run our analysis at the stock level and report the simple statistics of the coefficients on α across stocks. The implications are similar. Table 14 illustrates that short-term trading skill is negatively correlated with liquidity proxies overall. The relationship is statistically significant for the logarithm of share volume, turnover, ILLIQ, and ES. Overall, our findings are not consistent with the liquidity-timing hypothesis.

9.2. Execution in the dark pools

As mentioned above, skilled investors may also differ from their unskilled counterparts with regards to their desire to trade in dark pools. As illustrated in Zhu (2014), execution risk in the dark pools

[17] We use TAQ data stamped to the second to compute ES with the corrections proposed by Holden and Jacobsen (2014). We compute depth as the ratio between the sum of shares available at the best bid and offer prices and the total shares outstanding.

disincentivizes informed traders to send their orders to dark pools. This uncertainty in execution emerges as there may be additional informed orders accumulating at the same side of the book and compete for execution with the investor's order.

Our data set allows us to verify this theoretical conjecture cleanly as the investors may opt out of dark venue executions in the pre-trade phase by marking a check box. We have information about the venue of child-order executions for roughly 20% of the out-of-sample data. Using this data set, we can compute the ratio of executed shares in the dark pools. We let $DPsh_i$ ($DPdol_i$) be the percentage of the shares (dollar volume) traded in the dark pools for the ith execution. We fit the following regression model with stock dummies and control variables to formally test whether the allocation to dark pools has statistical dependence on the skill level of the investor in out-of-sample executions:

$$DP_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \mathit{ControlVariables}_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i, \tag{13}$$

where DP is either $DPsh$ or $DPdol$. We consider different sets of execution-level control variables consisting of participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock.

[Insert Table 15 and Table 16 here]

The regression results for both dark pool utilization ratios are summarized in Table 15. In columns (1) and (4), the coefficient on α is negative and significant at the 5% level. Running the regressions at the stock level provides similar findings. Table 16 reports that approximately 70% of the coefficients on α are negative. Overall, our findings are consistent with theory presented in Zhu (2014) suggesting that informed traders may shy away from dark pools. These findings also provide empirical support to our earlier conjecture that market venues may significantly differ in terms of the proportion of skilled and unskilled investors. Given that alpha is negatively correlated with liquidity measures as shown in Subsection 9.1, this segregation has further implications on the liquidity measures reported by different market venues.

We also re-run our regressions by replacing the alpha terms with two indicator variables:

SkilledAndUnId (*UnSkilledAndUnId*) refers to an indicator variable that takes a value of 1 if the investor is skilled (unskilled) or unidentified. Table 15 also reports the results of these regressions. We find that the coefficient on *UnSkilledAndUnId* is positive and significant, suggesting that skilled investors are different in their propensity to trade in the dark pools when compared to the remaining group of investors.

9.3. Trade size

In a theoretical model, Easley and O'hara (1987) show that informed investors can choose to trade a larger amount of shares. Thus, in this section, we study the relationship between trading skill and order size decision. We let $SIZEsh_i$ and $SIZEdol_i$ be the order size in shares and dollars, respectively, for the ith execution. We compute the dollar size of the position using the mid-quote of the stock at the start time of the execution. We can fit the following regression to formally test whether out-of-sample order sizes have statistical dependence on the short-term trading skill level of the investor:

$$\log(SIZE_i) = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i, \tag{14}$$

where $SIZE$ is denoted in shares or dollars: $SIZEsh$ or $SIZEdol$. We use stock dummies and execution-level control variables that may affect the quantity to be traded. These can include prior stock and market returns, average share volume, turnover over the past month, logarithm of number of analyst recommendations, index, and active ownership of the executed stock.

[Insert Table 17 and Table 18 here]

Table 17 reports the estimated coefficients of the model. In columns (1) and (4), we observe that the coefficient on alpha is positive and significant at the 5% level. We observe that regressions with $SIZEsh$ provide higher R^2s. These findings imply that skilled investors indeed prefer to execute larger order sizes compared to their unskilled counterparts. Stock-level regression results in Table 18 are also aligned with these implications. We find that 70% of stock-level regressions deliver positive coefficients on α and the mean coefficient is highly significant.

Finally, we re-run our regressions by replacing the alpha terms with aggregate binary variables of skill: *SkilledAndUnId* and *UnSkilledAndUnId*. The second and the fifth columns in Table 17 report that the coefficient on *SkilledAndUnId* is positive and significant, providing further evidence that unskilled investors choose smaller order sizes when compared to the skilled and *unindentified* investors.

9.4. Size and price clustering

Alexander and Peterson (2007) show that NYSE and NASDAQ trades cluster on multiples of round shares such as 500, 1,000, and 5,000. With the increase in algorithmic trading, the mode of the trade size has come down to 100 shares. Since our data include information about the exact order size selected by the investor, we can examine the sensitivity of this choice and its potential clustering around round numbers with regards to the skill level of the investor.

Table 19 reports the most frequently used order sizes by the clients. Overall, we observe that clients prefer round sizes that are divisible by round numbers such as 25,000, 10,000 or 1,000. We test whether this propensity to round numbers is also related to the skill level of the investor. We define the binary variable *RoundX* that takes a value of 1 if the order size is a multiple of X.

We fit the following logistic regression model with stock fixed effects and control variables to formally test whether round order sizes have statistical dependence on the investor's short-term skill:

$$RoundX_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i. \tag{15}$$

where *RoundX* can be *Round25K*, *Round10K*, *Round1K*, *Round100*, *Round10*, or *Round5*. We consider execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock.

[Insert Table 20 and Table 21 here]

Table 20 reports the estimated coefficients of the models. Overall, we find that coefficients on α are not significant and the signs are mixed. These findings suggest that there is no marked difference in size clustering between skilled and unskilled investors. We also run our regressions using $|\alpha|$ as the main independent variable instead of α. Table 21 reports that the coefficient on $|\alpha|$ is negative and significant for *Round25K*, *Round10K*, and *Round1K*, suggesting that compared to unidentified investors, both skilled and unskilled investors avoid trading in round sizes.

Related to the liquidity-timing skill, skilled investors may also strategically time their execution so that the expected liquidity trading is at the highest level (e.g., Admati and Pfleiderer, 1988). On the other hand, unskilled investors may be more prone to having a higher propensity to trade when the underlying asset price is close to round prices (e.g., Osborne, 1962). We test whether the propensity to trade around round prices is related to the skill level of the investor. We use two proxies for round prices. First, we define the binary variable, *RoundDollar*, which takes a value of 1 if the floor of the arrival mid-price of the execution is divisible by 10 and 0 otherwise. Second, we use the binary variable, *RoundCent*, which takes a value of 1 if the decimal part of the arrival mid-price, the average of the prevailing bid and offer price in the market, is in the set of $\{.000, .005, .995, .500, .505, .495\}$ and 0 otherwise. Note that the decimal part of the arrival mid-price can take the following values: $\{.000, .005, .010, \ldots, .985, .990, .995\}$.

We fit the following logistic regression model with stock fixed effects and control variables to formally test whether round arrival prices have statistical dependence on the investor's short-term skill:

$$\mathit{RoundPrice}_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \mathit{ControlVariables}_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i, \tag{16}$$

where *RoundPrice* is either *RoundDollar* or *RoundCent*. We consider execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock.

[Insert Table 22 here]

Table 22 reports the estimated coefficients of the models. Overall, the coefficients on α are not significant, implying no pronounced difference in price clustering between skilled and unskilled investors. We also run our regressions using $|\alpha|$ as the main independent variable. The last two columns in Table 22 report that the coefficient on $|\alpha|$ is negative but insignificant for both measures of round prices.

9.5. Stock picking or passive portfolio trading

We expect that the skilled investors would be trading small number of assets as it would be unlikely for them to have informative signals about large number of stocks at the same time. Similarly, if an institution is rebalancing their portfolio for liquidity reasons, they may trade a passive benchmark consisting of many names. For example, if an investor is trading the broad market portfolio such as the S&P 500 Index, we would not expect to see abnormal returns. We now test whether our α estimates are consistent with these hypotheses.

At the execution-level, we define the binary variable, *Passive*, that equals 1 if the investor is trading 50 or more different stocks on the same day of this execution. Our findings are robust to different choices of this threshold value for the number of stocks traded.

We fit the following logistic regression model with stock fixed effects and control variables to formally test whether the propensity of trading large sets of stocks on a single day is correlated with the skill level of the investor:

$$Passive_i = c_0 + \beta_\alpha \alpha_i + \sum_j c_j \, ControlVariables_j + \sum_{k=1}^{S} \gamma_k \mathbb{I}_{\{s(i)=k\}} + \epsilon_i. \tag{17}$$

We consider execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock.

[Insert Table 23 here]

Table 23 reports the estimated coefficients of the model. We find that α is negatively correlated with *Passive* with statistical significance. These findings are broadly consistent with the stock-picking hypothesis, suggesting that skilled traders trade small number of stocks on any given day.

10. Conclusion

We propose a model to explain the variation in short-term returns with the short-term trading skill of the investors, along with a parametric modeling of price impact. Motivated by the performance metrics for the fund management industry, we measure trading skill in a risk-adjusted way using short-term Sharpe ratios. We estimate our model on a novel data set of institutional trades on large-cap U.S. stocks and find the presence of both skilled and unskilled investors. This classification is robust and has predictive power about the future trading performance of the investor. Further, incorporating short-term predictive ability offers drastic improvements in explaining the variation in security returns over an execution horizon. We also observe that ignoring short-term trading skill may lead to biased price impact estimates.

We study the correlation between short-term trading skill and stock-level characteristics that are available to the investor at the time of the trading decision. We find that skilled trading can specifically emerge in stocks with weak information environments. We employ a simple measure of information-based trading based on permanent price changes and illustrate that short-term trading skill is correlated with this measure. We find that skilled traders follow momentum-based trading strategies and differ significantly from unskilled investors by trading larger orders, more shares in lit markets, and fewer number of stocks. Overall, skilled investors do not have liquidity timing ability. Instead, several measures of illiquidity seem to be positively correlated with skilled trading suggesting that these measures capture the information asymmetry.

These findings have important policy implications. Our results illustrate that mere comparison of execution costs cannot be a standalone measure of execution quality. We find that dark pools are avoided by skilled investors, which may consequently bias their measures of execution quality. In the presence of investor heterogeneity, these biased estimates may not ultimately lead to an optimal policy recommendation. Our methodology has broad applications where trader identities are readily available. From the perspective of large institutional investors that aggregate executions across distinct internal strategies (e.g., a multi-strategy hedge fund), our work suggests that the estimation of price impact should account for the origination of each order. Similarly, brokers that algorithmically execute large orders on an agency basis for clients can improve decision-making throughout the trading process by accounting for the short-term trading skill of the investor.

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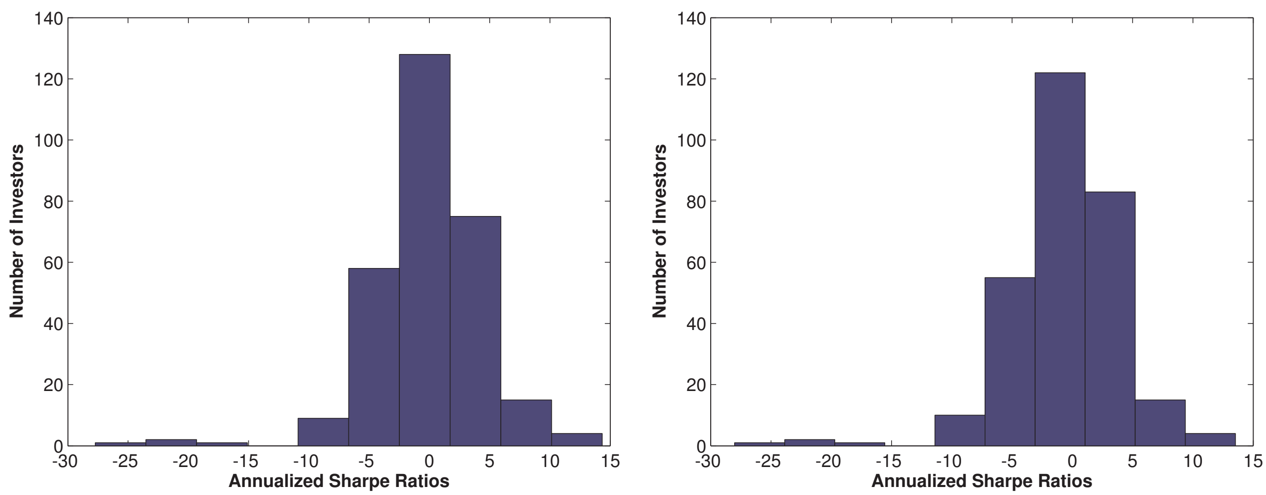

Figure 1: Distribution of annualized Sharpe ratios

Notes: This figure plots the histograms of investors' skill estimates expressed as annualized Sharpe ratios, when the price impact is proportional to the participation rate (left) and when the price impact is proportional to the square root of participation rate (right).

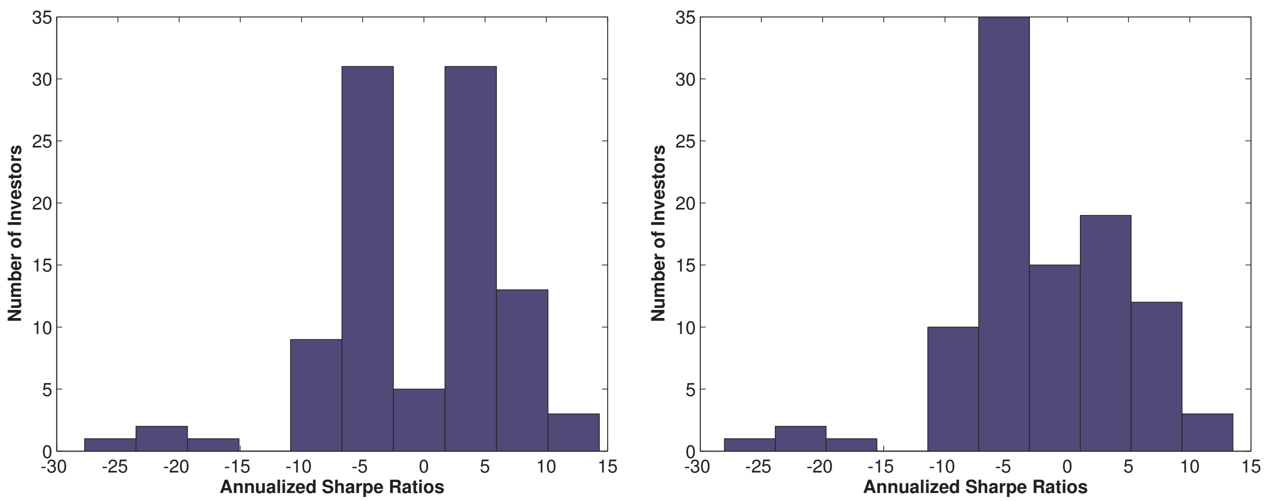

Figure 2: Distribution of statistically significant annualized Sharpe ratios

Notes: This figure plots the statistically significant investor skill estimates, expressed as annualized Sharpe ratios, when price impact is proportional to the participation rate (left) and when the price impact is proportional to the square root of the participation rate (right).

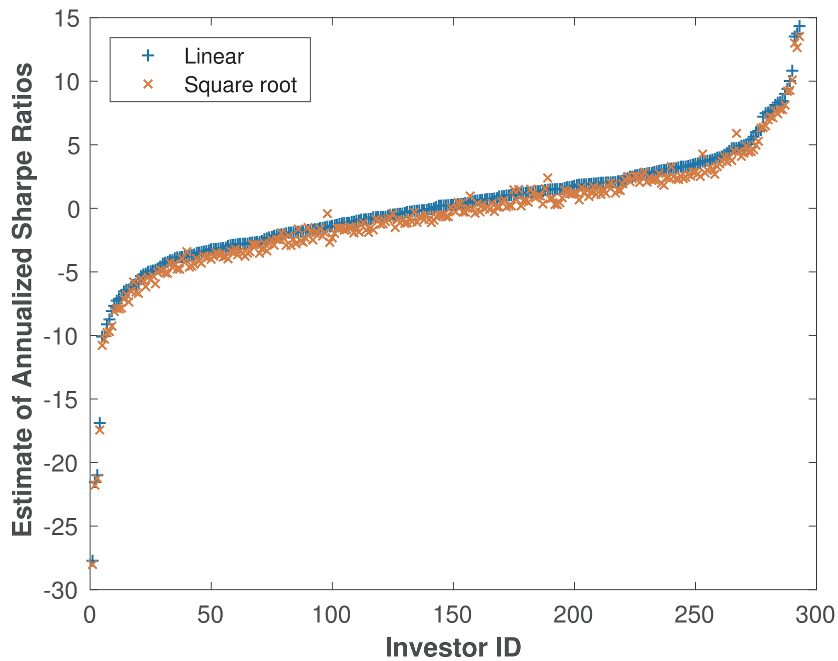

Figure 3: Trading skill estimates in the linear and square root price impact models
Notes: This figure plots the differences in alpha estimates between the linear and square root price impact models given in equations (2) and (3).

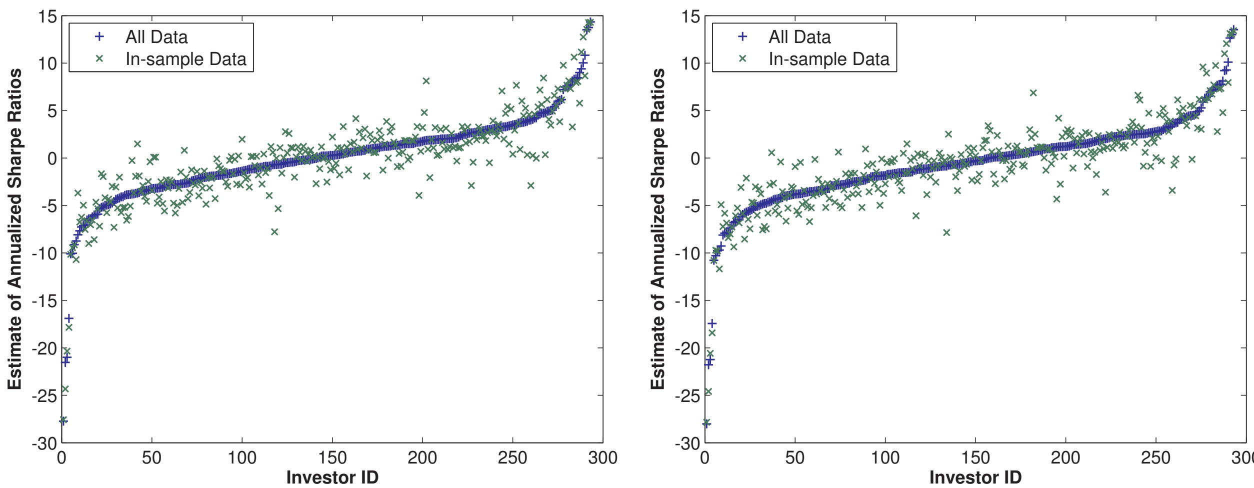

Figure 4: Robustness of the skill coefficients

Notes: As a robustness check, we compare trading skill estimates computed from the complete data set and a randomly constructed in-sample data set in which for every investor only random half of his executions are considered. We use two price impact specifications: the linear model (left) and the square root model (right).

Table 1: Summary statistics for the main attributes in our execution data

Notes: The bid-ask spread is normalized using the mid-quote price. Average daily volatilities are computed using the previous 20 trading days before the execution date. The duration of a full trading day in U.S. equity markets is 390 minutes.

Statistic	Interval Return (%)	Bid-Ask Spread (bps)	Average Daily Volatility (%)	Execution Duration (mins)	Participation Rate (%)	Percentage of Daily Volume (%)
Min.	-18.102	0.68	0.128	5.00	0.0001	<0.01
1st Qu.	-0.307	2.45	0.980	15.23	0.17	0.06
Median	0.000	3.35	1.267	59.82	1.59	0.26
Mean	0.003	4.16	1.417	148.13	6.44	0.64
3rd Qu.	0.333	4.87	1.685	324.50	10.50	0.72
Max.	10.793	54.76	25.740	390.00	100.00	28.25

Table 2: Regression results for two price impact models with and without trading skill terms

Notes: Two price impact specifications are estimated: linear and square root. With skill terms, the full model is given by

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \epsilon_i\,,$$

where $\gamma = 1$ for the linear model and $\gamma = \frac{1}{2}$ for the square root model. We also fit a reduced model to the data by ignoring trading skill terms, i.e., $\alpha_j = 0$,

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \epsilon_i.$$

We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear		Square Root	
Trading Skill	Yes	No	Yes	No
Intercept (bps)	1.26	−1.34	1.51	−3.27
	(1.24)	(2.42)	(1.22)	(2.69)
λ	1.811***	2.277***	0.744***	0.837***
	(0.291)	(0.363)	(0.173)	(0.154)
Number of skilled investors	49	N/A	35	N/A
Number of unskilled investors	48	N/A	63	N/A
R^2	10.5%	0.5%	10.5%	0.4%
Adj. R^2	10.1%	0.5%	10.0%	0.4%

Table 3: Regression results of the models using buy and sell order data separately

Notes: We estimate the linear price impact model with and without skill terms for buy and sell orders. The full model with skill terms is given by:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i + \epsilon_i.$$

We also fit a reduced model to the data by ignoring trading skill terms, i.e., $\alpha_j = 0$,

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \lambda\sigma_i\sqrt{T_i}\rho_i + \epsilon_i.$$

We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Buys		Sells	
Trading Skill	Yes	No	Yes	No
Intercept (bps)	0.50**	−1.35	1.01	−1.33
	(0.22)	(5.50)	(2.37)	(3.41)
λ	1.454***	2.374***	1.595***	2.177***
	(0.387)	(0.764)	(0.467)	(0.445)
Number of skilled investors	46	N/A	47	N/A
Number of unskilled investors	48	N/A	45	N/A
R^2	18.6%	0.6%	12.0%	0.5%
Adj. R^2	17.8%	0.6%	11.3%	0.5%

Table 4: Estimation with control variables

Notes: In this table, we provide the regression results for two price impact models with and without trading skill terms when a number of control variables and stock fixed effects are included. As controls, we use proportional bid-offer spread, logarithm of average daily volume, logarithm of market capitalization, logarithm of price level, and dummies for listing venue (*IsNasdaq* takes a value of 1 if the stock is NASDAQ-listed), trading algorithm (*IsVWAP* takes a value of 1 if the trading algorithm is to match VWAP). Two price impact specifications are estimated, linear and square root. We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear		Square Root	
Trading Skill	Yes	No	Yes	No
λ	1.47***	1.83***	0.62***	0.75***
	(0.33)	(0.40)	(0.20)	(0.20)
Bid-Offer Spread	0.0001**	−0.0000	0.0001**	−0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
Log ADV	−0.0002	−0.001	−0.0002	−0.001
	(0.0003)	(0.001)	(0.0003)	(0.001)
Log Mkt Cap	−0.001	0.0001	−0.001	0.0003
	(0.001)	(0.001)	(0.001)	(0.001)
Log Price	0.0005	−0.0001	0.001	−0.0001
	(0.0004)	(0.001)	(0.0004)	(0.001)
IsVWAP	−0.0005***	−0.0006***	−0.0006***	−0.0009***
	(0.0002)	(0.0002)	(0.0002)	(0.0003)
IsNasdaq	−0.0001	0.001	−0.0000	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Stock Dummies	Yes	Yes	Yes	Yes
Number of skilled investors	56	N/A	36	N/A
Number of unskilled investors	44	N/A	48	N/A
R^2	11.3%	1.5%	11.3%	1.6%
Adj. R^2	10.1%	0.7%	10.1%	0.8%

Table 5: Controlling for dark pool executions

Notes: In this table, we provide the regression results for the impact of dark pool executions using the subset of execution data. *HasDP* is a binary variable that takes a value of 1 if there is a child-order executed in a dark pool and 0 otherwise. We report the estimation results with and without trading skill terms. For brevity, we only estimate the linear price impact model. We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear			
Trading Skill	Yes	No	Yes	No
λ	1.70**	2.36***	1.70**	2.43***
	(0.82)	(0.81)	(0.82)	(0.86)
HasDP			−0.001	−0.0003
			(0.0004)	(0.001)
Observations	12,890	12,890	12,890	12,890
Number of investors	118	118	118	118
Number of skilled investors	23	N/A	23	N/A
Number of unskilled investors	20	N/A	20	N/A
Adj. R^2	13.4%	0.3%	13.4%	0.3%

Table 6: Estimation with in-sample data

Notes: In this table, we provide the regression results for two price impact models with an in-sample data set constructed using random half of each investor's executions. Two price impact specifications are estimated: linear and square root. With skill terms, the full model is given by:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \sigma_i\sqrt{T_i}\sum_{j=1}^{J}\mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \epsilon_i\,,$$

where $\gamma = 1$ for the linear model and $\gamma = \frac{1}{2}$ for the square root model. We also fit a reduced model to the data by ignoring trading skill terms, i.e., $\alpha_j = 0$:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \beta_0 + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \epsilon_i.$$

We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear		Square Root	
Trading Skill	Yes	No	Yes	No
Intercept (bps)	1.41	−0.76	1.55	−2.93
	(1.54)	(2.41)	(1.53)	(2.62)
λ	1.793***	2.160***	0.767***	0.838***
	(0.310)	(0.366)	(0.179)	(0.156)
Number of skilled investors	42	N/A	32	N/A
Number of unskilled investors	45	N/A	53	N/A
R^2	11.4%	0.5%	11.4%	0.5%
Adj. R^2	10.6%	0.5%	10.6%	0.5%

Table 7: Prediction errors between in-sample and out-of-sample data

Notes: In this table, we provide the root mean squared prediction errors (rMSPE) between in-sample and out-of-sample execution returns and in-sample and out-of-sample R^2. Predicted execution returns use the skill and price impact coefficients estimated from in-sample data set. rMSPE values are reported in basis points.

	rMSPE		R^2	
Model	In-Sample	Out-of-Sample	In-Sample	Out-of-Sample
Linear	93.19	95.06	10.6%	8.2%
Square root	93.19	95.07	10.6%	8.1%

Table 8: Robustness to other execution cost proxies

Notes: In this table, we regress implementation shortfall (IS) and VWAP slippage (VS) on our skill estimates, α, and execution-level control variables including including participation rate, bid-offer spread, mid-quote volatility, and turnover during the execution horizon. Formally, we run the model with stock dummies specified in equation 7. We use the out-of-sample data constructed for robustness checks in Section 7. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:	
	IS	VS
	(1)	(2)
α	35.61***	1.53**
	(5.13)	(0.67)
Participation Rate	24.52***	3.27***
	(6.45)	(1.26)
Spread	0.34	0.22***
	(0.35)	(0.07)
Volatility	95.01	6.73
	(129.93)	(31.75)
Turnover	−0.31	0.07
	(0.23)	(0.05)
Observations	31,690	31,690
Adj. R^2	0.03	0.02

Table 9: Robustness to another alpha specification

Notes: In this table, we provide the regression results for two price impact models assuming that each investor has a constant daily Sharpe ratio. We only consider the presence of trading skill terms. We fit the following model:

$$\operatorname{sgn}(Q_i)\log\left(\frac{P_{i,T_i}}{P_{i,0}}\right) = \sigma_i T_i \sum_{j=1}^{J} \mathbb{I}_{\{c(i)=j\}}\alpha_{c(i)} + \lambda\sigma_i\sqrt{T_i}\rho_i^{\gamma} + \epsilon_i\,,$$

where $\gamma = 1$ for the linear model and $\gamma = \frac{1}{2}$ for the square root model. We label an investor as skilled (unskilled) if his short-term trading skill estimate is positive (negative) and is statistically significant under the 10% level. In each column, we report estimated coefficients and their standard errors, adjusted by clustering on calendar day and stock, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear	Square root
Intercept (bps)	1.48	1.08
	(1.03)	(1.20)
λ	1.875***	0.759**
	(0.243)	(0.140)
Number of skilled investors	45	35
Number of unskilled investors	61	71
R^2	10.9%	10.9%
Adj. R^2	10.5%	10.5%

Table 10: Alpha and stock characteristics.

Notes: The dependent variable is the short-term trading skill term of each investor, α. We regress this measure on stock characteristics that are available to the investor at the time of the trading decision. These measures include the average proportional spread, volatility, turnover, and Amihud illiquidity measure (*ILLIQ*) estimated from the prior month. We complement these measures by the logarithm of the number of analyst recommendations from the prior month, index, and active ownership of the executed stock as of the most recent quarter-end. We use the out-of-sample data constructed for robustness checks in Section 7. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: α							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Avg Spread	0.001*							0.001
	(0.001)							(0.002)
Avg Volatility		−0.62						−1.06
		(1.13)						(1.49)
Avg Turnover			−0.0002					−0.0001
			(0.0004)					(0.0003)
Past ILLIQ				3.02***				1.78
				(1.13)				(1.38)
Log NumRecs					−0.01**			−0.01
					(0.004)			(0.004)
Index Holding						0.89**		0.68**
						(0.36)		(0.34)
Active Holding							0.07	0.06
							(0.05)	(0.05)
Observations	31,670	31,670	31,670	31,670	31,670	31,670	31,670	31,670
Adj. R^2	0.0003	0.0001	0.00000	0.001	0.0003	0.001	0.0003	0.002

Table 11: Alpha and permanent price impact

Notes: The dependent variable is the proxy for the permanent price impact in basis points (*PPI*). We regress this measure on our skill dummies and execution-level control variables including participation rate, daily mid-quote volatility, past yearly and monthly returns, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. We also include stock fixed effects. Formally, we run the model specified in equation 10. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: *PPI (bps)*	
	(1)	(2)
α	39.11**	40.00**
	(18.87)	(18.72)
Participation Rate	22.28	23.88
	(24.88)	(24.79)
Day Volatility	119.08	165.00
	(864.33)	(862.31)
Past Year Return	−7.79	−9.31
	(12.20)	(12.32)
Past Month Return	5.06	7.27
	(34.53)	(34.65)
Log NumRecs		−5.75
		(10.35)
Index Holding		1,206.43
		(938.71)
Active Holding		175.71
		(120.08)
Observations	31,670	31,670
Adj. R^2	0.04	0.04

Table 12: Skilled trading in value and momentum stocks

Notes: The dependent variable is the binary variable *Buy* that takes a value of 1 if the investor wants to buy and 0 otherwise i.e., buy (sell) orders have *Buy* variable equal to 1 (0). We regress these measures on skill coefficients, value and momentum measures and execution-level control variables. Formally, we run the model with stock dummies specified in equation 11. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:
	Buy
α	-0.11
	(0.24)
Value	-0.01
	(0.04)
Momentum	-0.13
	(0.11)
$\alpha \times$ Value	0.0001
	(0.04)
$\alpha \times$ Momentum	0.68^{**}
	(0.22)
Participation Rate	-0.06
	(0.09)
Spread	-0.002
	(0.001)
Volatility	-0.36
	(0.87)
Turnover	0.001
	(0.001)
Log Mkt Cap	-0.01
	(0.01)
IsVWAP	-0.07^{***}
	(0.02)
Log NumRecs	-0.004
	(0.01)
Index Holding	-0.45
	(0.52)
Active Holding	-0.10
	(0.06)
Observations	31,670

Table 13: Alpha and liquidity measures

Notes: The dependent variables are liquidity measures based on quoted spread (QS), logarithm of share volume, turnover, Amihud illiquidity measure (*ILLIQ*), effective spreads (ES), and depth realized during the execution period. We regress these measures on our skill dummies and execution-level control variables including volatility, average spread and logarithm of average volume over the past month, absolute values of asset and market return over the past week, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 12. We use the out-of-sample data constructed for robustness checks in Section 7. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:					
	QS	Log Volume	Turnover	ILLIQ	ES	Depth
α	0.10**	−0.28	−1.41	0.03*	0.14***	−0.0001
	(0.04)	(0.17)	(0.87)	(0.02)	(0.05)	(0.0004)
Volatility	103.49***	−4.52	19.60	5.95***	111.26***	−0.13***
	(3.77)	(2.95)	(16.04)	(0.75)	(4.30)	(0.02)
Avg Spread	0.10	0.01	−0.02	−0.001	0.08	0.003*
	(0.08)	(0.004)	(0.02)	(0.01)	(0.06)	(0.002)
Log Avg Volume	0.60***	0.53***	1.85***	−0.06***	0.35***	−0.0003
	(0.15)	(0.07)	(0.26)	(0.02)	(0.12)	(0.002)
|Prior Market Return|	−3.38	7.57*	40.54**	−0.42	−13.29***	0.02
	(2.11)	(4.27)	(19.72)	(0.46)	(1.99)	(0.01)
|Prior Week Return|	−0.92*	0.96	9.37***	−0.11	−1.98***	0.005
	(0.51)	(0.61)	(3.45)	(0.10)	(0.51)	(0.01)
Log NumRecs	−0.25***	−0.02	−0.12	0.03**	−0.23***	−0.01*
	(0.08)	(0.04)	(0.18)	(0.01)	(0.06)	(0.004)
Index Holding	11.99***	9.30*	26.84	−2.75***	7.52**	1.18**
	(4.15)	(5.59)	(22.85)	(1.00)	(3.77)	(0.59)
Active Holding	−3.57***	−0.32	−0.47	0.04	−4.24***	−0.07*
	(0.70)	(0.65)	(4.29)	(0.23)	(0.66)	(0.04)
Observations	31,670	31,670	31,670	31,670	31,670	31,670
Adj. R^2	0.76	0.40	0.19	0.26	0.62	0.89

Table 14: Alpha and liquidity measures: stock-level evidence

Notes: The dependent variables are liquidity measures based on quoted spread (QS), logarithm of share volume, turnover, Amihud illiquidity measure (*ILLIQ*), effective spreads (ES), and depth realized during the execution period. We use stock-level analysis and regress these measures on our skill coefficient at the stock-level and execution-level control variables including volatility, average spread and logarithm of average volume over the past month, absolute values of asset and market return over the past week, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. We use the out-of-sample data constructed for robustness checks in Section 7. We report the simple distribution of β_α across all of the stock-level regressions.

	Dependent variable:					
	QS	Log Volume	Turnover	ILLIQ	ES	Depth
Mean β_α	0.002	-0.20	-1.04	0.04	0.17	-0.0003
$t(\beta_\alpha)$	0.08	-3.78	-3.99	2.34	1.95	-0.87
% positive	0.52	0.41	0.37	0.59	0.55	0.56
% positive and significant	0.06	0.03	0.03	0.10	0.04	0.04
% negative and significant	0.05	0.13	0.17	0.03	0.06	0.04

Table 15: Alpha and execution in the dark pools

Notes: The main dependent variables are the fraction of shares or dollars executed in the dark pools at the parent-order level. The main independent variable is the estimated skill terms for each investor, α. We also use *SkilledAndUnId* and *UnSkilledAndUnId* as independent variables where *SkilledAndUnId* (*UnSkilledAndUnId*) refers to an indicator variable that takes a value of 1 if the investor is skilled (unskilled) or unidentified. We use execution-level control variables including participation rate, bid-offer spread, mid-quote volatility, turnover during the execution horizon, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 13. We use the out-of-sample data constructed for robustness checks in Section 7. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:					
	DP (shares)			DP (dollars)		
	(1)	(2)	(3)	(4)	(5)	(6)
α	-0.03^{***}			-0.03^{***}		
	(0.01)			(0.01)		
SkilledAndUnId		-0.01			-0.01	
		(0.01)			(0.01)	
UnSkilledAndUnId			0.04^{***}			0.04^{***}
			(0.01)			(0.01)
Participation Rate	-0.28^{***}	-0.29^{***}	-0.29^{***}	-0.28^{***}	-0.29^{***}	-0.29^{***}
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
Spread	0.0003	0.0002	0.0005	0.0003	0.0002	0.0004
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Volatility	-2.03^{***}	-1.95^{***}	-1.88^{***}	-2.03^{***}	-1.95^{***}	-1.88^{***}
	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)	(0.39)
Turnover	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}	0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log NumRecs	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Index Holding	2.99^{***}	2.93^{***}	3.00^{***}	2.99^{***}	2.93^{***}	2.99^{***}
	(1.13)	(1.13)	(1.12)	(1.13)	(1.13)	(1.12)
Active Holding	-0.09	-0.09	-0.09	-0.09	-0.09	-0.09
	(0.19)	(0.18)	(0.18)	(0.19)	(0.18)	(0.18)
Observations	6,633	6,633	6,633	6,633	6,633	6,633
Adj. R^2	0.04	0.04	0.05	0.04	0.04	0.05

Table 16: Alpha and execution in the dark pools: stock-level evidence

Notes: We regress the fraction of shares or dollars executed in the dark pools at the stock-level on our short-term trading skill estimates and execution-level control variables including participation rate, bid-offer spread, mid-quote volatility, turnover during the execution horizon, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. We use the out-of-sample data constructed for robustness checks in Section 7. We report the simple distribution of β_α across all of the stock-level regressions.

	DP (shares)	DP (dollars)
	(1)	(2)
Mean β_α	-0.04	-0.04
$t(\beta_\alpha)$	-2.23	-2.23
% negative	0.61	0.61
% negative and significant	0.12	0.12
% positive and significant	0.04	0.04

Table 17: Alpha and order size

Notes: We regress logarithm of order size denoted in number of shares, $SIZEsh$, and in dollars $SIZEdol$ on our skill coefficients and execution-level control variables including logarithm of average daily volume (over the past month), absolute values of prior weekly asset and market return and average turnover (over the past month), logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 14. We use the out-of-sample data constructed for robustness checks in Section 7. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:					
	log($SIZEsh$)			log($SIZEdol$)		
	(1)	(2)	(3)	(4)	(5)	(6)
α	0.42***			0.43***		
	(0.13)			(0.13)		
SkilledAndUnId		0.35***			0.35***	
		(0.13)			(0.13)	
UnSkilledAndUnId			−0.15			−0.15
			(0.10)			(0.10)
Log Avg Volume	0.41***	0.40***	0.40***	0.07	0.06	0.06
	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)	(0.10)
|Prior Week Return|	2.59***	2.58***	2.59***	2.28***	2.27***	2.28***
	(0.67)	(0.68)	(0.68)	(0.67)	(0.68)	(0.68)
|Prior Market Return|	−3.81	−4.35	−5.08	−4.73	−5.27	−5.99
	(3.14)	(3.30)	(3.68)	(3.14)	(3.28)	(3.66)
Avg Turnover	−0.01***	−0.01***	−0.01***	−0.01	−0.01	−0.01
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Log NumRecs	−0.05	−0.05	−0.04	−0.05	−0.05	−0.05
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Index Holding	−3.71	−3.49	−3.40	−7.26	−7.04	−6.96
	(7.02)	(6.89)	(7.07)	(7.06)	(6.93)	(7.11)
Active Holding	−0.14	−0.15	−0.15	1.08	1.07	1.07
	(0.66)	(0.66)	(0.67)	(0.67)	(0.67)	(0.67)
Observations	31,670	31,670	31,670	31,670	31,670	31,670
Adj. R^2	0.12	0.12	0.11	0.06	0.06	0.06

Table 18: Alpha and order size: stock-level evidence

Notes: We regress logarithm of order size (number of shares and dollars) at the stock-level on our skill estimates and execution-level control variables including logarithm of average daily volume (over the past month), absolute values of prior weekly asset and market return and average turnover (over the past month). logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Here, we present the summary of these regression estimates. We report the simple distribution of β_α across all of the stock-level regressions.

	$\log(SIZEsh)$	$\log(SIZEdol)$
	(1)	(2)
Mean β_α	0.38	0.38
$t(\beta_\alpha)$	6.83	6.86
% positive	0.71	0.71
% negative and significant	0.03	0.03
% positive and significant	0.17	0.17

Table 19: Frequency of the most frequent order sizes

Notes: We only include order sizes that appear more than 100 times.

Size	Frequency
25000	959
50000	793
10000	698
20000	542
5000	437
15000	409
1000	341
100000	307
30000	257
100	251
200	242
300	242
500	234
2000	220
400	216
600	200
3000	200
800	189
1500	186
2500	175
1200	165
1300	157
700	152
40000	152
900	151
4000	143
1100	142
1800	141
35000	137
1700	122
1400	118
1900	118
3500	118
6000	117
12000	112
1600	110
12500	109
2100	108
2200	107
2400	105
8000	104

Table 20: Alpha and round order sizes

Notes: The dependent variables are binary variables, *RoundX*s, that take a value of 1 if the order size is divisible by *X*. We regress these measures on our skill coefficients, α, and execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 15. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:					
	Round25K	*Round10K*	*Round1K*	*Round100*	*Round10*	*Round5*
α	0.06	0.12	0.15	−0.11	−0.23	−0.25
	(0.13)	(0.14)	(0.11)	(0.22)	(0.25)	(0.25)
Participation Rate	9.59***	7.60***	6.57***	3.32***	3.01***	3.07***
	(0.34)	(0.29)	(0.27)	(0.49)	(0.57)	(0.61)
Spread	−0.08***	−0.04**	−0.05***	−0.04***	−0.05***	−0.06***
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Volatility	17.30***	11.62***	9.70***	1.99	2.02	2.19
	(3.28)	(3.00)	(2.59)	(4.14)	(4.06)	(4.07)
Turnover	−0.0001	−0.002	0.004	−0.002	0.0002	−0.003
	(0.01)	(0.004)	(0.003)	(0.01)	(0.01)	(0.01)
Log NumRecs	−0.18*	−0.22***	−0.10	−0.09	−0.13*	−0.19**
	(0.10)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)
Index Holding	−6.83	−7.54	−7.49	−12.63	−11.19	−11.44
	(9.26)	(8.24)	(5.88)	(10.25)	(11.61)	(12.05)
Active Holding	−1.36	0.98	0.33	0.94	−0.06	−0.11
	(1.54)	(1.29)	(0.88)	(0.93)	(1.03)	(1.10)
Observations	31,670	31,670	31,670	31,670	31,670	31,670

Table 21: Alpha magnitude and round order sizes

Notes: The dependent variables are binary variables, *RoundX*s, that take a value of 1 if the order size is divisible by X. We regress these measures on the absolute value of skill coefficients, $|\alpha|$, and execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 15. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:					
	Round25K	*Round10K*	*Round1K*	*Round100*	*Round10*	*Round5*
$\lvert\alpha\rvert$	-1.21^{***}	-0.96^{***}	-0.66^{***}	0.08	0.27	0.27
	(0.21)	(0.21)	(0.15)	(0.27)	(0.32)	(0.33)
Participation Rate	9.42^{***}	7.46^{***}	6.47^{***}	3.33^{***}	3.06^{***}	3.12^{***}
	(0.34)	(0.29)	(0.27)	(0.48)	(0.57)	(0.60)
Spread	-0.08^{***}	-0.04^{***}	-0.05^{***}	-0.05^{***}	-0.06^{***}	-0.06^{***}
	(0.02)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)
Volatility	18.76^{***}	12.98^{***}	11.02^{***}	1.98	1.68	1.88
	(3.13)	(2.99)	(2.60)	(4.14)	(4.17)	(4.20)
Turnover	0.001	−0.0004	0.005	−0.002	0.0002	−0.003
	(0.005)	(0.004)	(0.003)	(0.01)	(0.01)	(0.01)
Log NumRecs	-0.20^{**}	-0.24^{***}	−0.10	−0.09	-0.14^{*}	-0.19^{**}
	(0.10)	(0.08)	(0.06)	(0.06)	(0.07)	(0.08)
Index Holding	−6.30	−7.13	−6.88	−12.76	−11.61	−11.87
	(9.44)	(8.31)	(5.87)	(10.21)	(11.54)	(11.98)
Active Holding	−1.28	1.05	0.37	0.95	−0.06	−0.10
	(1.53)	(1.28)	(0.88)	(0.93)	(1.03)	(1.11)
Observations	31,670	31,670	31,670	31,670	31,670	31,670

Table 22: Alpha and round stock prices

Notes: The dependent variables are *RoundDollar* and *RoundCent*. *RoundDollar* takes a value of 1 if the floor of the arrival mid price of the execution is divisible by 10 and 0 otherwise. *RoundCent* takes a value of 1 if the decimal part of the arrival mid-price is in the set of $\{.000, .005, .995, .500, .505, .495\}$ and 0 otherwise. We regress these measures on our skill coefficients, α, and their absolute values, $|\alpha|$, and execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of the number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 16. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable:			
	RoundDollar		*RoundCent*	
α	0.10	0.04		
	(0.07)	(0.10)		
$\|\alpha\|$			−0.05	−0.26*
			(0.09)	(0.14)
Participation Rate	0.55*	0.83**	0.55*	0.79*
	(0.28)	(0.40)	(0.28)	(0.40)
Spread	−0.04***	−0.01	−0.04**	−0.01
	(0.02)	(0.02)	(0.02)	(0.02)
Volatility	4.43	−13.47**	4.37	−12.65**
	(3.11)	(5.72)	(3.14)	(5.79)
Turnover	0.004	0.01*	0.004	0.01*
	(0.003)	(0.004)	(0.003)	(0.004)
Log NumRecs	0.27**	−0.19	0.27**	−0.19
	(0.12)	(0.14)	(0.12)	(0.14)
Index Holding	−9.21	−22.75**	−9.16	−22.52**
	(8.13)	(10.17)	(8.14)	(10.17)
Active Holding	3.04**	3.30*	3.04**	3.27*
	(1.31)	(1.95)	(1.30)	(1.95)
Observations	31,670	31,670	31,670	31,670

Table 23: Alpha and passive trading

Notes: The dependent variable is a binary variable of passive trading. At the execution-level, we define the binary variable, *Passive*, that equals 1 if the investor is trading 50 or more different stocks on the same day of this execution. We regress this measure on our skill dummies and execution-level control variables including participation rate, interval bid-offer spread, interval mid-quote volatility, interval turnover, logarithm of market capitalization, logarithm of the number of analyst recommendations, index, and active ownership of the executed stock. Formally, we run the model with stock dummies specified in equation 17. Standard errors are given in parentheses and are adjusted by clustering on calendar day, as suggested by Petersen (2009). *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: *Passive*
α	-1.30^{**}
	(0.61)
Participation Rate	-15.52^{***}
	(3.35)
Spread	-0.03
	(0.03)
Volatility	15.71
	(11.35)
Turnover	-0.01
	(0.02)
Log Mkt Cap	0.13
	(0.41)
Log NumRecs	-0.08
	(0.07)
Index Holding	-32.71
	(35.58)
Active Holding	0.09
	(1.94)
Observations	31,670

Appendix A Bootstrap Analyses

In this section, we run two bootstrap analyses to formally assess whether price impact coefficients estimated from the full and reduced model is statistically different and whether the number of skilled or unskilled investors are statistically significant and hence the heterogeneity in short-term trading skill exists.

[Insert Table A.1 here]

In the first bootstrap test, we sample our data with replacement and randomly construct 1,000 data sets, each consisting of 63,379 parent-order executions (i.e., same sized data sets with randomly chosen parent orders. For each data set, we estimate the full and the reduced models and store the price impact coefficients, $\hat{\lambda}$ and $\hat{\lambda}^{\mathsf{base}}$, for both linear and square root price impact specifications. Table A.1 reports the empirical probability that $\hat{\lambda}$ is less than $\hat{\lambda}^{\mathsf{base}}$. We find that in the specification with linear (square root) price impact, this probability is 99.7% (96.8%), providing evidence for the statistically significant over-estimation of the price impact parameter in the absence of the skill terms.

[Insert Table A.2 here]

In the second bootstrap analysis, we create 10,000 different samples of our execution data set by randomly permuting the investor identifiers across executions. Each investor still has the same number of assigned executions and the total number of executions remains the same but each investor is now assigned a random selection of executions. This bootstrap procedure allows us to generate the empirical distribution of the number of skilled and unskilled traders under the null hypothesis that investor identifiers are unrelated to log-returns during the execution horizon.

For each randomly sampled data set, we estimate our full model with skill terms and compute the number of the number of skilled or unskilled investors. We then derive the empirical distribution for the desired parameters: the numbers of skilled and unskilled investors. Table A.2 illustrates the p-values of our original estimates of the numbers of skilled and unskilled investors with respect to the empirical distribution. In both the linear and square root models, we find strong evidence that the estimated number of skilled or unskilled investors is indeed abnormally high, suggesting that investor heterogeneity is present with statistical significance. Finally, this analysis also shows that, the estimated price impact coefficient, $\hat{\lambda}$, is also statistically different than what we would obtain under the null hypothesis that investor identities do not matter.

Table A.1: Bootstrapping results in the price impact coefficients

Notes: In this table, we present the bootstrapping results for the difference in price impact coefficients by constructing 1,000 random data sets each with 63,379 executions by choosing parent orders from the original data set with replacement. In each column, we report the empirical probability that $\hat{\lambda}$ is less than $\hat{\lambda}^{\mathsf{base}}$ based on these 1,000 trials.

	Linear	Square Root
$\mathsf{P}(\hat{\lambda} - \hat{\lambda}^{\mathsf{base}} < 0)$	99.7%	96.8%
Number of samples	1,000	1,000

Table A.2: Bootstrapping results analysis shuffling investor identifiers

Notes: Results of the falsification test based on a bootstrapping analysis via shuffling investor identifiers across executions. We randomly construct 10,000 different samples of our execution data set by permuting the investor ids. In each column, we report the estimated coefficients from the original models and their corresponding p-values in square brackets. Empirical distribution for the parameters are obtained under the null hypothesis that investor identifiers are unrelated to log-returns realized during each execution horizon. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	Linear	Square Root
Number of skilled investors	49^{***}	35^{***}
	[< 0.001]	[< 0.001]
Number of unskilled investors	48^{***}	63^{**}
	[0.001]	[0.016]
$\hat{\lambda}$	1.811^{***}	0.744^{***}
	[< 0.001]	[< 0.001]
Number of samples	10,000	10,000