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THREE ESSAYS ON FINANCIAL ECONOMICS

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THREE ESSAYS ON FINANCIAL ECONOMICS

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An Abstract of
A Dissertation submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
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Doctor of Philosophy
in Business
2021

Abstract

THREE ESSAYS ON FINANCIAL ECONOMICS
By Yanbin Wu

This dissertation contains three essays on financial economics. In the first essay ("Closing Auctions: Information Content and Timeliness of Price Reaction"), we first document that closing auction volume has increased dramatically from 2010 to 2018 and currently accounts for about 11% of the total trading volume. We argue that ETF arbitrage trades significantly contribute to this growth, but these trades likely constitute less than 15% of the closing auction volume. We find that the closing auction price impact for the decile of stocks with the largest buy order imbalance is 32 basis points bigger than that for the decile with the largest sell order imbalance. About 83% of the price impact reverses over the next 3–5 days, but the remaining impact is permanent. Trading strategies that exploit these price effects and reversals are significantly profitable. In the second essay ("the Effect of Passive Investing on Initial Public Offering Stocks"), I investigate the impact of index investing on initial public offering by examining the Russell quarterly IPO additions. The findings show that stocks more likely to be included in the next quarterly additions experience bigger first-day returns, consistent with the hypothesis that underwriters do not fully incorporate the effect of potential inclusion in Russell indices on stock prices when they set the IPO prices. During quarterly addition periods, included IPOs experience significant abnormal returns that are subsequently reversed, consistent with the price pressure hypothesis. In the third essay ("Price Impact Reversal and The Illiquidity Premium,"), we find that a small subset of stocks with poor returns drives the illiquidity premium, consistent with it representing a return reversal. Stock transactions show that institutional investors sell illiquid losers, and that these stocks are subject to large transaction costs. The positive abnormal return associated with illiquid stocks stems directly from the reversal of the group of stocks with poor recent returns and downward price pressure. Our results suggest that these abnormal returns do not represent a broad premium that compensates investors for holding illiquid stocks. In fact, the mirror image group of illiquid winners shows an illiquidity discount.

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Introduction

This dissertation investigates the impact of passive investing on financial markets and the linkage between institutional trading and illiquidity premium. It consists of three essays. In the first essay ("Closing Auctions: Information Content and Timeliness of Price Reaction"-co-authored with Jegadeesh Narasimhan), we first document that closing auction volume has increased dramatically from 2010 to 2018 and currently accounts for about 11% of the total trading volume. We argue that ETF arbitrage trades significantly contribute to this growth, but these trades likely constitute less than 15% of the closing auction volume. Given the large trading volume that are executed at close, we investigate the price impact of these trades and find that the closing auction price impact for the decile of stocks with the largest buy order imbalance is 32 basis points bigger than that for the decile with the largest sell order imbalance. About 83% of the price impact reverses over the next 3–5 days, but the remaining impact is permanent. Trading strategies that exploit these price effects and reversals are significantly profitable. Also, the price impact of closing auctions and subsequent reversals explains the positive relation between ETF ownership and volatility.

In the second essay ("the effect of passive investing on initial public offering stocks"), I investigate the impact of index investing on initial public offering by examining the Russell quarterly IPO additions. The findings show that stocks more likely to be included in the next quarterly additions experience bigger first-day returns, consistent with the hypothesis that underwriters do not fully incorporate the effect of potential inclusion in Russell indices on stock prices when they set the IPO prices. During quarterly addition periods, included IPOs experience significant abnormal returns that are subsequently reversed, consistent with the price pressure hypothesis. By exploiting the variation of time schedule of inclusion into Russell indexes, we show that inclusion into an index increases comovement.

In the third essay ("Price Impact Reversal and The Illiquidity Premium," joint work with Jeffrey Busse), we find that a small subset of stocks with poor returns drives the illiquidity premium, consistent with it representing a return reversal. Stock transactions show that institutional investors sell illiquid losers, and that these stocks are subject to large transaction costs. The positive abnormal return associated with illiquid stocks stems directly from the reversal of the group of stocks with poor recent returns and downward price pressure. Our results suggest that these abnormal returns do not represent a broad premium that compensates investors for holding illiquid stocks. In fact, the mirror image group of illiquid winners shows an illiquidity discount.

FIRST ESSAY:
Closing Auctions: Information Content and Timeliness of Price Reaction

Introduction

Closing auctions are the last event of the trading day across all major US exchanges. The trade volume in closing auctions has grown significantly in recent years, increasing from about 3% of the trading volume in 2010 to about 11% in 2019. According to the NYSE, closing auctions are the busiest time in the US equity market trading day and they produce the day's most important price point for investors.[1] The closing auction price is the most widely published reference price for mutual funds and many exchange-traded products (ETPs).

We examine closing auctions in detail and address a number of research questions. The volume of trade in closing auctions grew contemporaneously with assets invested through exchange-traded funds (ETFs). Is closing auction volume related to ETF growth? And if so, what is the nature of this relationship? What is the price impact of closing auction trades? Is this price impact permanent or temporary? Does the closing order flow contain value-relevant information for stocks and does the market incorporate this information in a timely manner? How does the cost of trade executions in closing auctions compare with that during regular trading hours? Finally, do closing auctions influence stock volatility computed using closing prices?

The growth of ETFs potentially contributes to the rapid growth of closing auction volume. Arbitrageurs use convergence arbitrage with ETFs to exploit differences between ETF prices and their net asset value (NAV). As we discuss in more detail later, closing auctions allow ETF-arbitrage traders to simultaneously take positions on both sides of such arbitrage trades. We examine whether they contribute to the growth of closing auctions.

[1] https://www.nyse.com/article/nyse-closing-auction-insiders-guide.

Because we do not observe these arbitrage trades, we use two proxies for trading volume due to ETF arbitrage. ETF convergence arbitrage trades involve two legs: (a) a position in ETFs and (b) an opposite positions in the baskets of stocks that ETFs hold. Therefore, our first proxy is all ETF trades in closing auctions and corresponding trades in the basket of underlying stocks. This proxy potentially includes ETF trades that are not part of arbitrage trades, so it contains a measurement error. Therefore, we consider a second proxy which is the dollar value of the creation and redemption of stock ETFs. We find that both these measures of ETF-arbitrage trades are significantly related to closing auction volume.

Our first proxy indicates that ETF-arbitrage trades account for less than about 15% of the closing auction volume. Therefore, a significant portion of closing auction trades are not directly related to ETF-related arbitrages. What are the likely incentives for other traders to participate in closing auctions? Conceptually, ETF-arbitrage trades are not motivated by firm-specific information, hence they are uninformed trades in the context of models such as Admati and Pfleiderer (1988, 1991). These trades attract other uninformed traders to pool with them and thus minimize the price impact of their trades. Informed traders also join this pool to camouflage their informed trades with uninformed trades. Therefore, ETF-arbitrage trades likely act as a catalyst to attract other closing auction trades, although a large part of closing auction trades do not seem to be directly related to ETFs.

We also investigate the effect of closing auctions on stock prices. We document that significant order imbalances between buyer-initiated and seller-initiated typically precede closing auctions. Order imbalances could impact prices through the information it conveys and through potential price pressure. Price impact due to information would be permanent but any impact due to price pressure would be temporary and reversed in the future (for example, see Ho and Stoll, 1981 and Easley and O'Hara, 1987). Our next set of tests examines the price impact and the extent to which they are permanent or temporary.

Investors can place orders for execution in closing auctions before markets open and during trading hours until 3:45 p.m. Specifically, investors can place market-on-close (MOC) orders and limit-on-close (LOC) orders starting at 7:00 a.m. The market first receives information about these orders at 3:45 p.m., when the NYSE releases total *buy* and *sell* MOC orders for each NYSE-listed stock.[2,3] The MOC information available at 3:45 p.m. reveals the quantities of buyer- and seller-initiated trades and order imbalances; therefore, stock price changes from this time to close is the impact of closing auction trades.

We find that stock returns from 3:45 p.m. to close are significantly related to order imbalances announced at 3:45 p.m. To assess the economic significance of this relation, we consider a trading strategy that buys the decile of stocks with the largest *buy* imbalances and sells the decile with the largest *sell* imbalances at 3:45 p.m. This strategy earns 32 basis points (bps) from 3:45 p.m. to close, which yields an annualized return of about 80%.

We also estimate the permanent and temporary components of this price impact. We find that about 24% of the price impact is reversed by the open the next day. These reversals continue over the next three to five days, resulting in a cumulative reversal of about 83% of the initial price impact. Since this price impact is largely temporary, our findings indicate that uninformed traders account for most of the closing auction volume. However, we find that 17% of the price impact is permanent, which indicates that informed traders contribute a significant portion of the closing auction volume.

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[2] These timings were in force during our 2010–2018 sample period. Currently, MOC orders can be placed starting at 6:00 a.m., and the NYSE releases MOC order information at 3:50 p.m.

[3] Nasdaq first releases MOC information for Nasdaq-listed stocks at 3:50 p.m.

We consider trading strategies to evaluate the economic significance of the reversals as well. These strategies place MOC orders at 3:45 pm in the direction of order imbalances and keeps them open for up to five days. Specifically, an overnight trading strategy places offsetting market on open order the following day and the five-day strategy places offsetting MOC orders after five days. The overnight strategy earns about 5.64 bps and the five-day strategy earns 26 bps. The profits to these strategies are smaller than the 3:45 pm to close strategy profits, which is consistent with our results that only around 83% of the price changes from 3:45 pm to close are temporary.

We separately examine the trading volume and price impact of closing auctions for stocks that announce earnings after market close (hereafter earnings announcement date or "EAD" stocks). We find that closing auction volume on the announcement date is about 35% bigger than the average over the five previous days. However, closing auction volume as a fraction of the day's trading volume is about 18% smaller because total trading volume is bigger on earnings announcement dates. EAD stocks have roughly the same closing auction price impact as all stocks, but their price impact fully reverses over the next five days while we find only partial reversals for the full sample. This finding indicates that informed traders are not as active in closing auctions for EAD stocks as they are in the entire sample.

We compare the price impacts for trade execution during regular trading hours with that during closing auctions. We find that, except for relatively small buy trades, the price impact of trades in closing auctions is smaller than that during regular trading hours. The smaller price impact is likely an additional reason for the growth of closing auctions.

Our paper is one of the first detailed examinations of the price impact of closing auctions. A contemporaneous paper by Bogousslavsk and Myravyev (2020) also examines closing auctions. It notes that closing prices deviate from closing quote midpoints and examines its implications.

In contrast, our paper examines the information content and the price impact of closing auctions that begin with the NYSE's public disclosure of MOC orders at 3:45 p.m. We find that the order imbalances announced at 3:45 p.m. are significantly related to price changes until close and to price changes over the next 3–5 days. Because we measure order imbalances and price impact starting with the first disclosure of the information, we are able to present the complete picture.

Closing Auctions

The NYSE and Nasdaq conduct closing auctions for stocks listed on their respective exchanges in generally similar ways, but there are some differences in how these exchanges clear their auctions. Broadly, the NYSE closing auctions use three types of orders. First, investors can place market-on-close (MOC) orders on the NYSE for all NYSE-listed stocks from 7:00 a.m. to 3:45 p.m. Investors can also place limit-on-close (LOC) orders during this period. The NYSE announces *buy* and *sell* MOCs for all NYSE-listed stocks at 3:45 p.m., then the exchange updates this information every five seconds. Starting at 3:45 p.m., the NYSE allows investors to place *closing offset* (CO) orders, which are limit orders that execute only against order imbalances, and only if they improve the closing price.

NYSE floor brokers can also use closing discretionary orders, also known as closing *D orders*. Investors place D orders with floor brokers directly.[4] At 3:55 p.m., the closing D orders are added to the NYSE's order imbalance feed. D orders can be cancelled until 3:59:55 p.m. There are no restrictions on which side of the market closing D orders can be entered. Specifically,

[4] D orders are available throughout the trading day, but according to the NYSE, most D order executions occur in closing auctions. See https://www.nyse.com/article/trading/d-order.

closing D orders can be *buy* or *sell* orders regardless of the side of the MOC order imbalance. Floor brokers aggregate the MOC, LOC, CO, and D orders, then they determine the closing auction price that clears the market.

Nasdaq follows a similar procedure for MOC and LOC orders, although the end times differ slightly from NYSE timings. Nasdaq also accepts *imbalance-only* (IO) orders, which are effectively *limit* orders at the Nasdaq *bid* or *ask* prices as of 4:00 p.m.[5] Only IO orders against the direction of the closing order imbalance are executed. Additionally, Nasdaq accepts continuous market orders until the time closing cross commences. The closing process begins at 4:00 p.m., and it determines the closing price that clears all MOCs and viable limit orders.

We first examine the closing pattern trading volume. We use Trade and Quote (TAQ) data to compute both the total trading volume for each stock and the volume of trades through closing auctions. For NYSE- and Nasdaq-listed stocks, TAQ uses the identifiers "*6*" and "*M*", respectively, to denote closing auction trades. The dollar value of closing auction trades is the product of the number of shares traded and the closing auction price. Figure 1 plots the total dollar volume of closing auction trade as a proportion of the dollar volume of all trades for stocks in the S&P 500 index. The dollar volume of closing auction trade increases from about 3% in 2010 to about 11% in 2019.

[5] The *buy* and *sell* IOs are executed at the closing *bid* or *ask* prices, respectively, if these prices improve the corresponding prices at 4:00 p.m.

Closing auctions: Key factors

This section investigates the key factors that contribute to the rapid growth of closing auctions. The growth of closing auction volume closely mirrors the growth of ETFs. For instance, US stock ETF assets increased from about $0.99 trillion in 2010 to about $4.32 trillion in 2019.[6] We first examine whether the growth of closing auction contributes to ETF growth. We then investigate the relation between closing auction volume and stock characteristics.

ETF Arbitrage

Conceptually, why should the growth of ETFs and closing auction volume be related? Stock ETFs typically hold portfolios that passively track selected indices. ETFs designate authorized participants (APs) who are authorized to create and redeem ETF shares and trade.[7] Figure 2 illustrates the process that APs follow to create and redeem ETF shares. ETFs publish their portfolio holdings daily. To create new shares, designated APs acquire the stocks in the portfolio and sell (or short sell) ETF shares.[8] At the end of the trading day, APs deliver the underlying basket to the ETF. In exchange, the ETF delivers its shares to the APs. APs and ETFs undergo the reverse process to redeem ETF shares.

APs profit from these creation and redemption activities when an ETF's NAV deviates from its market price. APs buy the underlying portfolio, then they sell the ETF if its NAV is

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[6] Source: *Investment Company Institution Fact Book* (2019).

[7] Authorized participants are large institutions such as Goldman Sachs, Bank of America, and Morgan Stanley. On average, each ETF has 38 authorized participants (Antoniewicz and Heinrichs, 2015; and Lettau and Madhavan, 2018).

[8] Our sample is comprised of ETFs that physically hold underlying stocks, and our description applies to such ETFs. Some ETFs invest in derivatives (e.g., futures and swaps), so they are not included in our sample.

sufficiently smaller than the ETF market price. This offsets transaction costs and executes opposite trades if the ETF trades at a sufficiently large discount. APs settle these arbitrage trades directly with the ETF at the end of trading, and thus they have no need to trade in closing auctions.

APs undertake such arbitrage activities whenever profitable trading opportunities arise during the trading day. In fact, the closing auction per se may not be particularly suitable to initiate such arbitrage trades. Because closing prices are not known at the time MOC orders are placed, investors cannot predict whether closing prices for ETFs and their underlying stocks will allow for arbitrage.

Closing auctions are particularly suitable for ETF convergence arbitrage traders other than APs. These arbitrageurs could also initiate arbitrage trades during the trading day when profitable opportunities arise. Unlike APs, these arbitrageurs cannot settle trades directly with the ETFs. They can, however, close their arbitrage trades through offsetting orders for both ETFs and their holdings in closing auctions.

We do not observe ETF-arbitrage trades. Therefore, we use two proxies to investigate whether they contribute to closing auction volume. The first proxy, which we name *ETF_arb*, categorizes all closing auction trades of ETF shares as one leg of arbitrage trades. The other leg consists of orders for the underlying basket of stocks. While all ETF arbitrage involves trading these two legs, not all ETF trades in closing auctions are necessarily part ETF arbitrage trades. Therefore, this proxy for ETF arbitrage potentially overstates ETF-arbitrage trades.

Our second proxy is the volume of daily ETF creation and redemption. As we discuss earlier, both APs and other ETF arbitrageurs seek to profit from differences between the NAV and the market prices of ETFs. Therefore, we use creation and redemption as the second proxy for ETF arbitrage trades in closing auctions. We refer to this proxy as *ETF_cr*. We compute *ETF_cr* as the aggregate dollar value of US stock ETF units created and redeemed daily and the corresponding dollar value of trades in the basket of stocks that the ETFs hold.

We compute both *ETF_arb* and *ETF_cr* using all domestic stock ETFs for which the necessary data are available. We start with all domestic stock ETFs traded on US exchanges that are identified with code 73 in the Center for Research in Security Prices (CRSP) database. We obtain the holdings data for these ETFs from the Thomson-Reuters Mutual Fund Ownership database for each quarter, and we obtain daily creation and redemption data from Bloomberg.[9]

There are total of 463 ETFs with code 73 in the CRSP database. Our sample is comprised of 367 ETFs from the CRSP sample that we can match with the other two data sources. Table 1 presents the number of ETFs in our sample at the end of each calendar year as well as their assets under management (AUM). The total AUM of our sample is, on average, about 80% of the AUM in the CRSP sample.

To estimate ETF arbitrage–related trades that are reversed in closing auctions, we first determine the closing auction trading volume for each ETF in our sample from the TAQ data. We compute $ETF\_arb_{i,t}$, which represents the implied ETF-arbitrage trading volume for each underlying stock, as

$$ETF\_arb_{i,t} = \frac{\sum_{j=1}^{J_t} N_{j,t} S_{i,j,t}}{Dollar\ Volume_{i,t}}, \tag{1}$$

where *t* is the date subscript, J_t is the number of ETFs in the sample, $N_{j,t}$ is the number of shares of ETF *j* traded in the closing auction, $S_{i,j,t}$ is the dollar value of shares of stock *i* held per unit of ETF j, and $Dollar\ Volume_{i,t}$ is the day's total dollar trading volume of the stock.[10] We compute $ETF\_cr_{i,t}$ analogously with creation and redemption data.

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[9] We match the ETFs on CRSP and Bloomberg with their ticker symbols and CUSIP numbers.

[10] We determine the number of shares of stock *i* held by fund *j* from the most recent quarterly holdings data from Thomson Reuters, then we multiply this by the stock price on day *t* to compute $S_{i,j,t}$.

Panel B of Table 1 presents the summary statistics for the dollar volume of closing auction trades and ETF-arbitrage trades in closing auctions. The average closing auction trading volume is \$2.7 million, and its average proportion of the total trading volume is 6.37%. The average ETF-arbitrage volume is \$181,440. On average, ETF_arb comprises 15% of the closing auction volume. The average dollar value of ETF creation and redemption is \$1.57 million.

To examine the relation between ETF arbitrage and closing auctions, we run the following regression:

$$Closing\ Volume_{i,t} = \alpha + \beta \times ETF\_arb_{i,t} + \epsilon_{i,t}, \tag{2}$$

where $Closing\ Volume_{i,t}$ is the dollar value of stock i traded in the closing auction divided by $Dollar\ Volume_{i,t}$. For ease of interpretation, all variables are normalized each day by subtracting the sample mean then dividing by the standard deviation of that variable. We also include day and stock fixed effects in the regression to control for any time and stock effects.

Table 2, Column (1) presents the estimates of Regression (2). This table uses standard errors clustered at the stock and day levels, as recommended by Peterson (2009), to compute *t*-statistics. The slope coefficient on $ETF\_arb_{i,t}$ is .222, and the *t*-statistic is 31.69. Table 2, Column (2) presents the estimates of a univariate regression using $ETF\_cr_{i,t}$ as the proxy for ETF arbitrage trading, and the result is similar. The slope coefficient on $ETF\_cr_{i,t}$ is .333, and the *t*-statistic is 55.59. Overall, these results indicate that ETF-arbitrage trades contribute significantly to the growth of closing auction volume.

Stock characteristics and closing auction trades

On average, ETF_arb accounts for about 15% of the total closing auction volume during our sample period. For example, the average daily closing auction volume in 2018 was \$6.46

million, while the average *ETF_arb* was \$0.47 million. Thus a large part of closing auction volume are unrelated to ETF arbitrage activities. This subsection examines other factors that contribute to trading in closing auctions.

ETF arbitrage trades are motivated by differences between the NAV and the market prices of ETFs. As such, they are not based on any firm-specific information. Therefore, these are uninformed trades in the context of models such as the one proposed by Admati and Pfleiderer (1988). Admati and Pfleiderer show that a congregation of uninformed trades attracts other uninformed trades to pool with them because they collectively face a lower price impact than if they do not pool. Admati and Pfleiderer's model also predicts that informed traders will also optimally pool with these uninformed traders to minimize the price impacts.

The incentives to mitigate price impacts are stronger for less liquid stocks; therefore, based on Admati and Pfleiderer, we hypothesize that closing auction trading volumes will be higher for less liquid stocks. To test this prediction, we add the following variables as proxies for liquidity:

- *Quoted spread*. The equal-weighted average of the quoted spread at the time of each transaction during the day.
- *Amihud measure*. The ratio of the previous day's absolute return day divided by dollar volume (expressed in \$ million).
- *1/Price*. The inverse of the stock's closing price on the previous day.
- *Ln(Market cap)*. The natural log of market capitalization (in millions USD) at the end of the previous day.

Previous studies that use one or more of these proxies for liquidity include Nair and Radcliffe (1998); Chordia, Roll, Subrahmanyam (2000); and Hasbrouck (2009). We add these variables to Regression (2), and we fit the regression below to examine their relationship with closing auction volume:

$$Closing\ Volume_{i,t} = \alpha + \beta \times ETF\_arb_{i,t} + \boldsymbol{\gamma}'\boldsymbol{X_{i,t}} + \epsilon_{i,t}, \tag{3}$$

where $\boldsymbol{X}$ is the vector of liquidity characteristics. Here again, we normalize all variables, and we include day and stock fixed effects in the regression.

Column (3) of Table 2 reports the regression results. The slope coefficients on the inverse of price are significantly negative, and the coefficients on the *Amihud measure* and the *Quoted spread* are significantly positive. For example, the slope coefficient for the *Amihud measure* is 0.061 with a *t*-statistic of 26.49, and the *Quoted spread* coefficient is .29 with a *t*-statistic of 27.62. Only the slope coefficient on the market cap is insignificant, presumably because the other variables are better proxies for trading liquidity. The results shown in Column (4) are similar when we use $ETF\_cr_{i,t}$ as an alternative measure of ETF-arbitrage trading. Overall, our results indicate that the volume in closing auctions is higher for less liquid stocks.

Earnings announcements

What is the impact of earnings announcements on closing auction trades? Before earnings announcements, we expect more informed trading due to potential information leakage about the imminent news release. It is possible that informed traders pool with closing auction trades to minimize the price impact of their trades. Alternatively, any informational advantage before impending earnings announcements is likely to be short lived, hence informed investors may trade during the day and may not wait until closing auctions. In the latter case, fewer informed traders would participate in closing auctions.

This subsection examines whether the volume of closing auction trades is different on earnings announcement dates relative to other days. We obtain time-stamped earnings announcement dates from Compustat. We define the date on which earnings are announced after market close as *day 0*. To examine the EAD effect on closing auction volume, we add an earnings announcement date dummy variable on the right-hand side of Regression (3).

Columns (5) and (6) of Table 2 present the regression estimates. The slope coefficient on the EAD dummy is −.186 with a *t*-statistic of −42.73. This significantly negative estimate indicates that the volume of closing auction trade as a percentage of total trade is 0.182 standard deviations smaller on day 0, after controlling for other factors.

The average closing auction volume on day 0 is about 35% higher than the five previous days, but the ratio is smaller because day 0 has about double the total trading volume as non-event days. Some of this increased EAD trading volume potentially comes from informed traders. However, our results indicate that a larger fraction of them prefer to trade during regular trading hours.

Information content of closing auction trades and timeliness of stock price reaction

If uninformed trades dominate closing auctions, then the price impact of closing trades is largely a compensation for liquidity providers who absorb any imbalances between *buy* and *sell* orders, and the impact would fully reverse. If, on the other hand, informed trades dominate, then most of the price changes associated with closing auctions reflect new information and would tend to be permanent. This section examines the price impact of closing auctions and the timeliness of stock price reactions as the market receives information about closing auction trades.

The market receives its first piece of information related to closing auctions when the NYSE disseminates information about MOCs at 3:45 p.m. This information includes aggregate MOC orders on the *buy* and *sell* sides as well as the order imbalance for each NYSE-listed stock. Starting at 3:55 p.m., the NYSE adds closing D-orders to the MOC orders, and it publishes the combined statistics. The NYSE then updates this information every five seconds. This section examines the market reaction to information from the announcement of MOC orders, which we term *MOC information*.

Order imbalance trajectory

We first examine the trajectory of the MOC order imbalance from 3:45 p.m. to market close. We obtain from MOC information from the NYSE for the July 2010 to June 2018 sample period. We compute the order imbalance (OI) as

$$OI_{i,t} = \frac{MOC\_Buy_{i,t} - MOC\_Sell_{i,t}}{Total\ trade_{i,t}}, \tag{4}$$

where MOC_Buy and MOC_Sell represent the number of *buy* and *sell* MOC orders, respectively, as of 3:45 p.m. The variable $Total\ trade$ represents the total number of shares traded on day *t*. We divide the MOC order imbalance by the total trades because, given the same level of order imbalance, any price impact will differ depending on the total trading activity for that stock.[11]

Figure 3 plots the trajectory of order imbalances from 3:45 p.m. to market close separately for stocks that exhibit *buy* and *sell* order imbalances at 3:45 p.m. We set the order imbalance at 3:45 p.m. equal to 1, and we divide subsequent order imbalances by the 3:45 p.m. order imbalance. Figure 3 plots the equal-weighted averages of the order imbalances every minute. Order

[11] Our results are qualitatively similar when we use $MOC_{Buy} + MOC\_Sell$ in the denominator in place of $Total\ trade$. We choose the latter because small difference between MOC_Buy and MOC_Sell could be magnified if their sum is small.

imbalances remain roughly static for approximately 10 minutes after 3:45 p.m. After the D-orders are aggregated, OI declines rapidly. By 4:00 p.m., OI is about 30% of its 3:45 p.m. level. After the close of regular trading, LOCs are also added to the mix, and the price that clears the market is determined.[12] The pattern is similar for both *buy* and *sell* order imbalances.

MOC announcement to close

The market learns about the size of *buy* and *sell* MOC orders and order imbalances through the NYSE announcement, and the information conveyed from 3:45 p.m. to close is reflected in prices during this period.

Figure 4 presents the trajectory of price changes separately for stocks with *buy* and *sell* order imbalances as of 3:45 p.m. For *buy* imbalance stocks, the price increases by 3 bp when the announcement occurs. The price at 4:00 p.m. is about 4 bps above the 3:45 p.m. price. For *sell* imbalance stocks, the price drops by about 3 bp, on average, after the release of MOC information. The price continues to gradually drop, and the cumulative price decline is about 6 bps by 4:00 p.m. The NYSE aggregates D-orders with MOC orders starting at 3:55 p.m., but there is no discernible price change at this time.

The stock price response to MOC information potentially depends on other factors as well. For example, it is possible that highly liquid stocks may experience a lower price impact than illiquid stocks because they can absorb any supply or demand shocks. To examine whether these factors incrementally contribute to the price impact, we fit the following regression:

$$R_{i,t}^{3:45\ to\ close} = a + b \times OI_{i,t} + \boldsymbol{\gamma}'\boldsymbol{X}_{\boldsymbol{i,t}}^{\boldsymbol{s}} + \epsilon_{i,t}, \tag{5}$$

[12] In the NYSE, **designated market makers (DMMs)** for each stock set the closing price "…at a level that satisfies all interest that is willing to participate at a price better than the closing auction price, and supplying liquidity as needed" (see https://www.nyse.com/article/nyse-closing-auction-insiders-guide).

where $R_{i,t}^{3:45\ to\ close}$ is the return from 3:45 p.m. to close and $\boldsymbol{X_{i,t}^{s}}$ is the vector of liquidity proxies (defined earlier) multiplied by the sign of the order imbalance. In other words, liquidity proxies time +1 for stocks with a *buy* imbalance and −1 for stocks with a *sell* imbalance.[13] We multiply the liquidity variables by the sign of the order imbalance to account for asymmetry in the direction of price reactions for *buy* and *sell* imbalances.

Table 3 presents the regression results. When we fit a univariate with *order imbalance* as the only independent variable, the slope coefficient is 1.043, which is significantly positive. In the multiple regression that adds all liquidity variables, the slope coefficient is significantly negative for the market cap. This indicates a larger price reaction for smaller firms.[14] The slope coefficients are .008 and 1.157 for *Amihud measure* and *inverse of price*, respectively. Both these coefficients are significant, and they indicate that MOC information has a larger impact on less liquid stocks.

Price changes on subsequent days

This subsection examines the relation between order imbalances and price changes on subsequent days. Conceptually, if informed traders are dominant in closing auctions then order imbalances would reflect their collective information and price changes due to order imbalances would be permanent (see Easley and O'Hara, 1987). On the other hand, if uninformed traders are dominant in closing auctions then the resulting price pressure push prices away from fundamentals and the prices changes subsequently reverse (see Ho and Stoll, 1981). The relative magnitudes of the permanent and temporary components of price changes due order imbalances from 3:45 pm to

[13] We obtain *open* and *close* prices from the CRSP Daily file, and we obtain intraday price data from TAQ. Due to potential errors in some intraday price data, we exclude observations in which intraday returns fall in the 0.1 or 99.9th percentile.

[14] The slope coefficient measures the relation between the market cap and the difference between price reactions for stock with *buy* and *sell* OI; it does not account for the size of OI. In untabulated tests, we regressed $R_{i,t}^{to\ close}$ against $OI_{i,t}$. We find that the slope coefficient is larger for small firms.

close will therefore shed light on the composition of informed and uninformed traders in closing auctions.

We fit the following regression to examine the relation between $R_{i,t}^{3:45\ to\ close}$ and future returns and other variables:

$$R_{i,t+j} = a_j + b_j \times R_{i,t}^{3:45\ to\ close} + \epsilon_{i,t}, \tag{5}$$

where $R_{i,t+j}$ is future return.

Panel A of Table 4 presents Regression (5) estimates with $j = next\ day\ open$ and days 1 through 5. The slope coefficient on $R_{i,t}^{to\ close}$ is −.107 (*t*-statistic = −23.88) with overnight return as the dependent variable, and it increases to −.236 (*t*-statistic = −9.07) with the return over the next five days.[15] Therefore, more than 10% of $R_{i,t}^{to\ close}$ reverses overnight, and the reversal continues over the next few days.

What fraction of returns attributable to order imbalances ($OI_{i,t}$) is permanent, and what fraction is reversed? Because $R_{i,t}^{to\ close}$ is the independent variable in Regression (5), it measures the relation between the total returns during this time and future returns. If a part of $OI_{i,t}$ is attributable to informed traders pooling with noise traders, we would expect at least a part of the price change after the announcement of an order imbalance to be permanent. To estimate the permanent and temporary components of $R_{i,t}^{to\ close}$, we estimate an instrumental variable estimate of Regression (5) with $OI_{i,t}$ as the instrument. Specifically, we fit the first-stage regression $R_{i,t}^{3:45\ to\ close} = a + b \times OI_{i,t} + \epsilon_{i,t}$ and we use the fitted value, $\hat{R}_{i,t}^{3:45\ to\ close}$, in the following second-stage regression:

[15] In untabulated results, we find that the slope coefficients up to *j* = 10 are not significantly different from those at *j* = 5.

$$R_{i,t+j} = a_j + b_j \times \hat{R}_{i,t}^{3:45\ to\ close} + \epsilon_{i,t}. \qquad (6)$$

Panel B of Table 4 presents the IV estimates. The slope coefficient gradually becomes more negative, from −.241 for overnight returns to −.827 for 5-day returns. These point estimates indicate that about 83% of the returns associated with an order imbalance are temporary, and roughly 17% is permanent. The evidence that a large part of the price impact is temporary indicates that closing auction traders are predominantly uninformed, but the evidence of permanent price impact indicates that informed traders also pool with them.

Earnings Announcement Days

This subsection examines the extent to which the price impact on earnings announcement days are permanent. We fit the following regression:

$$R_{i,t+j} = a_j + b_j \times \hat{R}_{i,t}^{3:45\ to\ close} + c_j \times EAD\_Dummy_{i,t} \times \hat{R}_{i,t}^{to\ close} + \epsilon_{i,t}, \qquad (7)$$

where EAD_Dummy equals 1 for EAD stocks, and 0 otherwise.

Panel C of Table 4 presents the results. The slope coefficient on the EAD dummy is −.114 for overnight returns, and it increases in magnitude to −.454 for 5-day returns. All these coefficients are significantly less than zero.

These results show that more of the closing auction price impact reverses after EADs than on other days. In fact, our estimates indicate that the price impact is fully reversed by five days after EADs. These results indicate that informed traders do not have a significant presence in closing auctions for EAD stocks.

Economic significance: Trading strategies

This section evaluates the economic significance of the predictable price changes associated with order imbalances. We use two trading strategies in general. To exploit the price movements from 3:45 p.m. to close, we first sort stocks into deciles based on order imbalances. We take a long position in the decile with the largest order imbalances, and we take a short position in the decile with the smallest order imbalances. We close out the positions at market close by placing offsetting D-orders with the specialist. Institutional investors can place D-orders directly with specialists, and some brokerages (e.g., Interactive Brokers) also allow retail clients to place D orders through them.[16]

Table 5 presents the returns for all 10 decile portfolios. The equal-weighted raw returns on Deciles 1 and 10 are −8.06 bps and 22.94 bps, respectively. The returns increase almost monotonically from Deciles 1 through 10, with Decile 9 being the exception, since it shows marginally larger returns than Decile 10. The difference between the returns on Decile 10 and the returns on Decile 1 is 31.55 bps.[17]

To evaluate the economic significance of return reversals, we consider a strategy that places market D-orders in the opposite direction from the order imbalance. For instance, if the order imbalance at 3:45 p.m. is net *buy*, our strategy places a market D-order to *sell* at close. For overnight holding periods, our strategy places offsetting market-on-open orders. For holding periods of 1–5 days, the strategy places offsetting MOC orders on the corresponding dates.

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[16] See https://www.interactivebrokers.com/en/index.php?f=4103

[17] In untabulated results, we find that the difference between the returns of the extreme decile portfolios is 7 bps between the last trade before close and close. Therefore, most of the MOC information is incorporated in prices well before the last trade.

Table 5 presents decile portfolio returns for the overnight strategy and for strategies with holding periods of one and five days. The pattern of portfolio returns for longer holding periods are the opposite of that for the 3:45 p.m. to close strategy. Decile 1 has the largest returns and Decile 10 has the smallest returns. These returns are monotonic across deciles, with a few exceptions.

The difference between returns of Decile 1 and Decile 10 is 6.81 bps for the overnight holding periods and 25.20 bps for the 5-day holding period. These returns are 22% and 80% of the magnitude of the 3:45 p.m. to close strategy, which is consistent with the IV regression results shown in Table 4. All these differences are statistically significant.

Table 5 also presents abnormal returns estimated using the single-factor model,

$$R_{i,t} = \alpha_i + \beta_i \times R_{mkt,t} + \epsilon_{i,t}, \tag{8}$$

where $R_{mkt,t}$ is the market return. We use SPY, the ETF that tracks the S&P 500, as a proxy for the market. We assume that the risk-free rate is zero because our holding periods are short, and weekly interest rates are close to zero during our sample period. Therefore, α_i is the abnormal return.

Panel B presents abnormal returns for both equal-weighted and value-weighted extreme decile portfolios. The 3:45 p.m. to close abnormal returns is 25.77 bps for the equal-weighted strategy and 14.73 bps for the value-weighted strategy. The corresponding returns for the 5-day holding period strategy is 22.72 bps and 12.04 bps, respectively. The larger abnormal returns for the equal-weighted strategy reflects the fact that larger stocks are more liquid and can absorb order imbalances of the same magnitude (measured as a ratio of total trading volume) with lower price impacts.

The raw returns of 31.55 bps for the 3:45 p.m. to close strategy is roughly an 80% annualized return, and 25.20 bps return for the 5-day holding period is roughly a 64% annualized return. These returns are fairly large, and they seem economically significant. The profits from the 3:45 p.m. to close strategy exploit delayed price reaction to the announcement of order imbalances, but the returns from the other trading strategies serve as compensation for providing liquidity to absorb order imbalances.

Trading strategy with EAD stocks

Our earlier tests find that EAD stocks experience larger reversals than other stocks. We evaluate the economic significance of this result using a trading strategy that uses only EAD stocks. We first determine the decile cutoffs using all stocks, as in the last subsection. To determine the average returns earned by stocks in each OI decile, along with their standard errors, we fit the following regression using only EAD stocks:

$$R_{i,t} = \sum_{j=1}^{10} b_j \times Decile_{dummy}{}_{i,j,t} + \epsilon_{i,t}, \tag{5}$$

where $Decile\_dummy_{i,j,t} = 1$ if stock *i* is in decile *j*, and 0 otherwise. We fit the regression with $R_{i,t}$ equal to the 3:45 to close returns, the overnight returns, and the returns for 1-day to 5-day holding periods. The slope coefficients equal the average returns for stocks in each OI decile. We compute Driscoll-Kraay standard errors clustered at the day level, with a lag of 12 to account for autocorrelation, heteroscedasticity, and cross-sectional dependence.

Table 6 reports the regression results. For instance, the difference in the 3:45 p.m. to close returns between stocks in extreme deciles is 27.8 bps, which is about the same as all stocks.[18] The second set of strategies that we open at close and hold overnight or hold over longer periods earn

[18] We compute the standard errors of the difference between Decile 1 and Decile 10 stocks by fitting the following regression using only stocks in these deciles: $R_{i,t+j} = a + b_{10} \times Decile\_dummy_{i,10,t} + \epsilon_{i,t}$.

significantly larger returns. For example, the difference in 5-day returns between stocks in the extreme deciles is 83.8 bps, compared to 25.2 bps as shown in Table 5.

One reason for these larger returns is the more significant reversals we find for EAD stocks. However, the 5-day return difference is larger than the 3:45 p.m. to close return difference. This result suggests that price pressure due to order imbalances between buyer- and seller-initiated trades during regular trading hours are in the same direction as the order imbalances in closing auctions, and their cumulative effect is larger than the price impact that can be attributed to closing auctions. The results in this subsection reinforce our earlier conclusion that informed traders are less prevalent in closing auctions for EAD stocks. The resulting larger return reversals yield significantly higher trading profits with these stocks.

Price Impact: Closing auctions vs. regular trading hours

Investors who trade in closing auctions have the choice of trading during regular trading hours as well. How does the cost of trading in closing auction compare with the cost during regular trading hours?

One measure of the cost of trade during regular hours is half spread, which is the difference between the mid-point of quoted spreads and the ask price for buy orders and bid price for sell orders.[19] Box et al (2020, Table VI) report that the average half spread is about 6.2 bps, which is the trading cost for orders smaller than or equal to the quote depth.

The price impact for bigger orders would be outside the spread, and they depend on order size. For instance, Breen, Hodrick and Korajczyk (2002) find that price impact varies with the size

[19] We do not include any brokerage fees in our trading cost comparison because they are typically not different for trading during regular trading hours and at close.

of the order and other firm characteristics such as market cap, price and inclusion in the S&P 500 index. For our purposes, we will consider the price impact for an average stock traded on the NYSE. Breen et al. (2002, p. 473) report that their estimates imply a proportional price impact of 17.9 bps for a 1,000 share trade. Breen et al. also note that the estimates in Gloston and Harris (1988) and Hasbrouck (1991) imply a slightly bigger price impact for a similar trade.

Consider closing auction trades. The NYSE first releases MOC information at 3:45 p.m. and thus the price at that time can be used as pre-execution benchmark. The price impact based on this benchmark is $R_{i,t}^{3:45\ to\ close}$. The results in Table 5 indicate that $R_{i,t}^{3:45\ to\ close}$ depends on the OI at 3:45 pm. To facilitate comparison with the price impact during regular trading hours, Table 6 presents the average trade size per stock in closing auctions and average order imbalance per stock in each OI decile.

The unconditional average of $R_{i,t}^{3:45\ to\ close}$in Table 5 is 12.26 bps, or in other words, the closing auction price at close is 12.26 bps greater than the price at 3:45 pm. While this difference is a cost for buyers it is a negative price impact for sellers because closing auction trades cross buy and sell orders at this price.[20] Therefore, unconditionally, investors would face lower costs using MOCs to sell their shares than sell them during regular trading hours. Also, based on the price impact estimates from Breen et al. (2002), investors would face a smaller price impact on average if they use MOC orders to buy greater than about 1,000 shares.[21]

[20] The NYSE levies a fee of between $0.0004 and $.001 per share for MOCs from member organizations, which is less than 1 bps for stocks priced $10 or greater (source: https://www.nyse.com/publicdocs/nyse/markets/nyse/NYSE_Price_List.pdf)

[21] Breen et al. model implies a linear relation between proportional price impact and order size. The price impact of a trade of 685 shares (=1000×12.26/17.9) equals 12.26 bps, which is the unconditional MOC buy order price impact. Therefore, buy orders for more than 685 shares will have a bigger price impact during regular trading hours.

Perhaps such price impact trade-offs are more interesting when orders fall in the extreme order imbalance categories. The price impact for Decile 1, the extreme sell decile, is 8.06 bps. The results in Table 7 show that the average order imbalance per stock in this decile is 71,797. Yet, the price impact is smaller than that for a 1,000 share trade during regular trading hours. Therefore, the price impact of even large sell orders would be of similar magnitude as average half spread during regular trading hours.

For buy orders, the average price impact for Decile 10 stocks is about 23 bps, which is bigger than Breen et al. estimates for a 1,000 share trade. The average order imbalance per stock in Decile 10, however, is much larger at 70,471. Therefore, closing auction price impacts for trades bigger than about 1,000 trades would be smaller than their price impacts during regular trading hours.

Conclusion

Trading volume in closing auctions have significantly increased in recent years. Currently, about 11% of NYSE trades are executed in closing auctions. These closing auction prices are particularly important because they are used to price portfolios and derivative assets. For example, the NYSE states that the closing auctions determine "… the day's most important price point for investors and listed companies."[22]

We identify important factors that underlie the growth of closing auctions. One important factor is the growth of ETFs. ETF arbitrageurs execute convergence arbitrage trades that seek to exploit differences between the market prices of ETFs and their NAV. Closing auctions provide

[22] See https://www.nyse.com/article/nyse-closing-auction-insiders-guide.

these arbitrageurs with a venue to simultaneously close out their positions in ETFs as well as in the portfolio of stocks that the ETFs hold.

We estimate that less than 15% of the closing volume can be directly attributed to ETF arbitrage. Other uninformed traders as well as some informed traders pool with ETF arbitrageurs to mitigate the price impacts of their trades, as in the models developed by Admati and Pfleiderer (1988, 1991). Such strategic pooling (as in the Admati and Pfleiderer models) is more beneficial for less liquid stocks; therefore, we hypothesize that closing auction volume will be inversely related to liquidity. Consistent with this prediction, we find that closing auction volume is negatively related to proxies for liquidity such as *Amihud measure* and *quoted spread*.

Market on close and limit-on-close orders are important components of closing auctions. The market begins to receive information about MOC orders for NYSE-listed stocks at 3:45 p.m. Because MOC orders reveal information about buyer- and seller-initiated trades as well as order imbalances, the changes in stock prices between 3:45 p.m. and market close measure the price impact of closing auction trades.

We find that stock returns from 3:45 p.m. to close are significantly related to order imbalances announced at 3:45 p.m. To assess the economic significance of this relation, we consider a trading strategy that buys the decile of stocks with the largest *buy* imbalance and sells the decile with largest *sell* imbalances at 3:45 p.m. This strategy earns 32 bps from 3:45 p.m. to close, which is roughly an 80% annualized return.

We also use an instrumental variables regression to measure the permanent or transitory portions of price changes after the announcement. We find that about 24% of the price changes are reversed at the market opening the next day. The reversal continues over the next few days and the cumulative reversal over the next 3–5 days is about 83%. Therefore, although closing auction participants are mostly uninformed traders, closing auctions also attract significant participation by informed traders.

Our results indicate that price impacts of trades in closing auctions are generally smaller than that during regular trading hours. Therefore, it is unclear why regular trading hours attract far more trades that closing auctions despite the cost disadvantage. Traders with time sensitive information could find it advantageous to trade during regular trading hours and not wait until closing time, but as Grossman and Stiglitz (1980) show they alone cannot sustain an active market. An investigation of why an overwhelming majority of traders prefer regular trading hours to closing auctions would be a fruitful avenue for future research.

Figure 1: Time-Series Trends in Closing Auction Trading Volume

This figure presents the time-series 90-day moving average of the total dollar volume of closing auction trades as a fraction of total trading volume using S&P 500 stocks. The closing auction trading volume is based on the trading volume in the TAQ dataset, coded as '*6'* or '*M'* scaled by the total daily trading volume.

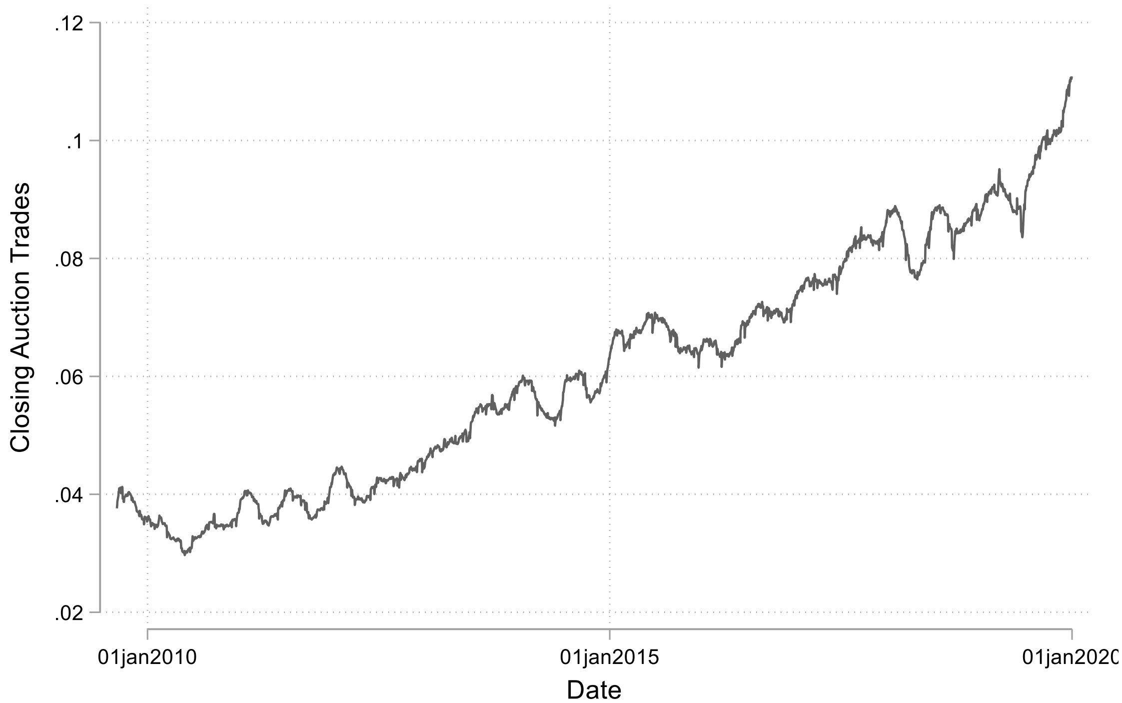


Figure 2: Creation and Redemption Process

The figure provides an illustration of creation and redemption of ETF units.

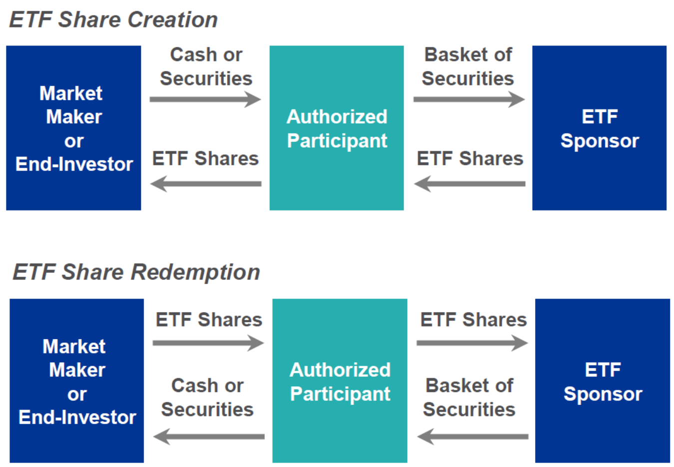
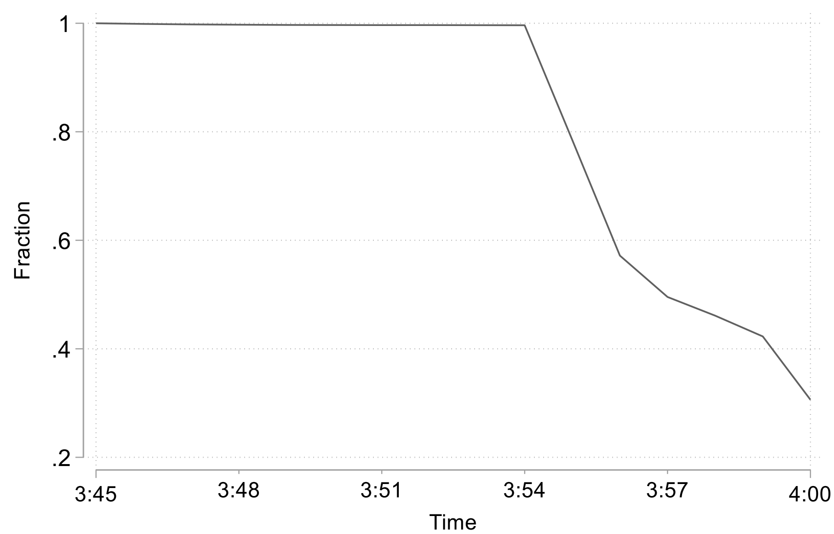


Figure 3: Order Imbalance for NYSE-Listed Stocks

This figure presents the relative order imbalance (OI) for NYSE-listed stocks from 3:45 p.m. to 4:00 p.m. Panels A and B present the time-series average of cross-sectional mean returns for stocks with *buy* and *sell* OIs, respectively, as of 3:45 p.m. The *y*-axis presents the OI at the end of each minute as a fraction of the OI as of 3:45 p.m. The sample period is from March 2010 to June 2018.

Panel A: Stocks with *buy* order imbalance as of 3:45 p.m.



Panel B: Stocks with *sell* order imbalance as of 3:45 p.m.

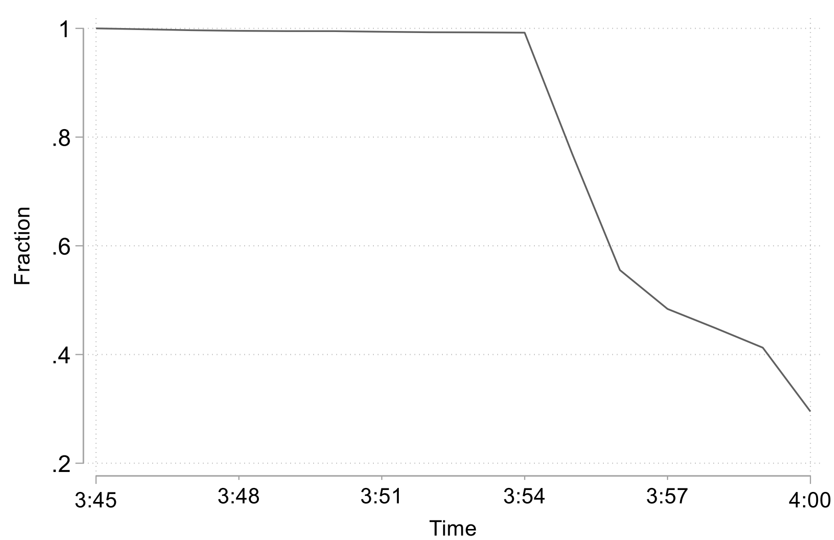
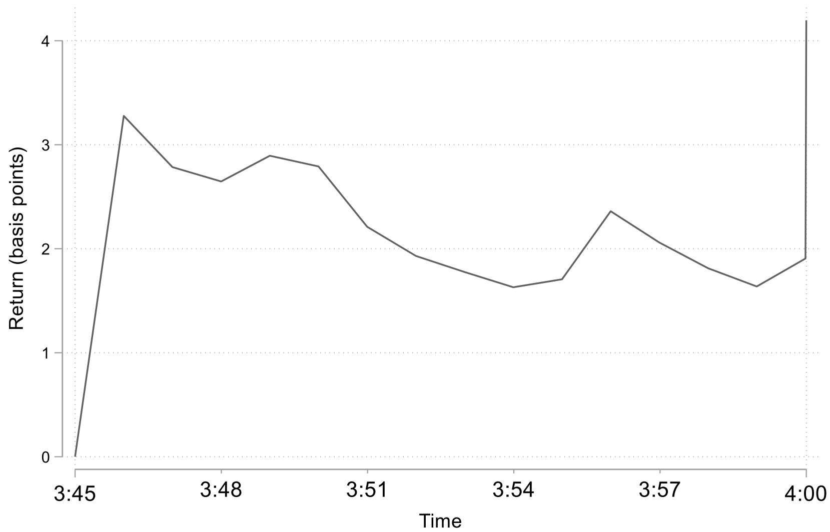


Figure 4: Returns for NYSE-Listed Stocks

This figure presents returns in basis points (bps) for NYSE-listed stocks from 3:45 p.m. to 4:00 p.m. Panels A and B present returns for stocks with *buy* and *sell* order imbalances, respectively, as of 3:45 p.m. The sample period is from March 2010 to June 2018. The stock prices are based on the last valid trade at the end of each minute from TAQ data. In addition to the price from the continuous market. The last price is the closing auction price is included.

Panel A: Stocks with *buy* order imbalance as of 3:45 p.m.



Panel B: Stocks with *sell* order imbalance as of 3:45 p.m.

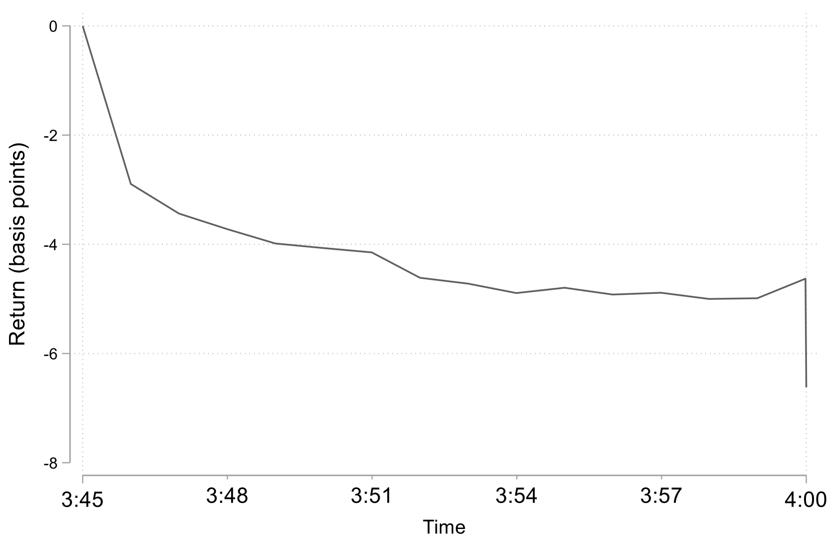


Table 1. Sample and Summary Statistics

The table reports the summary statistics for the variables used in the study. Panel A reports the number of ETFs in the sample as well as their assets under management for each year. Panel B reports the summary statistics for the closing auction trading volume and the proxies for ETF arbitrage trades. *ETF_arb* is the sum of the closing auction ETF trades and the stock trades implied by the ETF trades. *ETF_cr* is the dollar value of stock trades corresponding to the creation and daily redemption of ETFs. The sample period is from July 2008 to June 2018.

Panel A: ETF sample

Year	# of ETFs	Total AUM ($ billions)
2008	339	534
2009	342	764
2010	350	976
2011	363	1,019
2012	366	1,301
2013	367	1,633
2014	367	1,944
2015	367	2,052
2016	367	2,475
2017	367	3,197
2018	367	3,275

Panel B: Summary statistics

Variable	Mean	Median
Closing Auction Vol($)	2,737,002	230,230
Closing Auction/Total Trading	6.37%	4.14%
ETF_cr($)	1,566,492	257,690
ETF_arb ($)	181,441	9,718
ETF_arb/Closing Auction	15.03%	3.60%

Table 2. ETF Arbitrage Activity and Closing Auction Volume

The table presents estimates from panel regressions of daily closing auction trading volume on proxies for ETF arbitrage trades and trading liquidity. The sample is composed of all common stocks (share code of 10 or 11, excluding those priced less than $5). The dependent variable is market-on-close trading volume divided by the total daily trading volume. *ETF_arb* represents the closing auction stock trades implied by the closing auction ETF trades. *ETF_cr* represents the stock trades implied by the creation and redemption of ETFs. The proxies of liquidity are the lagged *Amihud measure*, the intraday *quoted spread*, the inverse of the lagged stock price, and lagged log market capitalization. All variables are standardized each day by subtracting the mean and dividing by the standard deviation. All models control for firm fixed effects and trading date fixed effects. Standard errors are double clustered at the stock and day level, and *t*-statistics are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ETF_arb	0.222***		0.209***		0.208***	
	(31.69)		(30.56)		(30.46)	
ETF_cr		0.333***		0.317***		0.316***
		(55.59)		(53.77)		(53.60)
Amihud			0.061***	0.057***	0.061***	0.057***
			(26.49)	(25.63)	(26.45)	(25.61)
Quoted Spread			0.290***	0.248***	0.293***	0.250***
			(27.62)	(26.24)	(27.74)	(26.37)
1/Price			−0.581***	−0.506***	−0.584***	−0.509***
			(−3.33)	(−3.03)	(−3.35)	(−3.05)
Ln(Market Cap)			−0.0103	−0.003	−0.009	−0.002
			(−0.55)	(−0.19)	(−0.48)	(−0.13)
EAD dummy					−0.186***	−0.167***
					(−42.73)	(−41.11)
N	6,662,992	6,662,992	6,635,787	6,635,787	6,635,787	6,635,787
Adj. R^2	0.267	0.299	0.278	0.307	0.279	0.308

Table 3. Price Response to Closing Auction Order Imbalance

The table presents coefficients estimated from the following panel regression:

$$R_{i,t}^{3:45\ to\ close} = a + b \times OI_{i,t} + \boldsymbol{\gamma}'\boldsymbol{X}_{i,t}^{s} + \epsilon_{i,t},$$

where $R_{i,t}^{3:45\ to\ close}$ is the return from 3:45 p.m. to close, and $\boldsymbol{X}_{i,t}^{s}$ is the vector of liquidity proxies (i.e., the lagged Amihud ratio, the intraday quoted spread, the inverse of the lagged stock price, and lagged log market capitalization) multiplied by the sign of the closing auction order imbalance ($Signed\ OI$). $Signed\ OI$ equals +1 for stocks with *buy* order imbalances and −1 for stocks with *sell* imbalances as of 3:45 p.m. The sample is comprised of NYSE-listed common shares (share codes 10 or 11 in CRSP, excluding those priced less than $5). All models control for firm fixed effects and trading date fixed effects. The sample period is from March 2010 to June 2018. Standard errors are double clustered at the stock and day level, and *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
$Closing\ Auction\ OI_{i,t}$	1.043***	0.769***
	(42.55)	(35.38)
$Signed\ OI_{i,t} * Amihud_{i,t}$		0.0078***
		(5.48)
$Signed\ OI_{i,t} * Quoted\ Spread_{i,t}$		0.0378***
		(14.84)
$Signed\ OI_{i,t} * \ln(Market\ Cap)_{i,t}$		−0.0020***
		(−0.81)
$Signed\ OI_{i,t} * 1/Price_{i,t}$		1.1568***
		(32.13)
N	2,856,841	2,854,947
Adj. R^2	0.377	0.389

Table 4. Price Impact and Future Returns

This table presents the relation between closing auction price impact $\left(R_{i,t}^{3:45\ to\ close}\right)$ and returns on subsequent days. Panel A presents coefficient estimates from panel regressions where the dependent variables are the future returns, including the overnight return, next day return, and returns up to five days; and the independent variable is the price impact. Panel B presents the coefficient estimates of an instrumental variables (IV) regression with order imbalance as the instrument for price impact. Panel C presents the IV regression for a subsample of stocks that announced earnings after market close on day *t*. The sample is comprised of NYSE-listed ordinary common shares (share codes 10 or 11 in CRSP). All models control for firm and trading day fixed effects. The sample period is from March 2010 to June 2018. Standard errors are double clustered at the stock and day level, and *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Panel Regression

	$R_{i,overnight}$	$R_{i,t,t+1}$	$R_{i,t,t+2}$	$R_{i,t,t+3}$	$R_{i,t,t+4}$	$R_{i,t,t+5}$
$R_{i,t}^{3:45\ to\ close}$	−0.107***	−0.147***	−0.192***	−0.205***	−0.228***	−0.236***
	(−23.88)	(−10.78)	(−10.56)	(−9.63)	(−8.04)	(−9.07)
N	2,856,336	2,856,425	2,855,888	2,855,400	2,853,909	2,854,410
Adj. R^2	0.517	0.361	0.339	0.328	0.309	0.315

Panel B: IV Regression

	$R_{i,overnight}$	$R_{i,t,t+1}$	$R_{i,t,t+2}$	$R_{i,t,t+3}$	$R_{i,t,t+4}$	$R_{i,t,t+5}$
$\hat{R}_{i,t}^{3:45\ to\ close}$	−0.241***	−0.575***	−0.667***	−0.693***	−0.809***	−0.827***
	(−38.58)	(−33.57)	(−26.24)	(−22.05)	(−22.22)	(−20.24)
N	2,856,336	2,856,425	2,855,888	2,855,400	2,853,909	2,854,410

Panel C: IV Regression with EAD Stocks

	$R_{i,overnight}$	$R_{i,t,t+1}$	$R_{i,t,t+2}$	$R_{i,t,t+3}$	$R_{i,t,t+4}$	$R_{i,t,t+5}$
$\hat{R}_{i,t}^{3:45\ to\ close}$	−0.239***	−0.571***	−0.659***	−0.686***	−0.804***	−0.821***
	(−38.05)	(−33.07)	(−25.75)	(−21.68)	(−21.91)	(−19.94)
$EAD * \hat{R}_{i,t}^{3:45\ to\ close}$	−0.114***	−0.319***	−0.563***	−0.500***	−0.392***	0.454***
	(−3.66)	(−3.72)	(−4.43)	(−3.18)	(−2.15)	(−2.22)
N	2,856,336	2,856,425	2,855,888	2,855,400	2,853,909	2,854,410

Table 5. Trading Strategies Based on Closing Auction Order Imbalances

The Panel A of the table reports raw returns (in basis points) for portfolios formed based on closing auction order imbalances (OIs). The sample is comprised of NYSE-listed ordinary common shares (share codes 10 or 11 in CRSP). Stocks are sorted into deciles based on order imbalances as of 3:45 p.m. Decile 1 and Decile 10 are the deciles of stocks with the largest *sell* and *buy* OI, respectively. The table reports equal-weighted returns for various holding periods. The trading strategy for 3:45 p.m. to close goes long for Decile 10 and short for Decile 1. For longer horizon returns, the trading strategy is long Decile 1 and short Decile 10. Panel B reports the market-model alpha with SPY as the market proxy. EW is for equal-weighted portfolios, and VW is for value-weighted portfolios. Robust *t*-statistics based on Newey–West (1987) corrected standard errors with 12 lags are reported in parentheses. The sample period is from March 2010 to June 2018.

Panel A:

OI Decile	$Ret_t^{3:45\ to\ close}$	$Ret_t^{overnight}$	$Ret_t^{t,t+1}$	$Ret_t^{t,t+5}$
1	−8.06	5.07	13.43	38.84
	(−7.23)	(3.44)	(4.30)	(6.23)
2	−2.78	4.43	11.21	35.16
	(−2.60)	(2.94)	(3.60)	(5.47)
3	−0.24	4.08	9.57	33.75
	(−0.26)	(2.64)	(3.06)	(5.13)
4	4.88	3.82	8.18	33.40
	(1.95)	(2.39)	(2.55)	(5.00)
5	4.15	4.23	7.73	32.51
	(4.20)	(2.64)	(2.44)	(4.84)
6	8.43	3.37	5.21	31.62
	(6.74)	(2.12)	(1.65)	(4.72)
7	9.73	2.25	3.39	29.52
	(9.24)	(1.41)	(1.07)	(4.46)
8	11.21	1.46	1.51	25.05
	(12.34)	(0.94)	(0.49)	(3.86)
9	24.48	0.44	−0.50	22.08
	(2.41)	(0.29)	(−0.16)	(3.47)
10	22.94	−1.74	−4.50	13.64
	(10.42)	(−1.19)	(−1.47)	(2.19)
Decile 10–1	31.55			
	(14.11)			
Decile 1–10		6.81	17.94	25.20
		(18.30)	(15.25)	(11.45)

Panel B:

	$Ret_t^{3:45\ to\ close}$		$Ret_t^{overnight}$		$Ret_t^{t,t+1}$		$Ret_t^{t,t+5}$	
	EW	VW	EW	VW	EW	VW	EW	VW
1	−3.17	18.38	2.84	1.49	6.93	3.86	12.04	7.60
	(−2.86)	(4.97)	(6.88)	(3.44)	(6.23)	(4.45)	(5.38)	(4.15)
10	22.59	33.17	−2.80	−0.61	−8.13	−1.87	−10.68	−4.44
	(10.41)	(6.62)	(−6.81)	(−1.48)	(−7.09)	(−2.24)	(−4.86)	(−2.56)
10–1	−25.77	−14.73	5.64	2.10	15.06	5.72	22.72	12.04
	(−11.20)	(−2.56)	(16.41)	(4.05)	(13.74)	(4.84)	(11.19)	(5.10)

Table 6. Trading Strategy with Earnings Announcement Stocks

This table reports raw returns (in basis points) for portfolios formed based on closing auction order imbalances (OIs). Stocks are sorted into deciles based on order imbalances as of 3:45 p.m., and decile cutoffs are determined with all stocks. Decile 1 and Decile 10 are the deciles of stocks with the largest *sell* and *buy* OI, respectively. The table reports equal-weighted for returns for NYSE-listed stocks that announce earnings after market close on day *t*. The trading strategy for 3:45pm to close goes long Decile 10 and short Decile 1. For longer horizon returns, the trading strategy is long Decile 1 and short Decile 10. The table computes average returns and standard errors based on the regression $R_{i,t} = \sum_{j=1}^{10} b_j \times Decile_{dummy_{i,j,t}} + \epsilon_{i,t}$, where $Decile\_dummy_{i,j,t} = 1$ if stock *i* is in decile *j* and 0 otherwise, where decile *j* is determined using the full sample. The dependent variables, $R_{i,t}$, equal the 3:45 to close return (Column 1), the overnight return (Column 2), and returns for 1- and 5-day holding periods (Columns 3 and 4). The slope coefficients equal the average returns for stocks in each OI decile. The sample period is from March 2010 to June 2018. Standard errors are clustered at the day level, and *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

OI Decile	$Ret_t^{3:45\ to\ close}$	$Ret_t^{overnight}$	$Ret_t^{t,t+1}$	$Ret_t^{t,t+5}$
1	−13.60***	8.27	32.00**	54.90**
	(−6.98)	(0.78)	(2.08)	(2.40)
2	−9.25***	9.24	26.10*	34.00
	(−6.27)	(0.91)	(1.72)	(1.58)
3	−8.03***	4.79	6.44	17.50
	(−5.99)	(0.59)	(0.56)	(0.99)
4	−2.76**	0.168	10.30	18.80
	(−2.39)	(0.02)	(0.76)	(0.98)
5	0.07	4.31	22.10*	35.50**
	(0.06)	(0.55)	(1.95)	(2.07)
6	4.30***	−11.30	−3.77	21.80
	(3.55)	(−1.30)	(−0.32)	(1.26)
7	5.67***	5.52	4.88	23.50
	(5.05)	(0.61)	(0.41)	(1.35)
8	8.44***	−8.27	−2.91	−2.82
	(6.28)	(−1.02)	(−0.23)	(−0.15)
9	9.90***	−18.00*	−17.80	−25.60
	(7.54)	(−1.95)	(−1.21)	(−1.22)
10	14.20***	−6.52	−2.49	−28.9
	(7.42)	(−0.62)	(−0.15)	(−1.29)
10–1	27.80***			
	(12.26)			
1–10		14.80	34.50	83.80***
		(1.02)	(1.59)	(3.02)

Table 7. Closing Auction Order Imbalance

This table reports average closing auction order imbalance (OI). Stocks are sorted based on OIs as of 3:45 pm and assigned to deciles. Decile 1 and Decile 10 are the deciles of stocks with the largest *sell* and *buy* OI, respectively. For each decile, the table presents the OI as a % of total daily trading volume, the dollar value and number of shares of OI per stock. The sample is comprised of NYSE-listed ordinary common shares (share codes 10 or 11 in CRSP). The sample period is from March 2010 to June 2018.

OI Decile	OI as a % of daily volume	Dollar value of OI per stock	Number of shares of OI per stock
1	-5.33%	3,066,726	71,797
2	-2.05%	1,403,256	33,396
3	-1.13%	894,471	22,603
4	-0.54%	587,818	16,277
5	-0.10%	457,773	13,763
6	0.32%	498,299	15,009
7	0.78%	688,988	19,515
8	1.39%	993,674	26,281
9	2.36%	1,436,208	36,036
10	5.69%	2,975,797	70,471

SECOND ESSAY
The Effect of Passive Investing on Initial Public Offering Stocks

Introduction

Passive investing has grown remarkably in recent years, with assets under management for passive funds increasing to $4 trillion dollars in 2018. The impact of index membership on underlying stocks is ubiquitous: many studies have found that stocks added to the index experience positive abnormal returns (e.g., Shleifer (1986); Harris and Gurel (1986); Chen, Noronha, and Singal (2004)). Recent studies have shown that the increase in index investing contributes to less price efficiency, higher volatility of underlying securities (Israeli, Lee, and Sridharan (2017), Ben-David, Franzoni, and Moussawi (2018)), and influences firms' corporate decisions and long-term performances (Appel, Gormley, and Keim (2016) and Schmidt and Fahlenbrach (2017)).

While previous studies have mainly focused on mature large public firms, it is less clear whether index investing affects the performance of initial public offering (IPO) firms, especially during the process of going public. One the one hand, passive investing might not affect valuation of IPO firms because these firms will not be considered to be added into certain indices until the stocks have been traded on exchanges for a period of time. Therefore, passive investors such as exchange traded funds (ETFs) and index funds will not engage in pre-IPO activities and will only trade IPO stocks when the benchmarks start to include them.

On the other hand, there are several reasons to believe passive investing does affect IPO firms. First, the tremendous increase in passive investing over the past decade and more importantly the timely inclusion of IPO stocks into major indices result in rapid increase in passive demand even for new-listed firms. Historically, IPO stocks were not considered for inclusion in widely used indexes until the stocks had been traded for a period of time. For instance, S&P composite indices (e.g., S&P 500 and S&P 1500) require that "initial public offerings should be traded on an eligible exchange for at least 12 months before being considered for addition to an index." Similarly, Russell indices treated IPO firms the same as other public firms and considered new-listed firms for inclusion during the annual reconstitution in June. Starting 2000s, all these indices have changed their methodologies to include IPO stocks in a timely manner. For instance, Russell indices started to include IPO stocks on a quarterly basis while S&P composite indices modified the methodology for fast-track IPO inclusion such that some large IPOs will be included even faster. Second, financial innovations such as IPO ETFs also create additional demand for IPO stocks in the secondary market.[23] Furthermore, Kashyap, Kovrijnykh, Li, and Pavlova (2021) propose a theory that the subsidy from benchmarking inclusion could affect firm's decision of going public and the value of IPO.

This paper provides the first empirical test on whether passive investing influences the price dynamics of initial public offering (IPO) stocks during the first-day trading (i.e., the underpricing of IPOs) and during the periods when stocks are actually added into the index through a unique quasi-natural experiment: the Russell quarterly additions of IPO stocks. Different from the traditional additions and deletions from the S&P 500 or the Russell annual reconstitution, the Russell indexes' quarterly IPO additions only consider the most recent IPO stocks on a quarterly basis in March, September, and December.[24] The rules are simple: the IPO must rank larger in the total market capitalization than the market-adjusted smallest company in the Russell 3000E Index as of the most-recent June reconstitution. The time schedule of quarterly reconstitution is known to the public.[25]

We begin our analysis by focusing on whether the passive demands in the secondary market has impact on the first day performance of the IPO stocks since it is well known that IPO stockson average are underpriced (See Rock (1986), Lowry and Schwert (2002), Lowry and Schwert (2004), Lowry (2003).) On the one hand, if underwriters can incorporate the future demand into consideration, we would expect a higher offer price or lower first-day underpricing. On the other hand, if underwriters fail to consider such demand, we expect a lower offer price or a higherfirst-

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[23]For example, First Trust U.S. Equity Opportunities ETF tracks a market-cap-weighted index of the 100 largest US IPOs over the first 1,000 trading days for each stock and it has a total asset management of $1.26 billion since 2006. Renaissance IPO ETF is another example of IPO ETFs that recently launched in 2013 with $ 0.5 billion as of May 2021.

[24] Stocks that went public from the middle of March to May will be treated indifferently than the rest of public stocks during the June annual reconstitution. We also consider these IPO stocks in our analysis.

[25] For instance, in 2013, any eligible IPOs that initially were price/traded between June 1 and August 31 will be included in the third-quarter additions with an announcement day of September 15 and effective date of September 30. We thank Russell Inc for providing the schedule of quarterly additions.

day return.

The baseline analysis, using all IPO stocks from 2008 to 2018 included in the Russell indexes as well as those not included, shows that former had higher first day returns compared to the latter. The result is consistent with the hypothesis that underwriters might fail to consider such demand during the primary market. Even though the results are robust after controlling for various variables related to the underpricing and time fixed effect to account for IPO trend, it is still possible that inclusion in the Russell indexes could be endogenously related to omitted stock variables that affect the first day return. To address this issue, we conducted two supplemental tests within those stocks that were ex-post included in the Russell indexes. Since the Russell indexes are market cap-weighted indexes, IPOs with larger market caps are more likely to be included in the indexes and will receive higher passive demand than IPOs with smaller market caps. Our analysis confirms such conjecture. Compared to stocks with a market cap smaller than the median of all included stocks, stocks with a larger market cap have, on average, 3% higher first-day returns. To avoid the confounding effect due to the first day returns, the market cap is calculated based on the offer price, instead of the first day closing price. This empirical evidence suggests that the passive impact is large, since theory has suggested that smaller firms should have higher first-day returns because small firms are harder to value and information asymmetry is higher.

To further confirm the impact of passive investing and alleviate the endogeneity concern, we exploit one unique aspect of the Russell quarterly additions. While the addition schedules are fixed, the dates that firms actually go public are not. There are substantial variations of the time gap between the filing date of going public and the actual IPO date due to reasons such as the review process of Securities and Exchange Commissions' (SEC) review process and the roadshow schedule of issuers. Therefore, firms and underwriters cannot precisely control for the exact date of listing in exchanges. Thus, the probability of inclusion into the next round schedule of Russell indexes additions is lower if the time that a firm plans to go public is close to the cutoff rank date of Russell inclusion and the market size of the firm is comparable to stocks at the bottom ranks of Russell. Let's take two firms that will go public during the third quarter for example. For these two firms, all things are equal and their stocks both meet the minimum requirement for inclusion based on the market cap. The first IPO firm is scheduled to go public during the first week of June, while the other one starts the roadshow and plans to be listed on the exchange during the last week of August. In the first case, it is guaranteed to be included in the next round. Yet, the second stock may not be listed on the exchange before the rank date of August 31, and therefore must wait for three additional months until the December addition arrives. Such an exogenous difference of time gap between issue date and pre-determined rank date results in differences of passive demand. All things equal, stocks that are more likely to be included in the next addition, proxied by the above-median time difference between IPO issue date and rank date, have higher first-day returns, which is consistent with the hypothesis that passive demand results in higher first-day returns.

Taken together, the evidence is consistent with the hypothesis that during the underwriting process, underwriters might fail to take the passive demand into consideration when determining an offer price. This results in higher first-day returns for stocks that are more likely to be included into the index due the passive demand.

Moving beyond the first-day returns, we also revisit the price effect of index membership among the Russell quarterly added IPOs stocks. The literature on changes in index constituents of the S&P 500 Index offers inconsistent views on the price impact of additions and deletions. For instance, the downward-sloping demand curve hypothesis (i.e., Shleifer (1986)) argues that the inclusion (removal) of a stock from the S&P 500 Index and its subsequent buying (selling) by index funds will result in a permanent increase (a decline) in the price of the stock. In contrast, the price pressure hypothesis (Harris and Gurel (1986)) argues that the price effects of additions and deletions are temporary. More recently, Chen, Noronha, and Singal (2004) proposed the investor awareness hypothesis, such that a stock's addition into the S&P 500 could increase investor awareness and thus the stock price would increase. In contrast, no permanent price effect is associated with the deletion since investors' awareness of the stock does not vanish immediately after it has been removed from the index. Furthermore, more recent studies such as Denis, McConnell, Ovtchinnikov, and Yu (2003), Kasch and Sarkar (2013), and Chen, Singal, and Whitelaw (2016), showed that the permanent changes in market value and return comovement attributed to S&P 500 index additions are endogenously related to stock characteristics, including earnings performance and return momentum.

We find that IPO stocks that are added into Russell indexes, on average, have abnormal positive returns following the announcement day. The abnormal returns persist from the announcement day to the effective day. However, such returns are subsequently reversed 30 days after the effective day, which is consistent with the price pressure hypothesis. Trading volume pattern shows similar results. Since the IPO additions into the Russell indexes are rule-based and is predictable, the price effect is less likely to be driven by stock characteristics. The placebo test using non-included IPOs shows no pattern around announcement days. Further analysis that examines separately IPO stocks added in quarters other than June and IPO stocks added in June annual reconstitutions shows that during June annual reconstitutions, the price effect is smaller, and reversal is faster. This is consistent with the fact that annual reconstitutions are well-known, market-wide, attention-grabbing events and attract not only passive investors but also quasi-arbitragers during the process. Frictions associated with shorting, or leverage have also fallen over time, which might lead to greater arbitrage capacity to offset the effects of rising indexing demand.[26]

In addition to the price effect during the inclusion period, stocks that are added into indexes shows increasing comovement. As previously mentioned, the unique feature about the IPO additions is that the time interval between the IPO issue date and the rank date for inclusion varies across different IPO stocks for reasons other than the inclusion of benchmark. We exploit a difference-in-difference approach to show that there is excess comovement after inclusion. The first difference is the difference of estimated R^2 (or β) before and after effective days. The second difference is the difference between stocks that were added earlier to the index and those added later. We find that stocks that were added earlier to the index have smaller changes in comovement, while stocks added

[26] The empirical results are consistent with the finding of McLean and Pontiff (2016) that showed once an anomaly is widely known, the abnormal return exploiting such anomaly has decreased.

later have larger changes in comovement and such a difference is statistically significant, providing support for the hypothesis that inclusion in index increases comovement.

In summary, this paper shows that passive investing affects the price dynamics of IPO stocks in the secondary market. Using data from the Russell indexes' quarterly additions, we show that IPO stocks that are more likely to be included in the index have higher first-day returns. An additional event study shows that additions lead to abnormal returns and abnormal trading volumes around the inclusion period and the return is subsequently reversed, consistent with the price pressure hypothesis. Finally, by exploiting a difference-in-difference approach, we show that index inclusion increases comovement.

This paper contributes to the literature in several ways, First, we contribute to a growing literature exploring the impact of passive investing on asset prices. In particular, recent studies on the ETF ownership have highlighted certain unintended consequences for underlying securities, such as an increase in non-fundamental volatility (Ben-David, Franzoni, and Moussawi (2018), Coles, Heath, and Ringgenberg (2017)), an increase of comovement in returns (Da and Shive (2018)), an increase of the commonality in liquidity (Agarwal, Hanouna, Moussawi, and Stahel (2018)), and a change of information efficiency (Israeli, Lee, and Sridharan (2017), Glosten, Nallareddy, and Zou (2016)). While prior studies on the passive investing primarily focus on the mature large firms, the present study, to our best knowledge, is the first empirical paper to study the impact of passive investing on IPO stocks.

This paper also contributes to the literature on IPO underpricing. IPO underpricing is a persistent phenomenon and several strands of studies have sought to explain the mechanisms of underpricing from different aspects. For instance, Rock (1986), Benveniste and Spindt (1989) and Beatty and Ritter (1986) explained the underpricing that is due to information asymmetry among different parties. Studies such as Hoberg (2007) and Liu and Ritter (2011) focuses on the role of underwriters during the IPO process. More recently, there has been an increasing trend over the past decade that non traditional institutional investors such as mutual funds managers are engaged in the primary market (Kwon, Lowry, and Qian (2020), Chernenko, Lerner, and Zeng (2017)). While all the literature on IPO underpricing mainly focus on the role of underwriters, issuers, and active institutional investors during the underwriting process, this paper sheds light on how the dynamics of underpricing are influenced by the recent rise of passive investing.

This paper also contributes to a large literature analyzing the effects of indexing on securities prices and quantities. Shleifer (1986) pioneered the most prominent test regarding whether demand curves for stocks slope downward. The test shows that a portfolio of stocks added to the S&P 500 index did not revert over the following three months, which can be interpreted as evidence for permanent investor demand effects.[27] On the other hand, Harris and Gurel (1986) argued that additions and deletions do not have a permanent impact on stock prices. More recently, several studies have called into question the plausibility of this interpretation since it is difficult to separate indexing from potential confounding factors such as news and investor recognition associated with S&P 500 membership. For instance, Chen, Noronha, and Singal (2004) shows an asymmetric price effect between deleted stocks and added stocks, consistent with the Merton (1987)'s investor recognition hypothesis. Kasch and Sarkar (2013) and Chen, Singal, and Whitelaw (2016) show that permanent changes in market value and return comovement attributed to S&P 500 index additions are endogenously related to stock characteristics. Instead of focusing on stocks from the S&P 500 index, this paper examines the price effect and comovement for those Russell quarterly added IPO stocks and finds that the effect is more consistent with the price pressure.[28]

The remainder of the article is organized as follows. Section 2 reviews institutional background and the data used in the paper. Section 3 provides empirical tests of passive investing on IPO stocks from three different aspects, and Section 3 provides empirical tests of passive investing on IPO

[27] Similarly, Beneish and Whaley (1996), Lynch and Mendenhall (1997), Dhillon and Johnson (1991), Wurgler and Zhuravskaya (2002), Barberis, Shleifer, and Wurgler (2005), and Petajisto (2011).

[28] Several studies examine similar issues under alternative settings. For instance, Chang, Hong, and Liskovich (2014) used the firms that switch between the Russell 1000 and 2000 as a random discontinuity design and Greenwood (2007) focused on the Tokyo Nikki Index reweight as a natural experiment.

stocks from three different aspects, and Section 4 offers concluding remarks.

Institutional Background and Data

Quarterly Inclusion of IPOs into Russell U.S Indexes

Russell indexes are among the most popular indexes used in the U.S. Starting in September 2004, Russell Inc. added eligible IPOs to U.S. indexes at the end of each calendar quarter following a pre-determined schedule. The motivation for Russell to add IPOs each quarter was to reflect the investing opportunity set in a timely manner. Like the Russell annual reconstitution, the quarterly inclusion of IPOs also has the same criteria. First, new companies must be U.S. incorporated companies or U.S. benefit-driven incorporated (BDI) companies.[29] Second, all eligible securities for inclusion in Russell indexes must trade on a major U.S. exchange. ADRs, ADSs, preferred stocks, redeemable shares, warrants, rights, and trust receipts are excluded. Third, the minimum closing price must be at or above $1.00 on the last trading day of the eligibility period in order to qualify for index inclusion. If a security has been previously traded publicly, even on a restricted basis, it is not eligible for inclusion as an IPO. Such a stock may, however, be eligible during the next annual reconstitution period, along with all the other eligible securities. Similar to annual reconstitution and based on the market capitalization on the rank date, stocks with a market cap greater than the market-adjusted smallest company in the Russell 3000 Index as of the latest June reconstitution, are then considered in the Russell 3000. On the announcement day, the list of IPO stocks is made available to the public. The actual index inclusion will occur on the effective date. This paper focuses on IPO stocks that are

[29] Companies incorporated in the following countries/regions are also reviewed for eligibility: Anguilla, Antigua and Barbuda, Bahamas, Barbados, Belize, Bermuda, British Virgin Islands, Cayman Islands, Channel Islands, Cook Is- lands, Faroe Islands, Gibraltar, Isle of Man, Liberia, Marshall Islands, Netherlands Antilles, Panama, and Turks and Caicos Islands. For companies incorporated in a BDI region, the index also requires the companies' headquarters is based in the U.S. or the headquarters is in a BDI-designated country or region, and the exchange with the most trading volume of local shares is in the U.S.

included into the Russell 3000.[30] We obtain the time schedule of quarterly additions from Russell Inc. starting in 2008. The time schedule of the additions is preannounced in the spring of each year with information including cut-off rank date, announcement date, and effective date for each quarter additions. The schedules vary across different years and different quarters. We obtain detailed lists of IPO additions from Bloomberg.

Regarding IPO-related variables, we obtain them from the SDC Global New Issues Databases. Since the Russell Inc. only provides us the time schedule of additions starting from 2008, we consider U.S.-listed IPOs from 2008 to 2018, excluding closed-end funds, depository issues, dual- class IPOs, warrants, trusts, and unit IPOs (Loughran and Ritter (2004)). We only consider common shares, ordinary shares, and Class A common shares. We obtain IPO underwriter reputation and IPO firm founding date from Prof. Jay Ritter's website.[31] The first day return is defined as the percentage change from the offer price to the closing price on the first trading day. We obtain financial statement variables and financial market variables from the Compustat and CRSP databases, respectively.

[Insert Table 8 here]

Table 1 reports summary statistics on the number of the IPOs added into the Russell indexes and those not added. The average number of IPOs that are added into the indexes is about 94 per year. The first-day return for IPO stocks added into the Russell index is, on average, 17.27% during the sample period from 2008 to 2018. Variable definitions are available in the Appendix.

Results

In this section, we investigate three aspects of the impact of passive investing on IPO stocks. Section1 investigates the first-day returns. Section 2 investigates the inclusion effects and Section 3 uses adifference-in-difference approach to investigate the comovement effects from index inclusion.

[30] According to the Russell survey on U.S. Equity Indexes (Institutional Benchmark Survey, December 2014), Russell 1000 and Russell 2000 are among the top three U.S. equity benchmarks ranked by usage and $5.7 trillion in assets have been benchmarked to the Russell indexes.

[31] https://site.warrington.ufl.edu/ritter/ipo-data/

Passive investing and the first-day returns: all eligible IPOs

In this section, we begin our baseline analysis by showing that the first-day returns for IPO stocks that were ex-post added to the indexes are significantly different from the returns of those IPO stocks that were not added in the indexes. Even though passive funds do not engage in pre-IPO activities, the rise of passive investing does exert additional hidden demand for IPO stocks in the secondary market. Such demand comes primarily from three sources. First, hidden demand comes from the passive funds that follow the widely used Russell indexes, which include IPO stocks on a quarterly base. Second, hidden demand originates from ETFs and passive mutual funds that focus on new issue securities, such as Renaissance IPO ETF and First Trust U.S. Equity Opportunities ETF. Third, hidden demand comes from quasi-arbitragers that actively exploit and engage in flipping activities by buying stocks ahead of inclusion and selling to passive funds when inclusion is announced.

We hypothesize that at the aggregate level, such hidden demand for stocks that will be added to index leads to higher first-day returns. Put differently, when underwriters and firms determine its IPO offer prices, they might fail to take this hidden demand into consideration, thereby resulting in a lower offer price. To formally test this hypothesis, we begin our baseline regression using all IPO stocks no matter whether they were added into the Russell indexes. Specifically, we estimate the following regression with the first-day return as the dependent variable:

$$\text{First day return}_i = \alpha + \beta_1 \text{inclusion}_i + \gamma \text{X}_i + \beta_2 \text{Time FE} + \beta_3 \text{Industry FE} + \varepsilon_i$$

Where the dummy variable *inclusion*$_i$ equals 1 if the stock is included into the Russell ex post and 0 otherwise. Following the IPO underpricing literature, X_i is a vector of controls for stock and deal characteristics in which we include age, which is the natural log of the firm's age in years at the time of the IPO. Other explanatory variables include dummy variable NASDAQ, an indicator for whether the IPO is listed on NASDAQ (e.g. Lowry, Officer, and Schwert (2010)); *ln*(*Proceeds*), the natural logarithm of total proceeds in millions of dollars, *Top_Tier*, an indicator for whether the lead underwriter's Carter and Manaster (1990) rank is greater than or equal to eight;

VentureBackedDeal, an indicator for whether the issuing firm has venture capital backing; *shareoverhang*,defined as the ratio of retained shares to the public float (e.g., Bradley and Jordan (2002)) to capture both incentive effects and valuation effects. In addition to deal and stock characteristics, we also include market return, defined as the compounded daily return on the CRSP-Value Weighted Indexover 15 trading days, which ends on the day prior to the offer, to measure the extent to which publicinformation on the true value of the firm obtained during the registration period is incorporated in the offer price (e.g., Lowry and Schwert (2004)). We also control for IPO year, industry fixed effects (i.e., based on Fama-French 30 group for industry classification) and cluster standard errors by IPO year.

[Insert Table 9 here]

Table 2 reports the coefficient estimates from various specifications. When regressing initial returns on *inclusion* by itself, we obtain a coefficient estimate of 11.59 with a t-statistic of 5.72. The coefficient estimate on *inclusion* suggests that stocks added to the Russell indexes, on average,have an increase of 11.59% in first-day returns compared to stocks that were not added into Russell indexes. The increase is economically meaningful given the fact that the average initial return in our sample is 17.27%.

When controlling for firm, deal, and market characteristics, the coefficient estimate on *inclusion* becomes 8.27 (t-statistic of 3.42). To further control for the seasonality of IPO wave and industry clustering (e.g., Ritter (1984), Pastor and Veronesi (2005)), we include IPO year fixed effects in Column 3 and IPO year fixed effects and industry fixed effects in Column 4. Controlling for these fixed effects increases the R^2 increases from 6.5% to 7.1% in Column 3 and to 11.5% in Column 4. The coefficients on *inclusion* in Columns 3 and Colum 4 are 7.99 and 7.42, respectively, and both are significant at the 1% level. The last column in Table 2 adds quarterly fixed effects to control for possible seasonality within a year since the Russell index additions occurred quarterly. The resulting coefficient estimate suggests that after controlling for various characteristics and time and industry fixed effects, IPO stocks that are included into Russell indexes on average have 7.41% higher returns than those not included.

Thus far, the finding that inclusion into Russell indexes is associated with higher first-day returns is consistent with our hypothesis that hidden demands from passive investing have not been taken into consideration by underwriters and firms when determining the offer prices. However, previous specifications may suffer from certain selection biases. Since Russell Inc. does not report the detailed inclusion procedure, it is possible that those excluded IPO stocks could have been screened out due to certain omitted characteristics. Furthermore, the selection bias also arises from the reversal causality: IPO stocks with higher first-day returns are more likely to result in larger market capitalization, and thus have a higher probability to be included into the Russell indexes in the next quarterly additions.

To overcome such selection bias and gauge the more accurate effect of passive investing on IPO underpricing, we exploit the passive demand variation within those added IPO stocks with two additional analyses. The first analysis is based on the fact that Russell indexes are market-capitalization weighted, so stocks with more market capitalization will receive higher demand from passive investing while those with less market capitalization will receive lower passive demand. Thus, we conjecture that those stocks with larger market capitalization have higher first-day returns thanstocks with smaller market capitalization. To formally test this, we run the following regressions only among the IPO stocks that were included in the Russell indexes:

$$\text{First\_day\_return}_i = \alpha + \beta_1 \text{market\_cap\_dummy}_i + \gamma X_i + \beta_2 \text{Time FE} + \beta_3 \text{Industry FE} + \varepsilon_i$$

Where the dependent variable *First_day_return*$_i$, control variables X_i and fixed effects are the same as in Eq. 1. The key variable of interest is *market_cap_dummy*$_i$, defined as a dummy variable that equals one if the pre-IPO market cap (offer price times total shares issued) is above the median of the sample estimate and equal to zero if the pre-IPO market cap is below the median of the sample estimate. For ease of interpretation, we only report the regression with all control variables and include year, quarterly fixed effects, and industry fixed effects. The standard errors are clustered by IPO year.

[Insert Table 10 here]

Column 1 of Table 3 reports the regression result. Consistent with our conjecture, we find that large cap stocks are associated with higher first-day returns. After controlling for various characteristics and time and industry fixed effects, the resulting coefficient estimate suggests that among all IPO stocks included into the Russell indexes stocks with a market cap above the sample median have, on average, 7.97% higher first-day returns than those below the sample median. Such a result is consistent with our hypothesis that underwriters and firms fail to incorporate the hidden demands from passive investing, but it is inconsistent with the information asymmetry hypothesis on IPO underpricing. Under the information asymmetry hypothesis, we expect that investors would demand higher returns for small cap stocks because such stocks are subject to higher information asymmetryduring the IPO process.

Using the dummy variable *market_cap_dummy* alleviates the concern of the extreme outliers, but it does not shed light on the monotonic relationship between market cap and first-day return. Column 2 of Table 2 repeats the same regression analysis using the natural log of market cap as the continuous independent variable instead of $market\_cap\_dummy_i$. The positive and significant coefficient estimate suggests that the higher the market capitalization, the higher the first-day returns.

Besides exploiting the passive-demand variation due to the market cap weight, we also exploit another dimension of passive demand that originates from the exogenous timing difference between IPO issue date and inclusion date. Even though the rank dates and the inclusion dates for the Russell indexes are pre-announced, uncertainty surrounds the exact issue dates. Therefore, stocks with an issue date farther away from the rank date (effective date) have lower uncertainty about inclusion into the next quarterly addition. Stocks that have an issue date closer to the rank date experience higher uncertainty about whether they will be included into the next round of inclusion. Such timing variation creates the variation of passive demand, especially from quasi-arbitragers. To formally test this hypothesis, we repeat the analysis using the following regression:

$$\text{First day return}_i = \alpha + \beta_1 \text{distance\_dummy}_i + \gamma X_i + \beta_2 \text{Time FE} + \beta_3 \text{Industry FE} + \varepsilon_i$$

where the only difference in this model from the previous one is that the key variable of interest is *distance_dummy*$_i$, defined as a dummy variable that equals 1 if the day interval between the IPO issue date and rank date is above the median of the sample estimate and 0 if the day interval between the IPO issue date and rank date is below the median of the sample estimate.

Column 3 and Column 4 of Table 2 reports the regression results using just the *distance_dummy* by itself and all control variables, including time fixed effects and industry fixed effects, respectively. The coefficient estimate on *distance_dummy*$_i$ from the univariate regression is 5.02 with a t-statistic of 3.06. Controlling for other characteristics and fixed effects, it becomes 4.53, which is significantly at 5% level. The coefficient estimate is consistent with the hypothesis that stocks with a high certainty of inclusion experience higher first-day return than stocks with low certainty of inclusion, further suggesting that the hidden demand from passive investing affects the first-dayreturn dynamics.

Taken together, the results comparing IPOs that were ex-post added and IPOs that were not added thus far are consistent with the hypothesis that passive investing affects the first-day return. We further exploit among added IPO stocks the variation of passive demand that originated from either the difference of the market cap weight or the time interval difference from IPO issue date to effective date. Our results are consistent with the hypothesis.

The price and volume effect of index inclusion

As the analysis has thus far focused on the first-day return for IPO stocks, we now turn to revisit theprice and volume effect of index inclusion for the added IPO stocks. There are mainly two reasonsfor revisiting the index membership effect. First, several studies focusing on S&P 500 additions and deletions have provided three main explanations for the index addition effects: the long-term, downward sloping of demand hypothesis, the price pressure hypothesis, and the investor awareness hypothesis. Furthermore, recent studies have shown that the index addition effects could be endogenously related to firms' characteristics. The Russell quarterly additions allow us to re-examine the price effect of inclusion for those stocks that are included not because of abovementioned stock characteristics, but because of the pre-determined rules. Thus, the use of Russell quarterly additions subjects to less endogeneity concerns. Second, frictions associated with shorting or leverage have fallen over time, which might lead to greater arbitrage capacity to offset the effects of rising index demand. The effect of index inclusion has been well documented and has decreased over the past decade (see Patel and Welch (2017)). It is unclear ex ante whether market participants are fully aware of this similar effect for Russell quarterly additions. McLean and Pontiff (2016) showed that academic publication destroys the anomaly value. While Russell Indexes are well known for their annual reconstitutions, quarterly IPOs additions receive less attention. We empirically investigate this subject in the following session.

Price dynamics

In this section we document the price effects for added IPO stocks. Following the previous literature on S&P additions and deletions, we report results based on abnormal and cumulative abnormal returns relative to the CRSP value-weighted index.[32]

[Insert Table 11 here]

Table 4 reports the excess returns. We first focus on the first column that contains all IPO stocks included in the Russell indexes and make three observations with respect to excess returns. The first observation relates to the returns on the following trading day after the rank day and the announcement day returns. During the sample period, the excess return during both days is significantly different from zero. For example, in regard to the return of the following day after the rank day, the abnormal return is about 34 basis points (bps) with a t-statistic of 2.60. The second observation relates to the change in price from the announcement day until the effective day. The rise in abnormal return suggests that the presence of price pressure up to the effective date is relieved after the stock is added to the index. One possible explanation is that with the pre-announcement of index changes, arbitrageurs buy added stocks in the hope of flipping around on the effective day at

[32] We do not use the market model or factor models to calculate the abnormal return because we are focusing on IPO stocks that do not have a long trading history to accurately estimate those factor coefficients.

more favorable prices (Chen, Noronha, and Singal (2004); Madhavan and Ming (2003); Beneish and Whaley (1996)).

The third observation relates to the permanence of the price effect. The results show that the cumulative excess return, calculated from the announcement day to 5, 10, 20, and 30 days after the effective day, is decreasing over the horizon and becomes insignificantly positive for the returnfrom the announcement day to 30 days after the effective day. This suggests that the price effectof additions to the index is not permanent and provides supporting evidence on the price pressure hypothesis.

While quarterly additions during March, September, and December only focus on IPO stocks, the additions during June (the annual reconstitution) do not— IPO stocks are treated the same as all other seasoned stocks when Russell Inc. determines the eligibility to which indexes the stock belongs. To test whether the price dynamics are different for quarterly additions than for annual IPO additions, we partition the sample into two subgroups. Column 2 reports the same analysis for added IPO stocks during non-June additions. Column 3 reports the same analysis for added IPO stocks during the June additions. The results show several distinct features between stocks added in the June annual reconstitution and stocks added in the non-June additions. First, during theannual reconstitution, abnormal returns are observed on the rank day instead of the day following the rank day. A similar pattern also shows up in the announcement day. Second, the price reversal ismuch faster during the annual reconstitution than during quarterly additions—the abnormal return becomes insignificant at the 5% level from the rank date to 10 days after the effective day. All of this evidence is consistent with the fact that annual reconstitution gains more attention from investors and arbitragers, thus price reaction during the annual reconstitution is faster than the one during thenon-June additions.

Finally, to alleviate concerns that the effects are due to other omitted market events, we also usethe IPO stocks that are ex-post are not included in the Russell index as placebo IPOs and repeat the analysis with the same event windows. We would expect that since these IPO stocks will not be considered into the Russell quarterly additions, there should be no price effect. Column 4 shows that consistent with our conjecture, we find no price effect for these stocks during the inclusion period.

Taken together, the analysis shows that there is a price effect for IPO stocks that are added intothe Russell index during the inclusion period. Consistent with the price pressure hypothesis, the abnormal return becomes insignificant 30 days after the effective day. Additional analysis shows that stocks added during the non-June quarter additions experience a larger price impact and slower reversal. Placebo test using IPO stocks that are not included in the Russell indexes confirms the existence of the price effect.

Volume dynamics

Following Harris and Gurel (1986), Elliott and Warr (2003), and Chen, Noronha, and Singal (2004), changes in trading volume are measured by the ratio of volume turnover for IPO stocks over volume turnover for all aggregate NYSE stocks. We use volume turnover instead of trading volume to demonstrate that unusually high volume in a few stocks does not disproportionately affect the market volume. Specifically, the turnover ratio is calculated as following:

$$Turnover\ Ratio = \frac{\frac{1}{N}\sum_{1}^{N}\frac{TO_{it}}{TO_{mt}}}{\frac{1}{10}\sum_{t=\tau-10}^{\tau-1}\frac{TO_{it}}{TO_{mt}}}$$

Where TO_{it} is the turnover for stock i at time t, the subscript m refers to the market, and τ represents the announcement day, which is the first trading day following the announcement. The denominator is the reference period turnover standardized by market turnover during the reference period, while the numerator is the event period turnover standardized by market turnover during the event period.

[Insert Table 12 here]

Table 5 shows the results for the volume effect. Consistent with previous studies on inclusion in the S&P 500, there is an abnormal increase in trading volume during both the announcement day and the effective day. Furthermore, the trading volume on the effective day is almost five times higher than that of the announcement day, suggesting that passive funds are more likely to rebalance a portfolio on the days when new index membership starts to take into effect. This result is consistent with several findings in the literature that passive funds trade to minimize the tracking errors. For instance, Elton, Gruber, and Busse (2004) suggest that there is no relation exists between tracking errors and investor flows into index funds, implying that investors may trade to minimize tracking errors.

Comovement: a difference-in-difference approach

The analysis in the previous session shows that there is a price and volume effect for added IPO stocks. In this section, we investigate whether index membership leads to excess comovement using a novel difference-in-difference approach from the Russell quarterly additions. Barberis, Shleifer, and Wurgler (2005) showed that return comovement increases after stocks are added into the S&P 500 index. However, Chen, Singal, and Whitelaw (2016) recently showed that such comovements are sensitive to unrelated factors, such as momentum winners. Instead of comparing comovement changes before and after the index additions as conducted in previous studies, we exploit one additional variation: the IPO issue date. Since firms cannot precisely control for the IPO issue date, the time gap from issue date to inclusion date varies; some firms are added into an index faster than the other firms even if they go to IPO in the same quarter. If index membership exhibits excess comovement, then in the case of firms added earlier into the index (i.e., the issue date is closer to the inclusion date), the change in comovement will be smaller. This is because such stocks already co-move with the index. Following the same logic, for firms that are added into the index later (i.e.,the issue date is farther from the inclusion date), the change in comovement will be larger.

To test this, for each addition we estimate the univariate regression for each addition,

$$R_{i,t} = \alpha_i + \beta_i R_{\text{Russell3000},t} + v_{i,t} \tag{5}$$

separately for the period from 10 days after IPO issue date to 100 days after IPO issue date (a total of 3 month daily returns), as well as the period from 120 days after IPO issue date to 210 days after IPO issue date (a total of 3 month daily returns). $R_{i,t}$ is the daily return for stock i and $R_{\text{Russell3000},t}$ is the contemporaneous daily return for Russell 3000 index, proxied by the return from iShare Russell 3000 ETF (IWV). We exclude returns from the first 10 trading days to avoid biases from the extreme price movements when IPO stocks start to trade as public firms. Since the maximum time gap between IPO issue date and effective day is around 100 days, the estimates from the later period are guaranteed to reflect the β and R^2 after the stocks are added into the indexes. The change in the slop coefficient, and the change in the R^2, ΔR^2 are recorded. Added IPOs are then classified into two groups based on whether the time gap between IPO issue date and effective date is above or below the median of the whole sample of added IPOs. The differences between these two groups are reported and the standard errors are clustered at the month level.

[Insert Table 13 here]

Panel A of Table 5 shows the results of this analysis. Consistent with the findings in prior studies, our evidence shows an increase in beta and R^2 across inclusion events and the differenceis statistically significant. For example, the increases in beta and R^2 are about 0.307 and 0.048 for stocks added earlier and 0.212 and 0.037 for stocks added later. The magnitude is similar to that found in Barberis, Shleifer, and Wurgler (2005) from S&P 500 inclusion events. What is unique to our analysis is that we further examine the difference of the increase in beta and R^2 between groups of stocks that are added earlier and groups of stocks that are added later. Consistent with theexcess comovement of index membership, the difference-in-difference measures for both beta and R^2 are positive. For R^2, the measure is positive and significant at the 5% level. The beta measure is insignificant, but it is in the positive territory.

One possibility of the insignificance could be the price movement of Russell indexes during the Russell annual reconstitution. As we previously discussed, the price and volume effects are slightly different during the annual inclusion events than the quarterly inclusion events and the former drives more attention than the latter. To alleviate this concern, we repeat the difference-in-difference analysis focusing on only quarterly added IPO stocks. Consistent with our conjecture, the results from the right three columns in Panel A show a stronger effect of index inclusion both in magnitude and significance.The difference-in-difference measures for beta and R^2 are 0.176 and 0.016, respectively, which are both significant at the 1% level.

As a robustness check, we also conduct a placebo test by calculating the change of β and R^2 for IPO stocks not added to the index. We compare the difference between these placebo IPO stocks and the added IPO stocks. Panel B of Table presents such results. For placebo stocks, there is an insignificant change in beta while the change in R^2 is positive. However, the significance of the difference-in-difference measure provides supportive evidence that compared to placebo IPO stocks, stocks added into the Russell indexes have higher $\Delta\beta$ and ΔR^2.

Conclusion

The increase in passive investing has been nothing short of remarkable. While recent academic studies have shown that the impact of passive investing is ubiquitous—from stock returns and volatility to firm's governance and investment—they mainly focus on the mature and larger firms.

This paper studies the impact of passive investing on IPO stocks. It seems less obvious that passive investors, who are unlikely to engage in pre-IPO activities, would influence IPO price dynamics. However, by examining quarterly added IPO stocks into Russell indexes, our analysis shows that in the secondary market, passive investing indeed affects the price dynamics of IPO stocks. Specifically, stocks with higher probabilities of receiving more hidden passive demand are more likely to have higher first-day returns. This results holds when exploiting the variation of passive demand due to the market cap weight from the Russell indexes and the time interval between IPO issue date and inclusion date. Our finding supports that hypothesis that underwriters and firms may fail to take into consideration hidden passive demands when determining the offer price. Our analysis provides the first empirical evidence regarding the theoretical prediction between benchmarking inclusion subsidies and IPO decisions.

An additional event study on inclusion of IPO stocks into the Russell indexes shows that there are abnormal positive returns and trading volumes during the inclusion period. Such price movement is subsequently reversed within 30 days after the effective day, consistent with the price pressure hypothesis. Finally, we employ a novel difference-in-difference approach to study the excess comovement of index inclusion and find supportive evidence of excess comovement.

Table 8. Summary Statistics

The table reports the summary statistics for the variables used in the study. The sample starts from 2008 to 2018. Panel A reports the summary statistics for main variables. Detailed definition of variables are availablein appendix. Panel B reports the number of IPOs per year.

Panel A: Descriptive statistics

	Mean	StdDev	p10	p50	p90
IPO stocks added into the Russell indexes					
First-day Returns	17.269	27.862	-5.357	9.478	50.296
Ln(proceeds)	4.981	0.902	4.025	4.787	6.205
Venture_backed deal	0.450	0.498	0.000	0.000	1.000
Shares_overhang	0.130	0.260	0.000	0.000	0.500
NASDAQ	0.555	0.497	0.000	1.000	1.000
Mktret15days_pre	0.010	0.029	-0.025	0.010	0.047
Top_tier	0.898	0.303	0.000	1.000	1.000
ME	993.791	1958.496	166.360	437.969	2039.076
Ln(me)	13.163	1.005	12.022	12.990	14.528
me_flag	0.601	0.490	0.000	1.000	1.000
IPO stocks not added into the Russell indexes					
First-day Returns	5.676	23.324	-13.714	0.450	31.706
Ln(proceeds)	4.009	1.378	2.303	3.931	5.848
Venture_backed deal	0.289	0.454	0.000	0.000	1.000
Shares_overhang	0.082	0.221	0.000	0.000	0.328
NASDAQ	0.762	0.427	0.000	1.000	1.000
Mktret15days_pre	0.010	0.030	-0.024	0.010	0.044
Top_tier	0.485	0.500	0.000	0.000	1.000
ME	714.735	2717.689	39.830	147.080	1393.405
Ln(me)	12.183	1.395	10.592	11.899	14.147

Panel B: The number of IPOs per year

	IPO stocks not added	IPO stocks added
Year	N	N
2008	14	12
2009	10	47
2010	41	75
2011	29	66
2012	23	93
2013	48	145
2014	78	162
2015	54	90
2016	19	65
2017	51	81
2018	51	105

Table 9. IPO underpricing and Russell index inclusion

This table reports the results of regressing IPO first-day return on whether the stock will be included into theRussell indexes. The dependent variable is *first day return*, which measures the percentage return from the offer price to the first-trading-day closing price. The key independent variables are *Inclusion*, which equals 1 if the stock is included into the Russell ex post and 0 otherwise. We also include the following control variables: *ln*(*proceeds*), *venture backed deal*, *shares overhang*, *NASDAQ*, *mktret*15*day pre*, *Top tier*, *ln*(*age*). The definitions of the control variables are reported in Appendix Table A1. We include year fixed effect, industry fixed effect, and quarter fixed effect. The standard errors are clustered by IPO year. Standard errors are reported in parentheses. *, **, and *** indicate statistical significance for it at the 10%, 5%, and 1% levels, respectively.

Inclusion	11.59***	8.27***	7.99***	7.42***	7.41***
	(5.72)	(3.42)	(3.09)	(3.48)	(3.32)
Ln(proceeds)		2.04***	1.82***	1.84***	1.90***
		(2.63)	(2.70)	(3.09)	(3.21)
Venture backed deal		11.31***	11.03***	10.39***	10.46***
		(9.01)	(8.23)	(6.37)	(6.50)
Shares overhang		1.17	3.54	2.70	2.33
		(0.32)	(0.84)	(0.69)	(0.61)
NASDAQ		3.82**	3.53*	3.72*	3.58*
		(2.18)	(1.97)	(1.94)	(1.90)
Mktret15day pre		22.89	27.33	29.44	20.66
		(0.78)	(0.99)	(1.13)	(0.80)
Top tier		-2.18	-1.56	-2.61**	-2.49**
		(-1.22)	(-0.90)	(-2.12)	(-2.02)
Ln(age)		0.50	0.34	-1.17***	-1.14**
		(1.37)	(1.10)	(-2.41)	(-2.29)
Year Fixed Effect			YES	YES	YES
Industry Fixed Effect				YES	YES
Quarter Fixed Effect					YES
N	1359	1224	1224	1221	1221
adj. R-sq	0.038	0.065	0.071	0.115	0.117

Table 10. IPO underpricing and Russell index inclusion: Robustness

This table reports the results of regressing IPO first-day return on whether the stock will be included intothe Russell indexes. The dependent variable is *first day return*, which measures the percentage return from the offer price to the first-trading-day closing price. The key independent variable in Column 1 is *market cap dummy*, which equals 1 if the pre-IPO market cap (offer price times total shares issued) is abovethe median of the sample estimate and equal to zero if the pre-IPO market cap is below the median of the sample estimate. The key independent variable in Column 2 is *ln*(*me*), which is the natural log of market cap.The key independent variables in Column 3 and Column 4 are *distance dummy*, which equals 1 if the day interval between IPO issue date and rank date is above the median of the sample estimate and 0 otherwise. Wealso include the following control variables: *ln*(*proceeds*), *venture backed deal*, *shares overhang*, *NASDAQ*,*mktret*15*day pre*, *Top tier*, *ln*(*age*). The definitions of the control variables are reported in Appendix Table A1. We include year fixed effect, industry fixed effect, and quarter fixed effect. The standard errors are clus-tered by IPO year and reported in parentheses. *, **, and *** indicate statistical significance for it at the 10%,5%, and 1% levels, respectively.

Market_cap_dummy	7.97**			
	(2.14)			
Ln(me)		3.97*		
		(1.88)		
Distance_dummy			5.02***	4.53**
			(3.06)	(2.06)
Ln(proceeds)	-1.21	-2.41		0.80
	(-0.64)	(-0.96)		(0.72)
Venture_backed_deal	12.21***	11.37***		11.53***
	(5.64)	(4.97)		(5.78)
Shares_overhang	0.75	0.86		2.05
	(0.20)	(0.23)		(0.58)
NASDAQ	2.17	2.16		2.28
	(1.19)	(1.17)		(1.14)
Mktret15day_pre	37.12	40.90		46.70
	(1.05)	(1.14)		(1.36)
Top_tier	-3.94*	-3.11*		-2.78
	(-1.80)	(-1.68)		(-1.37)
Ln(age)	-1.43***	-1.66***		-1.25**
	(-2.99)	(-3.32)		(-2.41)
Year Fixed Effect	YES	YES		YES
Industry Fixed Effect	YES			YES
Quarter Fixed Effect	YES			YES
N	899	899	941	899
adj. R-sq	0.129	0.123	0.007	0.123

Table 11. Price dynamics of quarterly IPO additions

The table reports the abnormal returns during the period of the Russell quarterly additions . The sample consists of all added IPO stocks between 2008 and 2018. Abnormal returns are calculated relative to the Russell 3000 index's total return. *Rank Day* is the abnormal return on the ranking date. *Rank Day* + 1 isthe abnormal return for the first trading day following the ranking date. *Ann Date* is the abnormal return on the announcement day. *AnnDate*(*the f ollowingday*) is the abnormal return for the first trading day followingthe announcement date. *Rank Date to Ann Date* is the cumulative abnormal return from the day following ranking date to announcement date. Other cumulative abnormal returns are defined in a similar way. The significance of the mean is tested with a standard t-test. *, **, and *** indicate statistical significance for it atthe 10%, 5%, and 1% levels, respectively.

	IPOs that Included			Control IPOs
	All	Quarterly Additions	Annual Additions	All
Sample Size	875	653	222	432
Rank Day	0.19%	-0.01%	0.78%***	-0.02%
	(1.58)	(-0.10)	(3.73)	(-0.08)
Rank Day+1	0.34%***	0.50%***	-0.13%	0.07%
	(2.60)	(3.68)	(-0.39)	(0.30)
Ann Date	0.29%**	0.13%	0.75%***	-0.38%**
	(2.39)	(0.90)	(3.45)	(-2.14)
Ann Date (the following trading day)	0.25%**	0.32%**	0.05%	-0.40%
	(2.09)	(2.32)	(0.20)	(-1.58)
Rank date to Ann Date	3.57%***	3.62%***	3.42%***	1.31%*
	(7.34)	(6.40)	(3.59)	(1.66)
Rank Date to Effect Date	4.13%***	4.35%***	3.49%***	-1.37%
	(6.71)	(5.87)	(3.26)	(-1.47)
Rank Date to Effect Date+5 days	4.14%***	4.69%***	2.52%**	-1.51%
	(5.97)	(5.55)	(2.22)	(-1.52)
Rank Date to Effect Date+10 days	3.65%***	4.17%***	2.15%*	-1.58%
	(4.90)	(4.60)	(1.72)	(-1.22)
Rank Date to Effect Date+20 days	2.18%***	2.79%***	0.41%	-2.85%**
	(2.58)	(2.69)	(0.30)	(-2.21)
Rank Date to Effect Date+30 days	0.09%	0.17%	-0.15%	-4.20%***
	(0.10)	(0.15)	(-0.09)	(-2.71)

Table 12. Volume effect of quarterly additions of IPOs

The table reports the abnormal volume turnover during the period of the Russell quarterly additions . The sample consists of all added IPO stocks between 2008 and 2018. Abnormal turnover for the firm and the market is taken to be the average turnover 10 trading days prior to the announcement day, which is thefirst trading day following the announcement. All turnover estimates are adjusted for the market, where the market is restricted to NYSE stocks. Ann Date is the abnormal turnover ratio on the announcement day. Ann Date to Effective Date is the average abnormal turnover ratio from the announcement date to effective date. Effective Date is the abnormal turnover ratio on the effective date. The significance of the mean is tested with a standard t-test with null hypothesis of the ratio equals one. *, **, and *** indicate statistical significance for it at the 10%, 5%, and 1% levels, respectively.

	Quarterly Additions	Annual Reconstitution	December Additions	March Additions	September Additions
Sample	696	222	236	184	276
Ann_Date	1.394	1.343	1.255	1.233	1.621
	(9.12)	(2.76)	(4.79)	(3.60)	(7.09)
Ann_Date to Effective_Date	2.234	1.803	2.523	1.986	2.152
	(19.88)	(10.73)	(11.38)	(10.73)	(13.50)
Effective_Date	7.748	6.701	6.386	7.956	8.774
	(24.15)	(12.53)	(12.77)	(14.83)	(15.24)

Table 13. Stock additions and return comovement

This table reports the changes in comovement of IPO stocks added to the Russell indexes. Panel A of this table includes stocks added to the Russell indexes between 2008 and 2018. For each event stock i, the univariate model are estimated

$$R_{i,t} = \alpha_i + \beta_i R_{\text{Russell3000},t} + v_{i,t}$$

separately for the period from 10 days after IPO issue dat to 100 days after IPO issue date (a total of 3 monthdaily returns), as well as the period from 120 days after IPO issue date to 210 days after IPO issue date (a total of 3 month daily returns). The mean change in slope ($\Delta\beta$) and the mean change in fit (ΔR^2) betweensuch two periods are reported. *Added Later* is among IPO stocks that the time gap between IPO issue date and effective date is above the median of the whole sample of added IPOs. *Added Sooner* is among IPO stocks that the time gap between IPO issue date and effective date is below the median of the whole sampleof added IPOs. The difference between these two groups of stocks is reported in the last row. Panel B reportsthe similar analysis using both IPO stocks added into the Russell indexes and IPO stocks not added into the Russell indexes. *Additions* is among IPO stocks that are added in the Russell indexes and *No Additions* is among IPO stocks that are not included in the Russell indexes. The last column reports the difference betweensuch two groups of stocks. The standard errors are clustered by month and reported in parentheses. *, **, and *** indicate statistical significance for it at the 10%, 5%, and 1% levels, respectively

Panel A: Evidence of co-movement: A difference in difference approach

	All			Exclude Annual Reconstitution		
	N	$\overline{\Delta\beta}$	$\overline{\Delta R^2}$	N	$\overline{\Delta\beta}$	ΔR^2
Added Later	453	0.307*** (0.044)	0.048*** (0.006)	343	0.359*** (0.051)	0.050*** (0.006)
Added Sooner	448	0.212*** (0.044)	0.037*** (0.006)	337	0.183*** (0.047)	0.033*** (0.006)
Difference in difference		0.095 (0.090)	0.012** (0.006)		0.176*** (0.059)	0.016*** (0.005)

Panel B: Comparing Quarterly added IPOs with control sample

	N	$\overline{\Delta\beta}$	ΔR^2
Additions	901	0.260*** (0.031)	0.042*** (0.004)
No Additions	440	-0.019 (0.065)	0.012** (0.005)
Difference		0.279*** (0.039)	0.031*** (0.005)

Figure 5: Abnormal returns for added IPOs during the Russell Inclusion period

The figure plots the abnormal returns during the Russell quarterly Inclusion period for IPO stocks that addedand IPO stocks that not added as a control group. Abnormal returns are calculated relative to Russell 3000 index's total return. *Ann Date* is the first trading day following the announcement date. *Rank Date* is the ranking date for the Russell quarterly IPO additions. *Rank date to E f f ect date* is the abnormal return fromthe rank date to the effective date of IPO additions. *Rank date to E f f ect date* +5 *days* is the abnormal return from the rank date to the five days after the effective date of IPO additions. Other abnormal returns are definedin similar way. The dark bar represents ex-post added IPO stocks and the gray bar represents IPO stocks thatare not added.

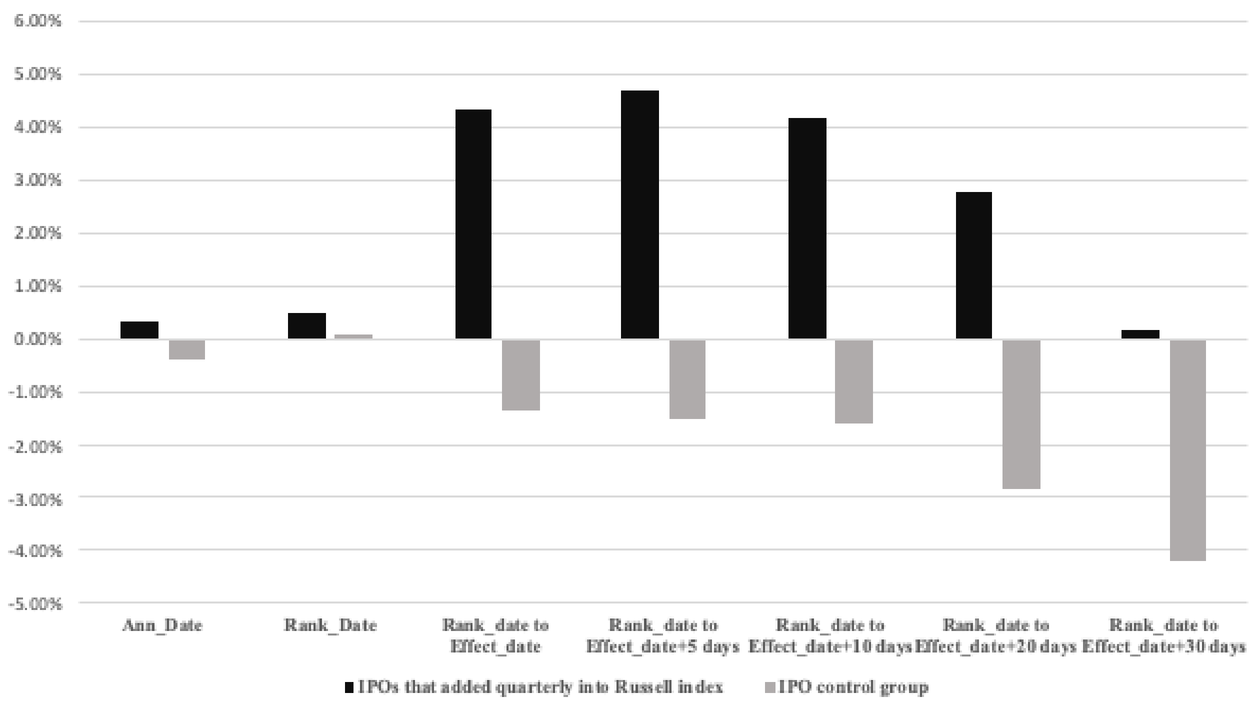

Figure 6: Abnormal volume turnover for added IPOs during the Russell Inclusion period

The figure plots the abnormal volume turnover during the Russell quarterly Inclusion period for IPO stocks that added. Abnormal turnover for the IPO firm and the market is taken to be the average turnover 10 tradingdays prior to the announcement day, which is the first trading day following the announcement. All turnoverestimates are adjusted for the market, where the market is restricted to NYSE stocks. Ann Date is the abnor-mal turnover ratio on the announcement day. Ann Date to Effective Date is the average abnormal turnover ratio from the announcement date to effective date. Effective Date is the abnormal turnover ratio on the effective date.

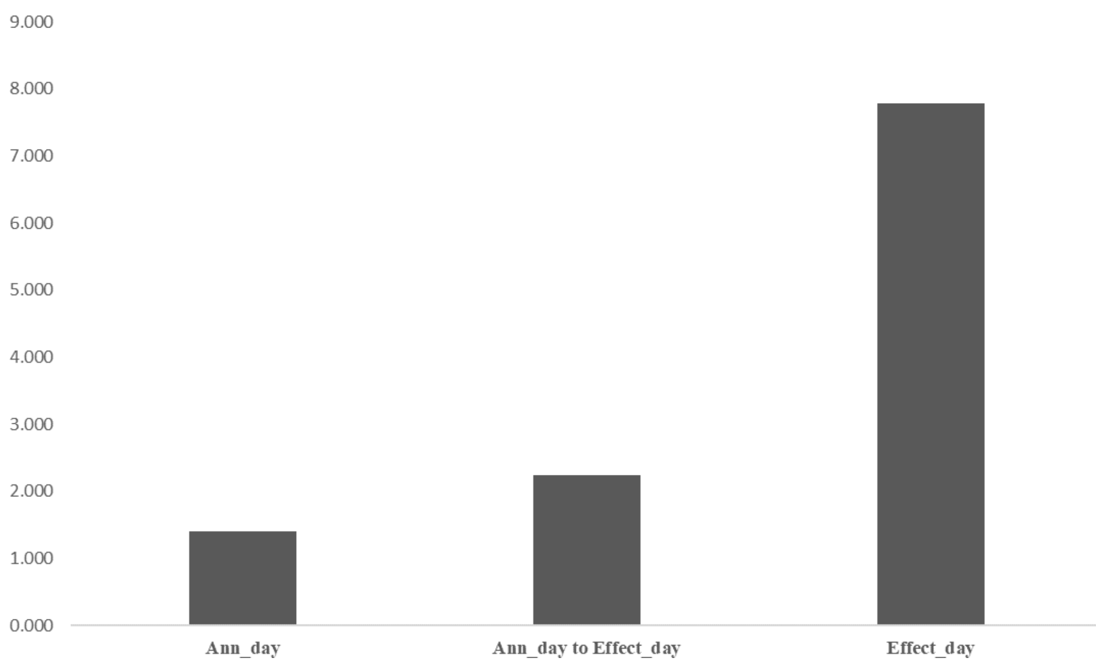

Table 14: Variable Definition

This table presents definitions of variables.

IPO-Related Variables	Variable Definition
First-day Return	The percentage return from the offer price to the first-trading-day closing price.
Inclusion	A dummy variable equals one if the IPO stock was addedinto the Russell indexes during the quarterly IPO additions.
Distance_dummy	A dummy variable equals one if the time gap between IPO issue date to rank date is above the median of the sample estimate.
Market_cap_dummy	A dummy variable equals one if the IPO's market cap (offer price times shares outstanding) is above the median of the sample estimate.
Ln (me)	The natural log of market cap (offer price times shares outstanding), in millions of dollars.
Top-tier Dummy	A dummy variable equals one if the startup has at least one underwriter with an updated ranking of nine, defined as in Loughran and Ritter (2004).
Venture Backed Deal	A dummy variable equals one if the startup is backed by venture capital based on SDC database.
Mktret15day_pre	The market return for the fifteen trading days preceding the IPO date.
NASDAQ	A dummy variable equals one if the IPO stock is listed in NASDAQ exchange.
Share Overhang	The ratio of retained shares to total shares offered. Retained shares are calculated as the difference between total sharesoffered and secondary shares offered.
Ln(Age)	The natural log of the IPO year minus the firm's found-ing year, where founding dates are obtained from the Field–Ritter dataset, as used in Loughran and Ritter (2004).
Ln(Proceeds)	The natural log of proceeds amount of issue, in millions ofdollars, calculated as the offer price multiplied by number of shares offered.

THIRD ESSAY

Price Impact Reversal and The Illiquidity Premium

Introduction

The extensive set of empirical asset pricing anomalies includes many effects that significantly correlate cross-sectionally with the CAPM alpha, with a recent study by Harvey, Liu, and Zhu (2016) identifying more than 300. Within this group, the illiquidity premium holds a prominent position in terms of the amount of attention it receives in the literature, the intuition for why it exists, and the abnormal returns that have been associated with it. In empirical tests, the illiquidity premium manifests itself as a positive cross-sectional relation between stock illiquidity, as measured by the Amihud (2002) measure, for example, and future performance.[1] Theoretical arguments by Amihud and Mendelson (1986) and Vayanos (1998) suggest that the positive cross-sectional relation exists to compensate investors for the high cost inherent in trading illiquid stocks. An institution that exits quickly a position in an illiquid stock, for instance, may be able to do so only at an unfavorable price, such that the trading of illiquid stocks is associated with price concessions relative to trading stocks of greater liquidity. These price concessions would be reflected in a positive relation between illiquidity and price impact, consistent with the findings of Keim and Madhavan (1997), Anand et al. (2012), and Busse et al. (2020).

We analyze the relation between the illiquidity premium, the reversal anomaly, and institutional trading activity. We initially document a strong correspondence between *past* stock returns and a stock's liquidity classification, with illiquid stocks experiencing relatively poor past performance. For instance, based on the Amihud illiquidity measure, the most illiquid quintile of stocks shows roughly 2% lower return per month than the most liquid quintile of stocks during the

[1] See Amihud (2019) for a comprehensive overview of the literature on illiquidity.

three-month period leading up to the liquidity classification. The poor prior performance of illiquid stocks is potentially important given the implications it has for future performance, since Jegadeesh (1990) and Lehmann (1990), among many others, document mean reversion in short-term stock returns.

Consequently, although a strong univariate relation between illiquidity and future performance provides prima facie evidence in favor of an illiquidity premium, at least part of the outperformance of illiquid stocks likely stems directly from the reversal effect. Consistent with this hypothesis, in double sorts on past return and stock illiquidity, positive abnormal returns are only associated with illiquid stocks that show relatively poor past performance. Moreover, illiquid stocks with relatively high past returns show significantly poor future performance, i.e., an illiquidity discount. As a simple control, when we exclude from our analysis illiquid stocks with outlier prior-month performance (both strong and weak), the performance of the remaining illiquid stocks does not significantly differ from zero.[2]

Moreover, illiquid loser stocks are disproportionately associated with an imbalance of sell transactions susceptible to negative price impact. Among illiquid loser stocks, the stocks associated with net institutional sell transactions during one month significantly outperform during the following month those associated with net institutional buy transactions, as the negative price impact of sell transactions reverses. Beyond statistical significance, the subsequent performance difference between net-sold and net-purchased illiquid stocks is economically large, with the sold stocks showing a return during the following month that is 3.4% greater than the return of the

[2] Our analysis relates to Avramov, Chordia, and Goyal (2006), who examine short-term reversals conditional on stock illiquidity. They find that the short-term reversal anomaly is stronger among illiquid stocks. Chen et al. (2017) find that the stronger reversal effect among illiquid stocks stems from institutions participating less in loser stocks. Neither paper, however, examines the illiquidity premium, which is our focus.

purchased stocks. When combined with the fact that 73.4% of illiquid loser stocks face net mutual fund selling pressure, we estimate that illiquid loser stocks that institutions sell drive most (approximately 86%) of the illiquidity premium among loser stocks. Consistent with the notion that illiquid loser stocks experience negative price impact, we find that illiquid loser sell transactions face significantly greater implicit costs than illiquid loser buy transactions, with the former costs greater than the latter by at least 1.4%. Overall, our results establish a close correspondence between the illiquidity premium and return reversals stemming from price impact.

Although our main analysis focuses on the Amihud illiquidity measure, we also examine whether the strong relation between the illiquidity premium, return reversals, and price impact exists when we use alternative measures of illiquidity, including two based on high frequency stock data. As Amihud (2002) explains, a shortcoming of measuring illiquidity based on high frequency stock data is the sample periods for high frequency samples are relatively short. Nonetheless, based on alternative illiquidity measures, our results again indicate that a positive relation between illiquidity and future performance exists only within the quintile of stocks with relatively low prior-month return. Moreover, the alternative illiquidity measures continue to show that institutional investors predominantly sell low return, illiquid stocks and that the sell transactions are subject to high price impact transaction costs.

Beyond relating to the vast illiquidity premium literature,[3] our paper relates to analyses that examine how trading frictions impact the implementation and performance of investment strategies based on cross-sectional anomalies. Among these papers, Lesmond, Schill, and Zhou

[3] In addition to the illiquidity premium papers reviewed by Amihud (2019), a series of recent studies examines the robustness of the illiquidity premium. Ben-Rephael, Kadan, and Wohl (2015) show that the illiquidity premium only exists among small cap stocks. Harris and Amato (2019) and Drienko, Smith, and von Reibnitz (2019) emphasize out-of-sample (i.e.., post-Amihud (2002)) empirical evidence. Brennan, Huh, and Subramanyam (2013) and Lou and Shu (2017) decompose the most commonly used proxy for illiquidity, the Amihud (2002) measure, to examine which component(s) of the measure drive the empirical regularities documented in the literature.

(2004) and Korajczk and Sadka (2004) examine the degree to which trading costs reduce the performance of price momentum strategies, and Avramov, Chordia, and Goyal (2006) show that it is difficult to invest based on reversal returns because short-term winner and loser stocks skew toward costly-to-trade illiquid stocks. Focusing on samples of mutual funds, Busse et al. (2020) show how expected trading costs impact the selection of investment strategies as a function of assets under management, and Patton and Weller (2020) examine how implementation costs affect the returns to value and momentum. Different than the studies that present evidence of important trading frictions, Frazzini, Moskowitz, and Pedersen (2015) find that actual trading costs are small compared to what previous studies suggest, such that anomalies are implementable.

An implication of the studies that assess the impact of trading costs on investment strategies is that an anomaly can persist when costs prevent investors from exploiting it. By contrast, we show that the existence of the illiquidity premium is directly attributable to investor trades, rather than their absence. As such, our paper relates to Lou's (2012) findings that the price impact associated with mutual fund trades affects several empirical relations concerning return predictability, including mutual fund performance persistence and stock price momentum. But whereas Lou (2012) shows that the price impact itself causes the various observed effects, we connect the subsequent reversal of the price impact to the outperformance of illiquid stocks.

The remainder of the paper proceeds as follows. Section 2 describes the data. Section 3 presents our empirical findings, focusing on the relation between the illiquidity premium, return reversals, and institutional trading activity. Section 4 concludes.

Data

We use data from the standard academic research databases. We base most of our analysis on a sample of U.S. stocks across a 1964–2017 sample period, though we look at an extended sample period that begins in 1926 in a robustness test. We retrieve stock returns, share prices, trading volume, shares outstanding, share class, and share codes from the CRSP daily and monthly stock files. We include in our sample NYSE, AMEX, and NASDAQ stocks classified as ordinary common shares (CRSP Share Code 10 and 11) with share price greater than $1.

In some of our analysis, we examine the portfolio holdings of U.S. mutual funds, and for this analysis we retrieve periodic holdings from the Thomson Reuters CDA/Spectrum database. We specifically focus on U.S. domestic equity funds (*crsp_obj_cd* = 'ED'), and we further require that the total net assets (TNAs) reported by CDA/Spectrum and CRSP do not differ by more than a factor of two, i.e., $0.5 < TNA_{CDA}/TNA_{CRSP} < 2$. Portfolio holdings are often available quarterly, though sometimes less frequently, and they exist within Thomson Reuters over a shorter 1990–2017 sample period compared to the CRSP stock data.

We also examine institutional trades included in the Abel Noser database of institutional stock transactions. The Abel Noser sample is limited to the period from 1999 through 2011, but it includes many trades, amounting to 130.3 million trade tickets. See Puckett and Yan (2011) and Anand et al. (2012) for additional details on Abel Noser. Lastly, we compute measures of liquidity based on high frequency data from the NYSE Trade and Quote (TAQ) database. Based on data availability, our analysis using TAQ data covers the period from January 2004 through December 2014.

We use daily stock returns and trading volume to compute the Amihud illiquidity measure for month *t*,

$$A_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|R_{i,d,t}|}{DVOL_{i,d,t}} \times 1{,}000{,}000. \quad (1)$$

In equation (1), $R_{i,d,t}$ is the return of stock i on day d in month t, $DVOL_{i,d,t}$ is stock i's dollar trading volume on day *d* in month *t*, and $D_{i,t}$ represents the number of days in month *t* that stock *i* trades. Due to interdealer trades, historical databases, including CRSP, typically double count the volume for NASDAQ stocks relative to NYSE/AMEX stocks during certain sample periods. To control for this issue, we use the Gao and Ritter (2010) volume correction for NASDAQ stocks when computing equation (1).[4] To compute equation (1), we require at least ten daily observations, consistent with Lou and Shu (2017). In addition to the Amihud illiquidity measure, we examine four alternative measures of illiquidity in robustness tests, including two (the effective spread and the quoted spread) based on high frequency TAQ data.

Table 15 reports characteristics of stocks sorted into quintiles based on the Amihud illiquidity measure. As expected, the statistics suggest that illiquid stocks tend to have low share price and low market capitalization. The statistics also suggest that illiquid stocks rank highly based on the book-to-market ratio, that is, they are value, rather than growth, stocks. Moreover, they stand out based on past returns, as both their short-term (past one month) and medium-term (past year, excluding the past one month) returns are relatively low. These outlier characteristics have implications from the standpoint of expected returns, given the robust relations between these characteristics and future performance documented in the empirical asset pricing anomaly literature. Low market capitalization (e.g., Banz (1981)), high book-to-market (e.g., Fama and French (1992)), and low past one-month return (e.g., Jegadeesh (1990) and Lehmann (1990)) are associated with relatively high future returns. By contrast, the low one-year return (excluding the

[4] We divide NASDAQ volume by 2 for the time period from 1983 through January 2001, by 1.8 from February to December 2001, and by 1.6 from 2002 to 2003.

past one-month) is associated with relatively poor future returns (e.g., Jegadeesh and Titman (1993)).

[Insert Table 15 here]

Prior studies often point out the strong positive relation between market capitalization and liquidity. Amihud (2002), for example, documents a high inverse relation between the natural log of market capitalization and illiquidity. By contrast, the prior literature does not explicitly emphasize the negative cross-sectional correspondence between past returns and illiquidity, though the Table 15 relation between these variables is strong. For example, the most liquid quintile (Q1) shows an average past one-month return of 1.56%, which is considerably greater than the 0.02% average one-month past return of the most illiquid quintile (Q5).

Empirical Analysis

3.1 Illiquidity and Future Stock Performance

We first establish baseline results to confirm that the positive relation between stock illiquidity and future return established in the literature exists within our sample. We examine the relation via univariate sorts. We sort stocks into quintiles each month (i.e., at time $t - 1$) based on the Amihud illiquidity measure and then compute the mean return during the following month (time t) across the stocks in each quintile.[5] In addition to computing mean return, we calculate mean single-, three- (Fama and French (1993)), and four-factor (Carhart (1997)) alpha. To estimate

[5] We report the results based on a two-month lag between returns and the Amihud illiquidity measure in Table 22 in the Internet Appendix. The results associated with a two-month lag are qualitatively similar and marginally stronger than the one-month lag results reported in Table 16.

the alphas of the quintiles, we equal-weight the monthly quintile returns and then run time series regressions of the equal-weighted quintile returns on the factors.

Table 16 shows the sort results. The results confirm the positive relation between illiquidity and subsequent performance, i.e., the illiquidity premium. For instance, following the sort, Q5 illiquid stocks (i.e., the most illiquid quintile) show a monthly return of 1.60%, whereas Q1 stocks show a return of 1.03%. The 0.57% difference is statistically significant at the 1% level. Q5–Q1 differences are similar for single- and four-factor alpha and approximately half as large for three-factor alpha. The differences are significant at the 1%, 10%, and 1% levels respectively for single-, three-, and four-factor alpha. These results are consistent with Drienko, Smith, and von Reibnitz (2019) and Harris and Amato (2019), who also analyze the illiquidity premium within samples that include recent time periods.[6,7]

[Insert Table 16 here]

Although the results in Table 16 are statistically strong, we note that, given the nature of liquidity as a stock characteristic, various changes to the analysis weaken the univariate relation. For example, we construct our stock sample using a $1 share price cutoff. As stock price is strongly correlated with liquidity, a higher share price cutoff weakens the univariate relation because it excludes some highly illiquid stocks. Similarly, Table 16 reflects equal-weighted quintile returns, consistent with the convention in the illiquidity literature to equally weight observations.[8] Since

[6] In line with Amihud (2002), Lou and Shu (2017), Drienko, Smith, and von Reibnitz (2019), and Harris and Amato (2019), among other studies of illiquidity, we focus on a sample period beginning around 1964. Brennan, Huh, and Subrahmanyam's (2013) sample period begins in 1971. Univariate results based on a December 1926 to December 1963 sample period provide similar inference to the results of Table 2. Please see Table IA.2 in the Internet Appendix.

[7] In untabulated results, we find that the effect exists among both NYSE/AMEX and NASDAQ stocks, but is stronger among the less-liquid NASDAQ stocks.

[8] Amihud (2002), Brennan, Huh, and Subramanyam (2013), Lou and Shu (2017), Drienko, Smith, and von Reibnitz (2019), and Harris and Amato (2019) estimate the relation between performance and illiquidity via cross-sectional regressions where individual stock observations are equally weighted.

value-weighting decreases the influence of illiquid stocks, a value-weighted analysis shows a weaker univariate relation. Bear in mind, however, that our goal is not to assess the robustness of the illiquidity-performance relation or to analyze the viability of illiquidity as a trading strategy. Rather, for whatever evidence exists consistent with an illiquidity premium, even if it hinges on relatively small market capitalization stocks, our objective is to explain why that evidence exists.

3.2 Illiquidity and Past Stock Returns

3.2.1 Univariate Relation

As noted above in reference to Table 15, the most illiquid quintile of stocks shows relatively low past one-month return. For instance, the most illiquid stocks in Q5 show an average (median) return of 0.02% (-1.17%) per month vs. 1.46% (0.45%) per month for stocks in the other four quintiles. Annualized, these return differences amount to approximately 17-19.5% lower returns for Q5 stocks compared to stocks in quintiles 1-4 during the month used to compute the Amihud measure associated with the sort. The relatively low past returns of the illiquid stocks suggest that some portion of their relatively high future returns (as shown in Table 16) is attributable to the reversal effect in stocks (e.g., Jegadeesh (1990) and Lehmann (1990)). Thus, a portion of Q5's 1.60% monthly return in Table 16 likely stems from return mean reversion.

To provide additional evidence on the relation between illiquidity and returns beyond the lag one-month return statistics in Table 16, Figure 7 plots the cumulative average abnormal return (relative to the CRSP value-weighted index) of the most illiquid (Q5) and the least illiquid (Q1) quintiles over a long time horizon. The plots begin 18 months prior to the sort month (denoted month 0) and extends through the twelfth post-sort month, representing a total period of 31 months. The upward sloping line associated with the Q5–Q1 cumulative return difference during the period following the sort month is consistent with an illiquidity premium that persists for at least a year following the sort.

[Insert Figure 7 here]

Perhaps even more interesting than the post-sort return pattern is the return pattern prior to the sort. Not only do illiquid stocks show poor performance just prior to the sort month, the negative returns extend far back in time, as reflected in the downward sloping cumulative return plot line between month -18 and the sort month. Moreover, the cumulative negative return plot line prior to the sort month is noticeably steeper than the cumulative positive return plot line following the sort. For example, the cumulative return difference prior to the sort is -31.64% over 18 months, or about -1.75% per month, whereas the cumulative return difference after the sort is 4.04% over 12 months, or about 0.33% per month. That is, the negative relation between illiquidity and past returns is far stronger (by a factor greater than five times) than the positive relation between illiquidity and subsequent returns usually emphasized in analyses of the illiquidity premium.

It is also worth noting that the cumulative average abnormal return plot of the illiquid quintile in Figure 1 aligns closely with the cumulative average abnormal return plot associated with mutual fund fire sale stocks in Coval and Stafford (2007).[9] Similarity to the fire sales plot exists both before and after sort month 0. Based on this similarity, we speculate that illiquid stocks are characterized by excessive selling pressure during month 0. We explore this hypothesis in detail later.

3.2.2 Double Sort of Past Returns and Illiquidity

[9] See Fig. 2 (page 495) of Coval and Stafford (2007).

Given the interesting return pattern prior to the sort month evident in Figure 1, we further analyze the relation between illiquidity and future return via double sorts that control for past one-month return. In the double sorts, we sort sequentially, first on return and then on illiquidity, both measured during month $t-1$, and then compute the mean return and three- and four-factor alphas of each cell during the following month.[10] We use a one-month lag between the sort variables (past one-month return and illiquidity) and the subsequent monthly return, like the Table 16 analysis. We present the results in Table 17, with Panel A showing post-sort returns, and Panels B, C, and D showing post-sort one-, three-, and four-factor alphas respectively.

[Insert Table 17 here]

The last column in the table shows the Q5–Q1 return difference (i.e., the most illiquid quintile minus the least illiquid quintile) associated with each past return quintile. The difference reflects whether the illiquidity premium exists for a given quintile level of past return. Interestingly, the table indicates that the illiquidity premium only exists in the lowest past return quintile (Q1), that is, only when past returns are relatively low. In Panel A, for the lowest past-return quintile, the most-illiquid quintile of stocks (Q5) shows a large, strongly significant 2.86% (*t*-stat.=10.28) greater monthly return than the most-liquid quintile of stocks (Q1). The alpha differences in Panels B, C, and D are also large, at 3.00%, 2.72%, and 2.89% per month respectively, and highly statistically significant (*t*-stats > 10). Beyond the outsized economic and statistical significance of these differences, they are approximately five times the performance difference associated with the univariate sort in Table 16 and are thus large relative to the average illiquidity premium across the universe of stocks.

[10] We analyze two robustness tests. First, we reverse the order in the sequential sorts, sorting first on illiquidity and then on return. Second, we repeat the analysis based on value-weighting the returns. For both alternative sets of analyses, the results are qualitatively similar to those reported in this section. Please see Table 24 and Table 25 in the Internet Appendix.

Contrary to the strong illiquidity premium apparent in the low return quintile, there is no statistically significant positive return, one-, three-, or four-factor alpha difference between the most illiquid and the least illiquid quintiles of stocks within the other four past-return quintiles (Q2 through Q5). In fact, the results all indicate that the performance difference for the high past-performance quintile (Q5) runs opposite to the typically positive correspondence between illiquidity and future performance, with the most illiquid quintile of stocks *underperforming* the least illiquid quintile of stocks by 1.13% per month based on return, by 1.04% per month based on one-factor alpha, by 1.32% per month based on three-factor alpha, and by 1.17% per month based on four-factor alpha. All four differences are highly statistically significant, with *t*-statistics less than -5. As these differences are roughly double in magnitude (but opposite sign) the Q5–Q1 difference associated with the univariate illiquidity sort, the results suggest that the illiquidity premium is small relative to the reversal effect in stocks.

We hypothesize that if we examine the cross-sectional relation between stock illiquidity and performance for a sample that excludes the top quintile illiquid stocks with large relative past one-month returns (positive or negative) we should no longer find a strong positive relation between illiquidity and subsequent return. Since illiquid stocks are of relatively small market capitalization, the subset of extreme return illiquid stocks represents a very small fraction of the aggregate market capitalization of the complete stock universe, amounting to 0.20% in our sample.

We run univariate regressions of performance vs. the natural log of Amihud illiquidity, i.e.,

$$R_{i,t} = \alpha + \beta ln\left(A_{i,t-1}\right) + \mu_{i,t}, \tag{2}$$

where $R_{i,t}$ represents the return, three-factor alpha, or four-factor alpha of stock *i* at time *t*, and $A_{i,t-1}$ represents the one-month lag Amihud illiquidity measure for stock *i* computed based on its daily returns and volume during month *t* – 1. In untabulated results, we find that when we include all stocks in the regressions, the t-statistics for β are 2.78, 2.72, and 3.04 respectively based on using return, three-factor alpha, and four-factor alpha as the performance measure. However, when we repeat the regressions except exclude stocks that show top or bottom quintile past one-month return that are simultaneously in the highest illiquidity quintile (i.e., excluding the Table 17 Q1/Q5 and Q5/Q5 return/illiquidity stocks), the t-statistics for β are -0.05, -0.93, and -0.72 respectively based on using return, three-factor alpha, and four-factor alpha as the performance measure. Thus, after excluding illiquid stocks with extreme past returns, evidence of an illiquidity premium disappears. We thus conclude that evidence of an illiquidity premium crucially depends on the small subsample of illiquid stocks with poor past returns. Illiquid stocks that are not among the bottom quintile of stocks based on past one-month return show no evidence of relatively high future returns.

By contrast to the finding in Table 17 that the illiquidity premium is sensitive to past returns, the table reflects a robust, monotonic, inverse relation between prior return quintile and subsequent one-month return, consistent with a strong return reversal effect regardless of stock illiquidity. Across the four panels, 17 (14) out of the 20 Q5–Q1 bottom row performance differences (i.e., controlling for stock illiquidity) are statistically significant at the 5% (1%) level, and a particularly large return difference exists among illiquid stocks.

3.3 Price Pressure of Illiquidity / Return Sorts

The Figure 1 and Table 17 results suggest a link between past returns and illiquidity that makes it difficult to disentangle the economic magnitude of the illiquidity premium from that of the short-term reversal effect, since stocks classified as illiquid show relatively low return during the months leading up to their illiquid classification. To try to differentiate empirically the illiquidity premium from the short-term reversal effect, we take our cue from theoretical arguments used to explain the illiquidity premium, which is often hypothesized (by Amihud and Mendelson (1986) and Vayanos (1998), for example) to represent compensation for bearing price impact risk.

As an example, illiquid stocks are characterized by relatively few shares available to be bought or sold at a given price and/or by a relatively large percentage bid-ask spread. When an illiquid stock is bought aggressively, the prevailing ask price typically increases, and the average transaction price is high relative to the stock's price prior to the trade. Conversely, when an illiquid stock is sold aggressively, the bid price decreases, and the average sell transaction price is relatively low. The theoretical arguments hypothesize that over time, the illiquidity premium serves to provide higher expected returns to offset the poor execution prices of illiquid stocks. Thus, according to theory, illiquidity premia compensate illiquid stocks on average across time, rather than only emerging soon after and in direct response to the price impact associated with a large transaction. This latter post-trade price impact reversal occurs when price-moving transactions are not driven by new information, and it differentially affects illiquid stocks that are aggressively bought compared to those that are aggressively sold: Price impact reversal positively impacts an illiquid stock's share price following a large sell transaction, but negatively impacts an illiquid stock's share price following a large buy transaction. In both instances, the share price reverts toward its pre-trade level.

We therefore examine the extent to which a price pressure reversal drives the illiquidity premium. We focus on the group of illiquid stocks with relatively poor prior performance since the Table 17 results indicate they play a central role in the positive relation between illiquidity and future performance. Relating to our double sort analysis, we examine low past return, illiquid stocks (i.e., stocks classified as Q1 past return and Q5 illiquidity in Table 17). Our goal is to discern the extent to which their positive future performance is driven by a price impact reversal stemming from executed transactions linked to an aggregate imbalance of sell transactions.[11] To analyze price pressure, we focus on the trades of institutional money managers for two main reasons. First, institutions represent an important category of investor. For instance, U.S. equity mutual funds invest $17.4 trillion as of the end of 2018 (Investment Company Institute, 2019). Second, we can use two widely available databases, Thomson Reuters mutual fund portfolio holdings and the Abel Noser database of institutional stock transactions, to estimate how institutional investors trade illiquid/loser stocks.

3.3.1 Inferred Mutual Fund Trades

We first analyze the stock trades of mutual funds, which we infer by examining differences in adjacent snapshots of each fund's portfolio holdings taken from the Thomson Reuters database (see Chen, Jegadeesh, and Wermers (2000), for example). The main shortcoming of this approach is the estimated transactions are subject to noise, since funds typically report their holdings at a relatively low, quarterly frequency (see Kacperczyk, Sialm, and Zheng (2008) and Puckett and Yan (2011)). Also note that the sample of stocks held by mutual funds represents a subset of the broader CRSP universe examined in most of our other analyses.[12]

At the end of each quarter, for each stock held by any fund in our sample, we calculate the aggregate holding change (across all funds that hold that stock) based on the difference in the aggregate change in holdings compared to the prior quarter. To control for extreme outliers, we

[11] The noted similarity between the plots of the most illiquid stock quintile in Figure 1 and Coval and Stafford's (2007) mutual fund fire sale stocks lends further credence to the possibility that the reversal of price impact associated with sell transactions contributes to the abnormal return of illiquid stocks.

[12] In addition, the mutual fund holding sample comprises a shorter sample period than the CRSP stock sample. To ensure the relevance of our 1990–2017 fund holdings analysis to our earlier results, we first confirm in Table 26 in the Internet Appendix that the main patterns associated with Tables 16 and 17 (i.e., a univariate relation between stock illiquidity and future performance with evidence in the double sort that the positive performance of illiquid stocks stems from past losers) exists during 1990–2017. Results for both the univariate sort in Panel A of Table 26 and the double sort in Panel B of Table 26 are qualitatively similar to the corresponding results in Tables 16 and 17.

winsorize the aggregate holding change measure at the 1% level. Thus, based on our sample of stocks held by mutual funds, we first double sort stocks sequentially based on the past one-month return and illiquidity using the breakpoints associated with the Table 17 double sort analysis of the broader CRSP stock sample. Next, focusing on the set of stocks classified as Q1 past one-month return and Q5 illiquidity, we estimate, for each stock, the aggregate net change in mutual fund ownership based on quarterly snapshots of mutual fund portfolio holdings.

We then divide the subsample of low return (Q1), high illiquidity (Q5) stocks into two groups based on whether mutual fund ownership increases or decreases during the quarter ending with the illiquidity sort month. We apply Coval and Stafford's (2007) rationale that coordinated fund buying activity creates positive price impact, and coordinated fund selling activity creates negative price impact. Lastly, we compute the mean next month return of each group. Essentially, we decompose the return associated with the loser/illiquid group of stocks into the component associated with stocks that were purchased, on net, by mutual funds during the time period prior to the illiquidity and return sort, and stocks that were sold, on net, by mutual funds during that time period. We report these results in Table 18, Panel A. Given their importance to the overall finding of an illiquidity premium, we are most interested in the results associated with the illiquid/loser group of stocks. However, for comparison purposes, we also report in Table 18 results associated with illiquid/winner stocks (analogous to the cell of stocks classified as Q5 past return and Q5 illiquidity in Table 3).

[Insert Table 18 here]

The entire group of Q1 past one-month return and Q5 illiquidity mutual fund stocks show an average next month return of 6.04%, somewhat greater than the 4.09% return for this category of stock based on the CRSP stock sample in Table 17. Among this group, we find that 73.4% of stocks were sold on net during the quarter ending at the end of the sort month, and that funds reduced their aggregate exposure to these stocks by $13.3 billion via reductions in holdings (i.e., beyond effects associated with the low Q1 stock returns). During the first post-sort month, the low return, illiquid stocks that funds sell show a very large mean return of 6.96%. By contrast, stocks in the low return/illiquid category purchased by funds during the sort month show mean return of 3.53%, roughly one half the return of the sold stocks. The 3.43% difference between stocks that funds sell and stocks that funds buy is statistically significant at the 1% level, with *t*-stat.=5.24.[13]

The combination of sold stocks' very large 0.734 weight and large 5.82% illiquidity premium together explain the vast majority (about 86%) of the 4.98% illiquidity premium associated with low return stocks.[14] In comparison, the illiquid/winner group of stocks show muted portfolio change imbalances and no return difference between stocks that funds buy and stocks that funds sell. Overall, the interpretation is that, on average, stocks sold by mutual funds experience negative price impact that subsequently reverses, and it is this positive price impact reversal that is captured by the positive performance of the low return, high illiquidity cell in Table 3.

3.3.2 Institutional Stock Trades

As an alternative to inferring trades based on changes in quarterly mutual fund portfolio holdings, we examine actual trades of institutional money managers using the Abel Noser trade

[13] Our Table 18, Panel A analysis classifies stocks based on whether ownership across all sample funds increases or decreases. As such, we fundamentally differ from the approach used by Frazzini and Lamont (2008) to estimate the "dumb money" effect, where they track the performance of an individual fund's net flow. For instance, a fund can replace one stock holding with another regardless of whether net fund flows are positive or negative. Our finding that stocks *sold* at time t outperform during month $t + 1$ also differs from Frazzini and Lamont (2008), who show that fund *inflows* at time t outperform during month $t + 1$, i.e., a short-term "smart money" effect exists. Frazzini and Lamont (2008) find that the dumb money effect begins the second quarter following investor flows.

[14] $(0.734 \times 0.0582)/0.0498 = 0.857$.

database, which includes trade data from 1999 to 2011.[15] We again focus on the illiquid/loser cell using the Table 17 illiquidity/return breakpoints and compute for each stock its net trade imbalance during the sort month. Net trade imbalance for a stock is the difference between the aggregate dollar amount purchased and the aggregate dollar amount sold during the month based on actual trade executions included in Abel Noser. We divide the illiquid/loser stocks into two groups: those with negative net trade imbalance and those with positive net trade imbalance. Like our mutual fund portfolio holding analysis, we compute for each group trade and return statistics, and we report the statistics in Table 18, Panel B. As before, the illiquid/winner group of stocks serves as a point of comparison.

The table indicates that institutions sell the illiquid/low return stocks, on net, during the sort month, as reflected by the $83 million net aggregate sell imbalance, with aggregate sell dollar transactions exceeding aggregate buy dollar transactions by roughly one third ($339 million vs. $256 million). By contrast, illiquid/high return stocks experience roughly equal sell and buy transaction dollar amounts, with just 6% greater aggregate sell dollar volume than buy dollar volume ($645 million vs. $608 million). Consistent with the evidence based on mutual fund holdings, the results suggest that selling price pressure contributes to the poor returns of illiquid/loser stocks, such that some price pressure reversal would be expected in these stocks going forward.

Also consistent with the mutual fund evidence, we find a strong correspondence between whether an illiquid loser stock is sold or purchased, on net, during the sort month and its subsequent

[15] As before, we repeat the univariate and double sort analyses associated with Tables 16 and 17 across the 1999-2011 sample period to ensure the relevance of the Abel Noser trade analysis, and we report these results in Table 27 in the Internet Appendix. Consistent with Drienko, Smith, and von Reibnitz (2019) and Harris and Amato (2019), the results for this relatively recent sample period are weaker than the full sample results in Tables 16 and 17. Nonetheless, the double sort results in Panel B of Table 27 indicate that evidence of an illiquidity premium is restricted to the low past return quintile of stocks.

return. Illiquid loser stocks that are sold during the sort month show a return of 4.37% during the first post-sort month, and illiquid loser stocks that are purchased during the sort month show a return of 1.73% during the first post-sort month, with the 2.64% difference statistically significant at the 1% level (*t*-stat.=3.31). The combination of sold stocks' 0.584 weight and large 3.22% illiquidity premium together account for virtually the entire (about 98%) 1.92% illiquidity premium associated with low return stocks in the Abel Noser sample.

3.3.3 Institutional Stock Transaction Costs

We provide additional evidence regarding our hypothesis that selling activity among the low return, illiquid group of stocks leads to price impact that subsequently reverts by examining transaction cost estimates. We expect especially large transaction costs for the low return, illiquid sell transactions. Based on the Abel Noser transaction data, we estimate trading costs as,

$$TradeCost = D * \frac{Price - BenchmarkPrice}{BenchmarkPrice}, \tag{3}$$

where $Price$ is the execution price of a trade, D denotes the trade direction (1 for a buy and -1 for a sell), and *BenchmarkPrice* is the price at the time the fund places the order ticket. As such, the price benchmark is the same for all executions stemming from the same order ticket. These transaction cost estimates, commonly-referred to as *execution shortfall*, capture implicit trading costs, including price impact and costs related to the bid-ask spread, but exclude brokerage commissions, taxes, and other fees.

The Abel Noser database does not aggregate into a single ticket a fund's trades that execute via different brokers. Institutions could break up large orders into trades executed via different brokers and on different days. To capture this tendency, we estimate a set of alternative transaction costs based on the "stitched ticket" approach of Anand et al. (2012). We aggregate a fund's same-side trades (e.g., all trades are buys) involving the same ticker that occur on consecutive days, even when different brokers are involved. Via this alternative approach, we use the same pre-trade benchmark price for all trades associated with a particular stitched ticket. Like Anand et al. (2012), we cap the duration of a stitched ticket at five days.

We report the transaction cost estimates in Table 18, Panel C. The statistics represent the time series mean of cross-sectional averages. That is, we compute the mean cost estimate each month for each group based on its constituent stocks (e.g., the low return, illiquid stocks that are net sold) and then compute the time series mean. Based either on the standard execution shortfall estimates or on the stitched ticket estimates, implicit transaction costs are economically meaningful for the sell transactions, but not for the buy transactions. For instance, based on execution shortfall, the mean implicit transaction cost for a sell (buy) transaction is 1.23% (-0.16%). For both types of cost estimates, the difference in transaction costs between sell transactions and buy transactions is highly statistically significant, with *t*-stats greater than 8. Moreover, as Table 18, Panel B indicates, the institutional sell transactions of low return, illiquid stocks occur more often than the institutional buy transactions, such that these illiquid stocks suffer the negative price impact effects associated with institutional sells more often than the positive price impact effects associated with institutional buys.

By contrast to the low return, illiquid results, transaction costs associated with the high return, illiquid stocks are less than half as large, on average, and the buy transactions show significantly larger implicit costs than the sell transactions. Although we do not focus on the relatively low future returns associated with high past return, illiquid stocks (for instance, this category significantly underperforms compared to high past return, liquid stocks in Table 17), the results in Table 18, Panel C suggest that the underperformance is due, in part, to mean reversion stemming from high implicit transaction costs of the buy transactions.

Along with the mutual fund portfolio results, the institutional investor trade and transaction cost evidence thus indicates that the strong positive relation between stock illiquidity and future performance stems directly from the reversal of poor recent returns and downward price pressure. Because the illiquidity premium acutely manifests itself among the small set of loser stocks sold by institutions, our results suggest that it does not represent a broad premium demanded by investors as compensation for holding an illiquid stock.

3.4 Alternative Liquidity Measures

Our analysis thus far focuses exclusively on the Amihud illiquidity measure. We next examine whether our key findings hold based on four alternative measures of liquidity: the Pastor and Stambaugh (2003) gamma liquidity measure, the effective spread, the quoted spread, and the open-to-close Amihud measure (Barardehi et al., 2021). We estimate the Pastor and Stambaugh gamma measure and Barardehi et al.'s (2021) open-to-close liquidity measure based on daily frequency data, similar to the Amihud measure. By contrast, the effective and quoted spreads are based on high frequency TAQ price data.

For each stock *i* and each month *t*, we estimate Pastor and Stambaugh's gamma liquidity measure via the following time series regression based on stock *i*'s daily data during month *t*:

$$R_{i,d+1,t} - R_{m,d+1,t} = \theta + \emptyset R_{i,d,t} + gamma_i \times sign\left(R_{i,d,t} - R_{m,d,t}\right)\left(DVOL_{i,d,t}\right) + \varepsilon_{d,t}, \quad (4)$$

where $R_{i,d,t}$ is the return of stock *i* on day *d* in month *t*, $R_{m,d,t}$ is the CRSP value-weighted market return on day *d* in month *t*, $DVOL_{i,d,t}$ is stock *i*'s dollar trading volume on day *d* in month *t*, and $gamma_i$ represents stock *i*'s liquidity measure. Like Pastor and Stambaugh (2003), we require a minimum of 15 non-missing days of stock data during the month to estimate regression (4).

The effective spread for a particular transaction is:

$$Effective\ Spread = 2 \times \frac{|Transaction\ Price - Midpoint|}{Midpoint}, \quad (5)$$

where *Midpoint* is the average of the transacted stock's bid and ask one second before the transaction. The quoted spread associated with a particular transaction is half the bid-ask spread, i.e.,

$$Quoted\ Spread = \frac{Ask - Bid}{\frac{1}{2}(Bid + Ask)}. \tag{6}$$

For a given stock, we take the equal-weighted average of the effective or quoted spread across transactions during the trading day, and a stock's monthly effective or quoted spread is the equal weighted average of its daily effective or quoted spreads during the month.

Barardehi et al. (2021) show that estimating the Amihud (2002) illiquidity measure based on open-to-close returns rather than the usual close-to-close returns better explains the cross-section of returns and doubles estimated liquidity premia. The idea is that stock trades occur and trading costs are realized during the trading day, whereas the close-to-open return reflects information. To calculate this measure, we replace the close-to-close return of stock *i* on day *d* in month *t*, $R_{i,d,t}$, in the numerator of equation (1) with the open-to-close return.

To provide an indication of the extent to which the alternative measures capture similar features of liquidity, for each pair of measures, we compute across stocks the cross-sectional correlation between the measures each month. We then take the time series average of the monthly cross-sectional correlations. We report these correlation statistics in Table 19. Like Chordia, Roll, and Subrahmanyam (2000) and Goyenko, Holden, and Trzcinka (2009), we find that the alternative measures show modest cross-sectional correlation with one another, with the mean correlations ranging from 0.23 to 0.59.

[Insert Table 19 here]

We repeat the main set of analyses to examine whether inference associated with the alternative liquidity measures is similar to that based on the Amihud measure. We focus on the double sort of illiquidity and past return vs. future performance (as in Table 17) and the institutional trading analyses (as in Table 18). We use the same methodology as before, except that we replace the Amihud measure with one of the alternative liquidity measures. In addition to the double sort and institutional trading analyses, we also report the univariate relation between future performance and the alternative liquidity measures in Table 28 in the Internet Appendix. The univariate relation between the Pastor and Stambaugh gamma liquidity measure and future performance shown in Panel A of Table 28 is similar to that based on the Amihud illiquidity measure in Table 16 and consistent, by in large, with an illiquidity premium. When we examine the univariate relation with the illiquidity measures based on high frequency data, the relation is not statistically significant. Note, however, that the sample period associated with the high frequency liquidity measures (2004-2014) is substantially shorter than that associated with the Amihud and Pastor and Stambaugh measures (1964-2018). And regardless of the strength of the univariate relation between various measures of illiquidity and future performance, our main goal is to identify important effects that positively impact the returns of illiquid stocks.

Table 20 reports results for the double sort analysis (past return/illiquidity vs. future performance) based on the alternative liquidity measures, with Panels A-D corresponding to the Pastor and Stambaugh gamma liquidity measure, the effective spread, the quoted spread, and the Barardehi et al. (2021) open-to-close measure respectively. The table reports the difference in return between the most illiquid quintile and the least illiquid quintile, i.e., the Q5–Q1 illiquidity premium, for each return quintile, rather than the entire five by five set of illiquidity/return cells. Similar to the Table 17 findings based on the Amihud illiquidity measure, Table 20 indicates that the illiquidity premium exists only within return quintile 1, i.e., only among stocks with relatively poor prior month returns. Among the other prior-return quintiles, the illiquidity premium either does not significantly differ from zero (in prior-return quintiles 2-4) or is significantly negative (in prior return quintile 5). Our finding that the positive relation between illiquidity and future performance is closely connected to return reversals in poorly performing stocks is thus robust to alternative liquidity measures, despite the modest cross-sectional correlations between the measures.

[Insert Table 20 here]

We next examine the institutional trading activity of the low return, illiquid cell of stocks (i.e., return quintile 1 and illiquidity quintile 5) based on using the alternative liquidity measures to define the illiquidity cell stock constituents. We report the results in Table 21, with Panels A-D again corresponding to analysis based on the Pastor and Stambaugh gamma liquidity measure, the effective spread, the quoted spread, and the Barardehi et al. (2021) measure respectively. Within each panel, we report institutional trading activity inferred from changes in mutual fund portfolio holdings (in Panels A1-D1) and actual stock trades (in Panels A2-D2), and we report transaction cost estimates in Panels A3-D3. Note that compared to Table 18, Table 21 does not include institutional trade statistics for the high return stocks, though they are qualitatively similar to the high return statistics shown in Table 21.

[Insert Table 21 here]

Focusing first on trades inferred from changes in mutual fund holdings in Panels A1-D1, based on all three alternative liquidity measures, mutual funds predominantly sell the illiquid loser stocks, with the fraction of stocks sold ranging from 68% to 76%. The subsequent monthly return of stocks sold by mutual funds is statistically and economically large, ranging from 7.55% in Panel A1 to 4.07% in Panel C1 and significantly larger than the subsequent return of stocks bought by funds based on the Pastor and Stambaugh gamma measure and the quoted spread. Moreover, the illiquidity premium for stocks sold by mutual funds is roughly double that for stocks bought by funds. The institutional stock trade results based on Abel Noser data in Panels A2-D2 provide similar inference, with the subsequent monthly return and illiquidity premium for illiquid stocks sold by institutions statistically and economically large and significantly greater than the returns and illiquidity premium for illiquid stocks bought by institutions.

Lastly, the transaction cost estimates in Panels A3-D3 indicate that illiquid loser stocks sold by institutional investors are subject to significantly greater price impact than the illiquid loser stocks bought by institutional investors. Across the four panels, the average price impact transaction cost of stocks sold by institutional investors is 1.15% (2.61%) based on execution shortfall (stitched tickets), whereas the average price impact transaction cost of stocks bought by institutional investors is -0.04% (-0.03%).

Summing up, analysis based on the alternative liquidity measures—Pastor and Stambaugh's (2003) gamma measure, the effective spread, the quoted spread, and the Barardehi et al. (2021) measure—confirms inference based on the Amihud measure. The consistent results across the alternative liquidity measures is meaningful because their modest cross-sectional correlations suggest that the various measures capture somewhat different aspects of liquidity. Nonetheless, regardless of the liquidity measure, we find that any positive premium that exists among illiquid stocks is attributable to the reversal of poor recent returns and downward price pressure among stocks sold by institutional investors. After accounting for these effects, illiquid stocks show no return premium.

4. Conclusion

Illiquid stocks are characterized by relatively poor recent returns. We find that the illiquidity premium is driven by the tendency for short-term stock returns to reverse. When we exclude a small set of stocks with outlier returns, both positive and negative, no illiquidity premium exists. Moreover, the subset of illiquid stocks with relatively positive past one-month returns shows negative future returns, i.e., an illiquidity discount.

Beyond past returns, we find that institutional trading activity significantly impacts an illiquid stock's future return. We show that a substantial fraction of illiquid loser stocks experiences large negative price impact stemming from an imbalance of institutional investor sell transactions. The poor short-term returns of these stocks revert, as does their negative price impact. The combination of the two effects explains the premium associated with a sort based on stock illiquidity.

Overall, our results shed light on the reason why illiquid stocks show positive mean abnormal returns. Our evidence does not support the idea that the abnormal return associated with illiquid stocks broadly compensates investors who hold stocks that are costly to trade. Rather, we show that the abnormal return stems directly from the reversal of poor recent returns and downward price pressure among a small slice of stocks disproportionately sold by institutional investors.

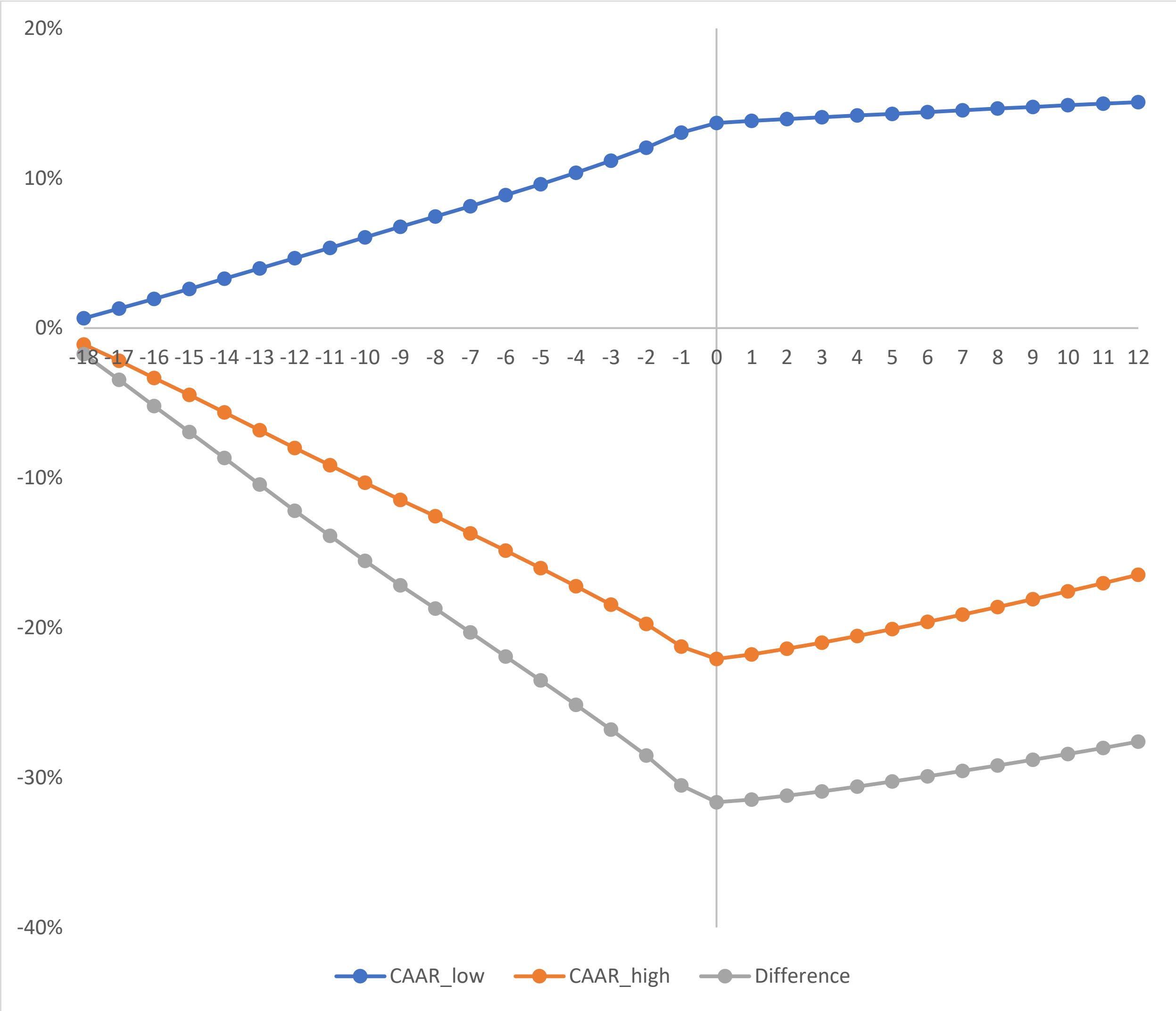

Figure 7. Cumulative Abnormal Return of High and Low Illiquidity Quintiles

The figure shows the cumulative average abnormal return of the most illiquid (Q5) and the least illiquid (Q1) quintiles over the time horizon from 18 months prior to the sort month to 12 months after the sort month. We calculate abnormal returns relative to the CRSP value-weighted market index from month t – 18 to t + 12 of equal-weighted returns of the quintile portfolios. The blue line represents the least illiquid quintile (Q1); the orange line represents the most illiquid quintile (Q5); the gray line represents the difference between the most illiquid and least illiquid quintiles (Q5–Q1).

Table 15. Summary Statistics

The table provides summary statistics of the stock sample sorted into quintiles based on the Amihud (2002) illiquidity measure. The sample includes ordinary common shares (share codes 10 or 11 in CRSP) listed on NYSE/Amex and NASDAQ from January 1964 to December 2017. We report the mean and median of key variables. Price is the stock price at the end of month. Return is the monthly return. Market Cap is market capitalization at the end of the prior year (in millions of dollars). Amihud is the Amihud (2002) measure, defined as the daily ratio of absolute return to dollar trading volume, averaged across all days in a month. When measuring the Amihud measure for NASDAQ stocks, we use the Gao and Ritter (2010) volume correction by dividing volume by 2 for the period from 1983 through January 2001, by 1.8 from February to December 2001, and by 1.6 from 2002 to 2003. B/M is the book-to-market ratio calculated as a firm's book value divided by the firm's market capitalization, where we use the book value of the fiscal year ending in calendar year *y* and market value at the end of year *y* to calculate book-to-market ratio and match it to stock returns in the one-year period from July of $y + 1$ to June of $y + 2$. We winsorize the book-to-market ratio in each month at the 0.5% and 99.5% level to reduce the influence of outliers. Ret[-13,-2] is the cumulative holding period return from month $t – 13$ to month $t – 2$. Volume is the monthly total dollar trading volume calculated as end-of-month price times total share trading volume (in millions).

		Illiquidity Quintile *t*				
Characteristic *t*	All	Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)
			Panel A. Mean			
Price	31.1	98.5	24.4	16.2	10.8	5.7
Return	1.18%	1.56%	1.83%	1.46%	1.00%	0.02%
Market Cap ($M)	1666	7430	600	202	75	26
Amihud	16.27	0.01	0.09	0.48	2.43	78.33
B/M	0.85	0.65	0.70	0.80	0.94	1.20
Ret[-13,-2]	15.1%	25.2%	27.4%	19.6%	9.6%	-6.6%
Volume ($M)	237.3	1065.5	95.5	21.0	4.3	0.7
			Panel B. Median			
Price	13.1	33.7	19.9	12.3	7.6	3.3
Return	0.00%	0.85%	0.95%	0.00%	0.00%	-1.17%
Market Cap ($M)	97	1661	277	90	36	11
Amihud	0.20	0.00	0.05	0.29	1.48	12.44
B/M	0.64	0.51	0.55	0.63	0.72	0.89
Ret[-13,-2]	5.5%	14.8%	13.0%	7.0%	0.4%	-13.2%
Volume ($M)	4.1	148.1	18.1	4.3	1.2	0.2

Table 16. Illiquidity vs. Performance

The table presents average monthly stock returns (in percentage) for quintiles sorted by the Amihud measure. The sample contains ordinary common shares (share codes 10 or 11 in CRSP) from January 1964 to December 2017. At the beginning of each month *t*, stocks are sorted into quintiles based on the Amihud measure of month $t-1$. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Illiquidity	Performance *t*			
Quintile $t-1$	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
Q1 (Liquid)	1.03	0.07	0.01	0.03
	(5.28)	(1.42)	(0.26)	(0.88)
Q2	1.16	0.12	-0.03	0.06
	(4.86)	(1.14)	(-0.62)	(1.53)
Q3	1.13	0.09	-0.16	0.03
	(4.39)	(0.62)	(-2.22)	(0.52)
Q4	1.19	0.20	-0.10	0.13
	(4.65)	(1.23)	(-0.96)	(1.37)
Q5 (Illiquid)	1.60	0.68	0.33	0.60
	(5.73)	(3.10)	(2.01)	(3.71)
Q5–Q1	0.57	0.61	0.33	0.57
	(2.80)	(2.98)	(1.87)	(3.33)

Table 17. Double Sort: Past Return and Illiquidity vs. Future Performance

The table presents performance for stocks double sorted by past return and the Amihud measure. Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on monthly return at $t-1$. Within each return quintile, stocks are sorted into quintiles based on the Amihud measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted returns for the portfolios during month t and report time-series average portfolio returns. The last column, labeled "Q5–Q1," shows the average raw return difference between high illiquidity and low illiquidity portfolios within each return quintile. Panel A presents the raw return of the quintile portfolios, Panel B presents single-factor alphas, Panel C presents Fama and French (1993) three-factor alphas, and Panel D presents Carhart (1997) four-factor alphas. The sample period is January 1964 to December 2017. All returns are expressed in percent. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Return Quintile $t-1$	Illiquidity Quintile $t-1$ Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			Panel A. Return			
Q1 (Low)	1.23	1.58	1.64	2.15	4.09	2.86
	(4.00)	(4.57)	(4.65)	(5.84)	(10.53)	(10.28)
Q2	1.30	1.37	1.22	1.19	1.34	0.04
	(5.82)	(5.55)	(4.78)	(4.73)	(5.10)	(0.21)
Q3	1.10	1.19	1.19	1.19	1.21	0.11
	(6.07)	(5.59)	(5.27)	(5.30)	(5.13)	(0.62)
Q4	0.89	1.04	0.99	1.13	1.08	0.19
	(5.01)	(5.00)	(4.54)	(5.07)	(4.61)	(1.10)
Q5 (High)	0.79	0.95	0.69	0.39	-0.33	-1.13
	(3.44)	(3.58)	(2.61)	(1.48)	(-1.24)	(-5.45)
Q5–Q1	-0.44	-0.62	-0.95	-1.75	-4.42	
	(-2.01)	(-2.66)	(-4.25)	(-7.66)	(-18.25)	
			Panel B. Single-factor Alpha			
Q1 (Low)	0.06	0.37	0.48	1.02	3.06	3.00
	(0.33)	(1.71)	(1.95)	(3.68)	(9.33)	(10.87)
Q2	0.29	0.33	0.19	0.22	0.45	0.15
	(3.20)	(2.75)	(1.33)	(1.34)	(2.18)	(0.79)
Q3	0.19	0.21	0.22	0.27	0.36	0.17
	(3.24)	(2.44)	(1.83)	(1.91)	(1.97)	(0.93)
Q4	0.01	0.08	0.04	0.21	0.23	0.22
	(0.09)	(0.93)	(0.32)	(1.53)	(1.26)	(1.26)
Q5 (High)	-0.19	-0.09	-0.33	-0.60	-1.22	-1.04
	(-1.55)	(-0.56)	(-1.98)	(-3.39)	(-5.71)	(-5.03)
Q5–Q1	-0.24	-0.46	-0.80	-1.62	-4.28	
	(-1.16)	(-1.99)	(-3.66)	(-7.16)	(-17.86)	

Table 3 continued

Return Quintile $t-1$	Illiquidity Quintile $t-1$ Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			Panel C. Three-factor Alpha			
Q1 (Low)	-0.05	0.17	0.20	0.69	2.67	2.72
	(-0.36)	(1.00)	(1.07)	(3.10)	(9.61)	(10.36)
Q2	0.21	0.16	-0.07	-0.08	0.12	-0.09
	(2.44)	(1.99)	(-0.81)	(-0.70)	(0.74)	(-0.52)
Q3	0.11	0.05	-0.04	-0.04	0.05	-0.07
	(2.03)	(1.04)	(-0.64)	(-0.46)	(0.32)	(-0.45)
Q4	-0.06	-0.05	-0.18	-0.08	-0.08	-0.02
	(-0.84)	(-0.93)	(-2.84)	(-0.91)	(-0.56)	(-0.14)
Q5 (High)	-0.20	-0.20	-0.55	-0.83	-1.53	-1.32
	(-1.90)	(-1.85)	(-5.18)	(-6.84)	(-9.11)	(-6.99)
Q5–Q1	-0.15	-0.37	-0.75	-1.52	-4.19	
	(-0.73)	(-1.60)	(-3.40)	(-6.71)	(-17.51)	
			Panel D. Four-factor Alpha			
Q1 (Low)	0.25	0.58	0.67	1.18	3.13	2.89
	(1.84)	(3.74)	(3.91)	(5.73)	(11.64)	(10.85)
Q2	0.31	0.31	0.11	0.12	0.33	0.01
	(3.71)	(3.97)	(1.26)	(1.16)	(2.09)	(0.08)
Q3	0.15	0.11	0.05	0.09	0.21	0.06
	(2.58)	(2.07)	(0.74)	(1.02)	(1.48)	(0.40)
Q4	-0.08	-0.05	-0.09	0.03	0.06	0.14
	(-1.19)	(-0.95)	(-1.50)	(0.36)	(0.43)	(0.93)
Q5 (High)	-0.25	-0.22	-0.46	-0.73	-1.42	-1.17
	(-2.28)	(-2.00)	(-4.33)	(-5.99)	(-8.36)	(-6.13)
Q5–Q1	-0.50	-0.80	-1.14	-1.92	-4.55	
	(-2.41)	(-3.62)	(-5.31)	(-8.79)	(-19.41)	

Table 18. Institutional Trades of Loser vs. Winner Stocks

The table reports return and trade statistics associated with stocks in the highest illiquidity quintile (Q5) and in the lowest ("Low Return", Q1) or highest ("High Return", Q5) past one-month return quintile. In Panel A, for each stock, we compute the change in portfolio holdings across all mutual funds. Stocks with a net reduction (increase) in aggregate holdings across mutual funds are categorized as "Sell" ("Buy"). Aggregate Absolute Change reflects the dollar value of the aggregate change in fund holdings attributable to changes in stock share holdings. In Panel B, for each stock, we aggregate transactions across all institutional investors. Stocks with a net negative trade imbalance are categorized as "Sell" ("Buy"). In Panel C, we compute the mean cost estimate each month based on the constituent stocks associated with each column and then take the time series average.

	Low Return (Q1)				High Return (Q5)			
	All	Sell	Buy	Sell-Buy	All	Sell	Buy	Sell-Buy
				Panel A. Changes in Mutual Fund Holdings				
Fraction of Stocks (%)	100.0	73.4	26.6	46.8	100.0	41.9	58.1	-16.2
Aggregate Absolute Change ($M)	17,785	13,316	4,469	8,847	64,685	28,319	36,366	-8,047
Return (%)	6.04	6.96	3.53	3.43	0.14	0.24	0.09	0.16
t-stat	(16.12)	(14.27)	(8.11)	(5.24)	(0.59)	(0.63)	(0.30)	(0.33)
Return, Illiq(Q5)–Illiq(Q1) (%)	4.98	5.82	2.68	3.14	-0.94	-0.98	-0.88	-0.10
t-stat	(13.55)	(12.15)	(6.33)	(4.91)	(-4.15)	(-2.60)	(-3.09)	(-0.21)
				Panel B. Stock Trades				
Fraction of Stocks (%)	100.0	58.4	41.6	16.8	100.0	48.4	51.6	-3.2
Aggregate Trade Value ($M)	595	339	256	83	1,253	645	608	36
Return (%)	3.19	4.37	1.73	2.64	1.09	0.68	1.45	-0.77
t-stat	(4.96)	(7.27)	(3.49)	(3.31)	(3.51)	(1.49)	(3.39)	(-1.03)
Return, Illiq(Q5)–Illiq(Q1) (%)	1.92	3.22	0.34	2.88	-0.26	-0.65	0.08	-0.73
t-stat	(4.96)	(5.49)	(0.69)	(3.70)	(-0.84)	(-1.44)	(0.19)	(-1.18)
				Panel C. Transaction Costs				
Execution Shortfall (%)	0.80	1.23	-0.16	1.39	0.28	0.01	0.63	-0.62
t-stat	(8.54)	(10.46)	(-1.67)	(8.33)	(3.62)	(0.13)	(7.23)	(-4.75)
Stitched Tickets (%)	1.63	2.59	-0.16	2.74	0.73	-0.33	1.98	-2.31
t-stat	(10.15)	(12.40)	(-0.92)	(9.02)	(3.25)	(-1.50)	(6.04)	(-5.83)

Table 19. Cross-Sectional Correlation across Alternative Liquidity Measures

The table reports the time series mean of monthly cross-sectional correlations for each pair of liquidity measures estimated across stocks. The liquidity measures include the Amihud (2002) measure, the Pastor and Stambaugh (2003) gamma measure, the effective spread, the quoted spread, and the Baradehi et al. (2021) open-to-close measure. The sample period is January 1964 to December 2017 for the Amihud (2002), Pastor and Stambaugh (2003), and Baradehi et al. (2021) measures and January 2004 to December 2014 for the effective and quoted spreads.

	Amihud (2002)	Pastor and Stambaugh (2003)	Effective Spread	Quoted Spread
Amihud (2002)	1			
Pastor and Stambaugh (2003)	0.43	1		
Effective Spread	0.23	0.24	1	
Quoted Spread	0.36	0.38	0.59	1
Barardehi et al. (2021)	0.43	0.33	0.35	0.47

Table 20. Illiquidity Premium Based on Double Sort of Past Return and Alternative Liquidity Measures

The table presents the illiquidity premium associated with past return quintiles for stocks double sorted by past return and the Pastor and Stambaugh (2003) gamma liquidity measure (Panel A), the effective spread (Panel B), the quoted spread (Panel C), or the Barardehi et al. (2021) open-to-close measure (Panel D). Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on monthly return at $t-1$. Within each return quintile, stocks are sorted into quintiles based on the illiquidity measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted returns for the portfolios during month t. Each column reports the Q5–Q1 average performance difference between high illiquidity and low illiquidity portfolios within each return quintile. The alternative columns present raw returns, single-factor alphas, Fama and French (1993) three-factor alphas, and Carhart (1997) four-factor alphas. The sample period is January 1964 to December 2017 for the Pastor and Stambaugh (2003) and Barardehi et al. (2021) measures and January 2004 to December 2014 for the effective and quoted spreads. All returns are expressed in percent. Robust t-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

	Q5–Q1 t			
Return Quintile $t-1$	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
	Panel A. Pastor and Stambaugh (2003) Gamma			
Q1 (Low)	2.67	2.77	2.51	2.75
	(9.71)	(10.09)	(9.60)	(10.41)
Q2	-0.04	0.06	-0.18	-0.04
	(-0.19)	(0.32)	(-1.09)	(-0.21)
Q3	-0.02	0.04	-0.20	-0.05
	(-0.11)	(0.22)	(-1.35)	(-0.36)
Q4	0.07	0.11	-0.12	0.07
	(0.40)	(0.66)	(-0.81)	(0.45)
Q5 (High)	-1.15	-1.09	-1.34	-1.12
	(-5.90)	(-5.58)	(-7.31)	(-6.11)
	Panel B. Effective Spread			
Q1 (Low)	1.29	1.50	1.48	1.56
	(2.54)	(3.01)	(2.96)	(3.20)
Q2	-0.51	-0.36	-0.35	-0.30
	(-1.46)	(-1.06)	(-1.01)	(-0.89)
Q3	-0.23	-0.16	-0.14	-0.10
	(-0.77)	(-0.52)	(-0.46)	(-0.32)
Q4	-0.07	0.01	0.06	0.07
	(-0.23)	(0.04)	(0.20)	(0.24)
Q5 (High)	-0.95	-0.87	-0.86	-0.85
	(-2.62)	(-2.39)	(-2.34)	(-2.31)
	Panel C. Quoted Spread			
Q1 (Low)	1.32	1.54	1.52	1.59
	(2.69)	(3.22)	(3.16)	(3.39)
Q2	-0.40	-0.24	-0.22	-0.18
	(-1.17)	(-0.72)	(-0.67)	(-0.55)
Q3	-0.25	-0.15	-0.13	-0.10
	(-0.85)	(-0.52)	(-0.45)	(-0.33)
Q4	-0.15	-0.06	-0.02	-0.01
	(-0.48)	(-0.18)	(-0.05)	(-0.03)
Q5 (High)	-0.86	-0.77	-0.76	-0.75
	(-2.40)	(-2.16)	(-2.10)	(-2.06)

Table 6 continued.

Return Quintile $t-1$	Q5–Q1 t			
	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
	Panel D. Barardehi et al. (2021)			
Q1 (Low)	2.77	3.03	3.04	3.32
	(6.53)	(7.24)	(7.22)	(7.95)
Q2	-0.16	0.04	-0.00	0.20
	(-0.63)	(0.17)	(-0.02)	(0.86)
Q3	-0.12	-0.00	-0.06	0.14
	(-0.50)	(-0.03)	(-0.24)	(0.65)
Q4	0.19	0.29	0.23	0.39
	(0.81)	(1.20)	(0.99)	(1.73)
Q5 (High)	-0.79	-0.66	-0.71	-0.60
	(-2.64)	(-2.20)	(-2.37)	(-1.99)

Table 21. Institutional Trades of Loser Stocks – Alternative Liquidity Measures

The table reports return and trade statistics associated with stocks in the highest illiquidity quintile (Q5) and in the lowest ("Low Return", Q1) past one-month return quintile. To measure liquidity, we use Pastor and Stambaugh's (2003) gamma liquidity measure (Panel A), effective spread (Panel B), quoted spread (Panel C), or Barardehi et al.'s (2021) open-to-close measure (Panel D). In Panels A1-D1, for each stock, we compute the change in portfolio holdings across all mutual funds. Stocks with a net reduction (increase) in aggregate holdings across mutual funds are categorized as "Sell" ("Buy"). Aggregate Absolute Change reflects the dollar value of the aggregate change in fund holdings attributable to changes in stock share holdings. In Panels A2-D2, for each stock, we aggregate transactions across all institutional investors. Stocks with a net negative trade imbalance are categorized as "Sell" ("Buy"). In Panels A3-D3, we compute the mean cost estimate each month based on the constituent stocks associated with each column and then take the time series average.

Panel A. Pastor and Stambaugh (2003) Gamma

	All	Sell	Buy	Sell-Buy
	A1. Changes in Mutual Fund Holdings			
Fraction of Stocks (%)	100.0	76.3	23.7	52.5
Aggregate Absolute Change ($M)	8,473	6,849	1,623	5,225
Return (%)	6.57	7.55	3.81	3.74
t-stat	(16.02)	(14.34)	(7.69)	(5.16)
Return, Illiq(Q5)–Illiq(Q1) (%)	5.54	6.52	2.80	3.72
t-stat	(13.81)	(12.65)	(5.79)	(5.27)
	A2. Stock Trades			
Fraction of Stocks (%)	100.0	58.0	42.0	16.0
Aggregate Trade Value ($M)	459	286	174	112
Return (%)	2.66	4.09	0.91	3.18
t-stat	(6.45)	(6.52)	(1.77)	(3.83)
Return, Illiq(Q5)–Illiq(Q1) (%)	2.09	3.55	0.31	3.25
t-stat	(5.18)	(5.80)	(0.61)	(4.10)
	A3. Transaction Costs			
Execution Shortfall (%)	0.92	1.40	-0.24	1.63
t-stat	(9.01)	(10.43)	(-2.29)	(9.31)
Stitched Tickets (%)	1.90	2.97	-0.42	3.39
t-stat	(10.45)	(12.91)	(-2.54)	(11.28)

Table 7 continued.

Panel B. Effective Spread

	All	Sell	Buy	Sell-Buy
	B1. Changes in Mutual Fund Holdings			
Fraction of Stocks (%)	100.0	68.8	31.3	37.5
Aggregate Absolute Change ($M)	5,101	3,574	1,527	2,047
Return (%)	3.96	4.38	3.03	1.36
t-stat	(9.36)	(7.69)	(5.82)	(1.76)
Return, Illiq(Q5)–Illiq(Q1) (%)	3.17	3.60	2.22	1.39
t-stat	(7.60)	(6.41)	(4.33)	(1.82)
	B2. Stock Trades			
Fraction of Stocks (%)	100.0	53.4	46.6	6.7
Aggregate Trade Value ($M)	1,127	808	319	489
Return (%)	2.58	3.49	1.52	1.97
t-stat	(5.55)	(4.76)	(2.67)	(2.11)
Return, Illiq(Q5)–Illiq(Q1) (%)	1.56	2.46	0.53	1.93
t-stat	(3.42)	(3.41)	(0.95)	(2.10)
	B3. Transaction Costs			
Execution Shortfall (%)	0.58	0.82	0.10	0.72
t-stat	(5.48)	(6.08)	(0.99)	(4.18)
Stitched Tickets (%)	1.34	2.11	0.28	1.83
t-stat	(6.73)	(8.17)	(1.37)	(5.52)

Panel C. Quoted Spread

	All	Sell	Buy	Sell-Buy
	C1. Changes in Mutual Fund Holdings			
Fraction of Stocks (%)	100.0	68.7	31.3	37.4
Aggregate Absolute Change ($M)	5,601	4,007	1,594	2,413
Return (%)	3.58	4.07	2.49	1.58
t-stat	(8.71)	(7.33)	(5.04)	(2.13)
Return, Illiq(Q5)–Illiq(Q1) (%)	2.77	3.23	1.76	1.47
t-stat	(6.87)	(5.93)	(3.61)	(2.01)
	C2. Stock Trades			
Fraction of Stocks (%)	100.0	53.2	46.8	6.3
Aggregate Trade Value ($M)	517	331	186	145
Return (%)	2.55	3.45	1.46	1.99
t-stat	(5.54)	(4.77)	(2.61)	(2.15)
Return, Illiq(Q5)–Illiq(Q1) (%)	1.53	2.45	0.46	1.99
t-stat	(3.40)	(3.44)	(0.84)	(2.20)
	C3. Transaction Costs			
Execution Shortfall (%)	0.60	0.89	0.05	0.83
t-stat	(6.41)	(7.32)	(0.57)	(5.27)
Stitched Tickets (%)	1.47	2.32	0.23	2.09
t-stat	(6.69)	(8.19)	(1.22)	(6.01)

Panel D. Barardehi et al. (2021)

	All	Sell	Buy	Sell-Buy
	D1. Changes in Mutual Fund Holdings			
Fraction of Stocks (%)	100.0	75.2	24.8	50.4
Aggregate Absolute Change ($M)	6,497	5,283	1,214	4,069
Return (%)	6.21	6.92	4.20	2.72
t-stat	(16.05)	(14.06)	(8.48)	(3.90)
Return, Illiq(Q5)–Illiq(Q1) (%)	5.09	5.76	3.21	2.55
t-stat	(13.49)	(11.99)	(6.65)	(3.75)
	D2. Stock Trades			
Fraction of Stocks (%)	100.0	59.5	40.5	19.0
Aggregate Trade Value ($M)	646	399	247	152
Return (%)	3.66	5.16	1.71	3.18
t-stat	(8.79)	(8.22)	(3.35)	(3.83)
Return, Illiq(Q5)–Illiq(Q1) (%)	2.98	4.59	0.92	3.68
t-stat	(7.30)	(7.45)	(1.83)	(4.46)
	D3. Transaction Costs			
Execution Shortfall (%)	1.04	1.50	-0.06	1.56
t-stat	(8.80)	(10.23)	(-0.63)	(8.44)
Stitched Tickets (%)	2.02	3.05	-0.22	3.27
t-stat	(10.88)	(13.42)	(-1.24)	(10.54)

Table 22. Amihud Measure vs. Performance, Illiquidity Lagged Two Months

The table presents average monthly stock returns (in percentage) for quintiles sorted by the Amihud measure. The sample contains ordinary common shares (share codes 10 or 11 in CRSP) from January 1964 to December 2017. At the beginning of each month *t*, stocks are sorted into quintiles based on the Amihud measure of month *t* – 2. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Illiquidity	Performance *t*			
Quintile *t* – 2	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
Q1 (Liquid)	1.01	0.05	-0.01	0.02
	(5.14)	(0.95)	(-0.34)	(0.48)
Q2	1.09	0.05	-0.09	0.01
	(4.57)	(0.48)	(-2.08)	(0.14)
Q3	1.10	0.06	-0.18	0.01
	(4.28)	(0.41)	(-2.52)	(0.21)
Q4	1.21	0.23	-0.07	0.15
	(4.77)	(1.41)	(-0.66)	(1.64)
Q5 (Illiquid)	1.69	0.77	0.41	0.67
	(6.03)	(3.49)	(2.49)	(4.08)
Q5–Q1	0.68	0.72	0.43	0.65
	(3.30)	(3.50)	(2.46)	(3.75)

Table 23. Illiquidity vs. Performance, Quintile Sorts, 1926-1963

The table shows average monthly stock returns (in percentage) for quintiles sorted by the Amihud measure among common stocks from December 1926 to December 1963. At the beginning of each month *t*, stocks are sorted into quintiles based on the Amihud measure of month *t* – 2. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and four-factor (Carhart (1997)) regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Illiquidity	Performance *t*			
Quintile *t* – 1	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
Q1 (Liquid)	0.91	-0.14	-0.15	-0.17
	(2.63)	(-3.15)	(-3.24)	(-3.62)
Q2	1.13	0.01	-0.02	0.00
	(3.00)	(0.08)	(-0.29)	(-0.03)
Q3	1.19	-0.02	-0.08	-0.04
	(2.82)	(-0.17)	(-1.39)	(-0.66)
Q4	1.40	0.07	-0.03	0.14
	(2.86)	(0.33)	(-0.41)	(1.95)
Q5 (Illiquid)	2.07	0.64	0.46	0.74
	(3.38)	(1.67)	(2.75)	(4.51)
Q5–Q1	1.16	0.79	0.61	0.91
	(2.84)	(2.03)	(3.25)	(4.94)

Table 24. Reverse Order Double Sort: Illiquidity and Past Return vs. Future Performance

The table presents performance for stocks double sorted by the Amihud measure and past return. Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on the Amihud measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. Within each illiquidity quintile, stocks are sorted into quintiles based on the monthly return at $t-1$. We then calculate monthly equal-weighted returns for the portfolios during month t and report time-series average portfolio returns. The last column, labeled "Q5–Q1," shows the average raw return difference between high illiquidity and low illiquidity portfolios within each return quintile. Panel A presents the raw return of the quintile portfolios, Panel B presents single-factor alphas, Panel C presents Fama and French (1993) three-factor alphas, and Panel D presents Carhart (1997) four-factor alphas. The sample period is January 1964 to December 2017. All returns are expressed in percent. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Return Quintile $t-1$	Illiquidity Quintile $t-1$ Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			Panel A. Return			
Q1 (Low)	1.23	1.58	1.64	2.15	4.09	2.86
	(4.00)	(4.57)	(4.65)	(5.84)	(10.53)	(10.28)
Q2	1.30	1.37	1.22	1.19	1.34	0.04
	(5.82)	(5.55)	(4.78)	(4.73)	(5.10)	(0.21)
Q3	1.10	1.19	1.19	1.19	1.21	0.11
	(6.07)	(5.59)	(5.27)	(5.30)	(5.13)	(0.62)
Q4	0.89	1.04	0.99	1.13	1.08	0.19
	(5.01)	(5.00)	(4.54)	(5.07)	(4.61)	(1.10)
Q5 (High)	0.79	0.95	0.69	0.39	-0.33	-1.13
	(3.44)	(3.58)	(2.61)	(1.48)	(-1.24)	(-5.45)
Q5–Q1	-0.438	-0.624	-0.947	-1.753	-4.424	
	(-2.01)	(-2.66)	(-4.25)	(-7.66)	(-18.25)	
			Panel B. Single-factor Alpha			
Q1 (Low)	0.06	0.37	0.48	1.02	3.06	3.00
	(0.33)	(1.71)	(1.95)	(3.68)	(9.33)	(10.87)
Q2	0.29	0.33	0.19	0.22	0.45	0.15
	(3.20)	(2.75)	(1.33)	(1.34)	(2.18)	(0.79)
Q3	0.19	0.21	0.22	0.27	0.36	0.17
	(3.24)	(2.44)	(1.83)	(1.91)	(1.97)	(0.93)
Q4	0.01	0.08	0.04	0.21	0.23	0.22
	(0.09)	(0.93)	(0.32)	(1.53)	(1.26)	(1.26)
Q5 (High)	-0.19	-0.09	-0.33	-0.60	-1.22	-1.04
	(-1.55)	(-0.56)	(-1.98)	(-3.39)	(-5.71)	(-5.03)
Q5–Q1	-0.243	-0.457	-0.805	-1.619	-4.284	
	(-1.16)	(-1.99)	(-3.66)	(-7.16)	(-17.86)	

Table IA.3 continued

Return Quintile $t-1$	Illiquidity Quintile $t-1$ Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			Panel C. Three-factor Alpha			
Q1 (Low)	-0.05	0.17	0.20	0.69	2.67	2.72
	(-0.36)	(1.00)	(1.07)	(3.10)	(9.61)	(10.36)
Q2	0.21	0.16	-0.07	-0.08	0.12	-0.09
	(2.44)	(1.99)	(-0.81)	(-0.70)	(0.74)	(-0.52)
Q3	0.11	0.05	-0.04	-0.04	0.05	-0.07
	(2.03)	(1.04)	(-0.64)	(-0.46)	(0.32)	(-0.45)
Q4	-0.06	-0.05	-0.18	-0.08	-0.08	-0.02
	(-0.84)	(-0.93)	(-2.84)	(-0.91)	(-0.56)	(-0.14)
Q5 (High)	-0.20	-0.20	-0.55	-0.83	-1.53	-1.32
	(-1.90)	(-1.85)	(-5.18)	(-6.84)	(-9.11)	(-6.99)
Q5–Q1	-0.153	-0.372	-0.752	-1.517	-4.192	
	(-0.73)	(-1.60)	(-3.40)	(-6.71)	(-17.51)	
			Panel D. Four-factor Alpha			
Q1 (Low)	0.25	0.58	0.67	1.18	3.13	2.89
	(1.84)	(3.74)	(3.91)	(5.73)	(11.64)	(10.85)
Q2	0.31	0.31	0.11	0.12	0.33	0.01
	(3.71)	(3.97)	(1.26)	(1.16)	(2.09)	(0.08)
Q3	0.15	0.11	0.05	0.09	0.21	0.06
	(2.58)	(2.07)	(0.74)	(1.02)	(1.48)	(0.40)
Q4	-0.08	-0.05	-0.09	0.03	0.06	0.14
	(-1.19)	(-0.95)	(-1.50)	(0.36)	(0.43)	(0.93)
Q5 (High)	-0.25	-0.22	-0.46	-0.73	-1.42	-1.17
	(-2.28)	(-2.00)	(-4.33)	(-5.99)	(-8.36)	(-6.13)
Q5–Q1	-0.495	-0.804	-1.137	-1.917	-4.554	
	(-2.41)	(-3.62)	(-5.31)	(-8.79)	(-19.41)	

Table 25. Double Sort: Return and Illiquidity vs. Performance, Value-Weighted Returns

The table presents performance for stocks double sorted by past return and the Amihud measure. Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on monthly return at $t-1$. Within each return quintile, stocks are sorted into quintiles based on the Amihud measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. We then calculate monthly value-weighted returns for the portfolios during month t and report time-series average portfolio returns. The last column, labeled "Q5–Q1," shows the average raw return difference between high illiquidity and low illiquidity portfolios within each return quintile. Panel A presents the raw return of the quintile portfolios, Panel B presents Fama and French (1993) three-factor alphas, and Panel C presents Carhart (1997) four-factor alphas. The sample period is January 1964 to December 2017. All returns are expressed in percent. Robust t-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Return Quintile $t-1$	Illiquidity Quintile $t-1$					
	Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			Panel A. Return			
Q1 (Low)	0.89	1.57	1.48	1.62	2.36	1.46
	(3.36)	(4.88)	(4.64)	(5.03)	(7.24)	(5.70)
Q2	1.11	1.34	1.17	1.11	0.94	-0.17
	(5.55)	(5.86)	(5.02)	(4.85)	(4.07)	(-0.97)
Q3	0.95	1.12	1.09	1.07	0.90	-0.05
	(5.59)	(5.62)	(5.26)	(5.29)	(4.46)	(-0.32)
Q4	0.88	0.91	0.87	1.03	0.81	-0.07
	(5.18)	(4.71)	(4.33)	(5.11)	(4.03)	(-0.40)
Q5 (High)	0.77	0.70	0.48	0.33	-0.72	-1.49
	(3.80)	(2.85)	(1.96)	(1.32)	(-2.99)	(-7.58)
Q5–Q1	-0.12	-0.87	-1.00	-1.30	-3.08	
	(-0.58)	(-3.87)	(-4.89)	(-6.14)	(-13.49)	
			Panel B. Three-factor Alpha			
Q1 (Low)	-0.22	0.25	0.10	0.23	1.01	1.24
	(-1.73)	(1.60)	(0.61)	(1.26)	(4.68)	(5.44)
Q2	0.17	0.20	-0.07	-0.11	-0.22	-0.39
	(2.14)	(2.40)	(-0.80)	(-1.12)	(-1.73)	(-2.76)
Q3	0.09	0.04	-0.08	-0.09	-0.19	-0.28
	(1.84)	(0.75)	(-1.19)	(-1.05)	(-1.70)	(-2.27)
Q4	0.04	-0.13	-0.24	-0.12	-0.26	-0.30
	(0.64)	(-2.22)	(-4.11)	(-1.47)	(-2.38)	(-2.45)
Q5 (High)	-0.09	-0.39	-0.70	-0.87	-1.85	-1.76
	(-0.90)	(-3.59)	(-6.89)	(-7.76)	(-12.63)	(-10.54)
Q5–Q1	0.127	-0.638	-0.792	-1.096	-2.864	
	(0.63)	(-2.89)	(-3.93)	(-5.21)	(-12.62)	
			Panel C. Four-factor Alpha			
Q1 (Low)	-0.01	0.60	0.47	0.64	1.38	1.39
	(-0.06)	(4.17)	(3.30)	(3.88)	(6.56)	(6.02)
Q2	0.24	0.34	0.08	0.04	-0.04	-0.28
	(3.08)	(4.24)	(1.00)	(0.40)	(-0.34)	(-1.99)
Q3	0.08	0.10	0.01	0.01	-0.0	-0.16
	(1.58)	(1.74)	(0.11)	(0.07)	(-0.74)	(-1.30)
Q4	0.00	-0.13	-0.17	-0.02	-0.19	-0.19
	(0.08)	(-2.14)	(-2.92)	(-0.21)	(-1.68)	(-1.56)
Q5 (High)	-0.18	-0.39	-0.61	-0.81	-1.80	-1.62
	(-1.71)	(-3.56)	(-6.01)	(-7.15)	(-12.06)	(-9.64)
Q5–Q1	-0.172	-0.997	-1.087	-1.459	-3.184	
	(-0.87)	(-4.63)	(-5.49)	(-7.18)	(-14.22)	

Table 26. Illiquidity vs. Performance, 1990-2017

Panel A presents average monthly stock returns (in percentage) for quintiles sorted by the Amihud measure. At the beginning of each month *t*, common stocks (share codes 10 or 11 in CRSP) are sorted into quintiles based on the Amihud measure of month $t-1$. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Panel B presents performance for stocks double sorted by past return and the Amihud measure. Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on monthly return at $t-1$. Within each return quintile, stocks are sorted into quintiles based on the Amihud measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted returns for the portfolios during month *t* and report time-series average portfolio returns. The last column, labeled "Q5–Q1," shows the average raw return difference between high illiquidity and low illiquidity portfolios within each return quintile. Panel B1 presents the raw return of the quintile portfolios, Panel B2 presents single-factor alphas, Panel B3 presents Fama and French (1993) three-factor alphas, and Panel B4 presents Carhart (1997) four-factor alphas. The sample period is January 1990 to December 2017. All returns are expressed in percent. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Panel A. Univariate Relation

Illiquidity	Performance *t*			
Quintile $t-1$	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
Q1 (Liquid)	1.05	0.07	0.03	0.07
	(3.97)	(0.88)	(0.63)	(1.38)
Q2	1.14	0.03	-0.02	0.09
	(3.40)	(0.21)	(-0.37)	(1.60)
Q3	1.08	-0.02	-0.13	0.10
	(2.98)	(-0.08)	(-1.06)	(0.96)
Q4	1.10	0.14	0.02	0.30
	(3.28)	(0.62)	(0.09)	(1.96)
Q5 (Illiquid)	1.62	0.81	0.71	1.03
	(4.80)	(2.90)	(2.90)	(4.46)
Q5–Q1	0.57	0.74	0.68	0.96
	(2.18)	(2.88)	(2.76)	(4.06)

Panel B. Double Sort: Past Return and Illiquidity vs. Future Performance

Return	Illiquidity Quintile $t-1$					
Quintile $t-1$	Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			B1. Return			
Q1 (Low)	1.15	1.44	1.30	1.78	4.17	3.02
	(2.54)	(2.74)	(2.50)	(3.35)	(7.80)	(7.67)
Q2	1.31	1.34	1.08	0.94	1.08	-0.23
	(4.23)	(3.94)	(3.04)	(2.91)	(3.55)	(-0.97)
Q3	1.11	1.19	1.07	1.04	1.01	-0.10
	(4.71)	(4.20)	(3.62)	(3.78)	(4.01)	(-0.49)
Q4	0.93	1.02	1.04	1.18	1.13	0.20
	(3.90)	(3.69)	(3.53)	(4.12)	(4.17)	(0.88)
Q5 (High)	0.85	1.12	0.90	0.74	0.05	-0.80
	(2.58)	(2.87)	(2.33)	(2.03)	(0.14)	(-2.69)
Q5–Q1	-0.31	-0.32	-0.40	-1.04	-4.12	
	(-0.87)	(-0.80)	(-1.12)	(-2.80)	(-10.90)	

Table IA.5 continued

Return Quintile $t-1$	Illiquidity Quintile $t-1$					Q5–Q1
	Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	
			B2. Single-factor Alpha			
Q1 (Low)	-0.19	0.04	-0.01	0.59	3.17	3.37
	(-0.75)	(0.12)	(-0.02)	(1.37)	(6.70)	(8.83)
Q2	0.26	0.26	0.01	0.01	0.31	0.05
	(1.84)	(1.40)	(0.04)	(0.02)	(1.25)	(0.24)
Q3	0.22	0.21	0.12	0.22	0.32	0.09
	(2.80)	(1.62)	(0.70)	(1.13)	(1.57)	(0.46)
Q4	0.06	0.07	0.09	0.33	0.42	0.36
	(0.59)	(0.51)	(0.54)	(1.67)	(1.91)	(1.64)
Q5 (High)	-0.16	0.02	-0.17	-0.23	-0.76	-0.60
	(-0.81)	(0.09)	(-0.65)	(-0.87)	(-2.52)	(-2.04)
Q5–Q1	0.03	-0.02	-0.16	-0.82	-3.94	
	(0.09)	(-0.05)	(-0.47)	(-2.21)	(-10.40)	
			B3. Three-factor Alpha			
Q1 (Low)	-0.22	-0.01	-0.06	0.52	3.10	3.32
	(-0.97)	(-0.02)	(-0.18)	(1.36)	(7.05)	(8.72)
Q2	0.21	0.18	-0.12	-0.13	0.20	-0.01
	(1.66)	(1.40)	(-0.83)	(-0.74)	(0.92)	(-0.04)
Q3	0.18	0.12	-0.03	0.05	0.20	0.02
	(2.38)	(1.61)	(-0.28)	(0.34)	(1.11)	(0.12)
Q4	0.03	0.00	-0.03	0.17	0.31	0.28
	(0.26)	(0.04)	(-0.33)	(1.19)	(1.62)	(1.35)
Q5 (High)	-0.15	0.00	-0.28	-0.33	-0.86	-0.71
	(-0.89)	(-0.01)	(-1.67)	(-1.67)	(-3.30)	(-2.46)
Q5–Q1	0.06	0.00	-0.22	-0.84	-3.96	
	(0.19)	(0.01)	(-0.62)	(-2.26)	(-10.43)	
			B4. Four-factor Alpha			
Q1 (Low)	0.09	0.46	0.48	1.12	3.63	3.54
	(0.43)	(1.81)	(1.72)	(3.29)	(8.71)	(9.30)
Q2	0.29	0.33	0.08	0.10	0.44	0.15
	(2.30)	(2.65)	(0.57)	(0.60)	(2.10)	(0.71)
Q3	0.20	0.18	0.07	0.20	0.39	0.19
	(2.63)	(2.35)	(0.73)	(1.47)	(2.27)	(1.01)
Q4	0.03	0.04	0.08	0.32	0.47	0.43
	(0.34)	(0.45)	(0.83)	(2.32)	(2.50)	(2.09)
Q5 (High)	-0.11	0.06	-0.11	-0.15	-0.70	-0.59
	(-0.62)	(0.32)	(-0.69)	(-0.77)	(-2.68)	(-2.04)
Q5–Q1	-0.19	-0.41	-0.59	-1.26	-4.33	
	(-0.58)	(-1.08)	(-1.73)	(-3.54)	(-11.71)	

Table 27. Illiquidity vs. Performance, 1999-2011

Panel A presents average monthly stock returns (in percentage) for quintiles sorted by the Amihud measure. At the beginning of each month *t*, common stocks (share codes 10 or 11 in CRSP) are sorted into quintiles based on the Amihud measure of month $t-1$. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Panel B presents performance for stocks double sorted by past return and the Amihud measure. Quintile portfolios are first formed by sorting common stocks (share codes 10 or 11 in CRSP) based on monthly return at $t-1$. Within each return quintile, stocks are sorted into quintiles based on the Amihud measure at $t-1$ so that quintile 1 (5) contains stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted returns for the portfolios during month *t* and report time-series average portfolio returns. The last column, labeled "Q5–Q1," shows the average raw return difference between high illiquidity and low illiquidity portfolios within each return quintile. Panel B1 presents the raw return of the quintile portfolios, Panel B2 presents single-factor alphas, Panel B3 presents Fama and French (1993) three-factor alphas, and Panel B4 presents Carhart (1997) four-factor alphas. The sample period is January 1999 to December 2011. All returns are expressed in percent. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Panel A. Univariate Relation

Illiquidity	Performance *t*			
Quintile $t-1$	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
Q1 (Liquid)	0.71	0.34	0.18	0.18
	(1.56)	(3.01)	(2.17)	(2.30)
Q2	1.00	0.60	0.17	0.20
	(1.72)	(2.31)	(1.41)	(2.03)
Q3	1.07	0.67	0.15	0.22
	(1.67)	(1.92)	(0.64)	(1.21)
Q4	1.19	0.81	0.38	0.46
	(2.01)	(2.20)	(1.22)	(1.81)
Q5 (Illiquid)	1.38	1.04	0.71	0.81
	(2.46)	(2.42)	(1.77)	(2.29)
Q5–Q1	0.68	0.71	0.54	0.63
	(1.65)	(1.75)	(1.34)	(1.74)

Panel B. Double Sort: Past Return and Illiquidity vs. Future Performance

Return	Illiquidity Quintile $t-1$					
Quintile $t-1$	Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			B1. Return			
Q1 (Low)	0.94	1.40	1.64	1.85	3.54	2.61
	(1.15)	(1.47)	(1.71)	(1.93)	(4.12)	(4.52)
Q2	0.89	1.23	0.91	0.78	0.88	-0.01
	(1.70)	(2.05)	(1.46)	(1.41)	(1.72)	(-0.03)
Q3	0.74	0.95	0.94	0.85	0.85	0.11
	(1.88)	(1.94)	(1.87)	(1.82)	(1.99)	(0.33)
Q4	0.66	0.88	0.85	1.15	1.15	0.49
	(1.57)	(1.90)	(1.70)	(2.37)	(2.52)	(1.35)
Q5 (High)	0.54	1.09	1.30	0.80	-0.01	-0.55
	(0.92)	(1.52)	(1.88)	(1.23)	(-0.01)	(-1.20)
Q5–Q1	-0.39	-0.32	-0.34	-1.04	-3.54	
	(-0.57)	(-0.41)	(-0.48)	(-1.54)	(-5.75)	

Table IA.6 continued

Return Quintile $t-1$	Illiquidity Quintile $t-1$ Q1 (Liquid)	Q2	Q3	Q4	Q5 (Illiquid)	Q5–Q1
			B2. Single-factor Alpha			
Q1 (Low)	0.48	0.93	1.17	1.40	3.16	2.68
	(1.07)	(1.51)	(1.82)	(1.99)	(4.41)	(4.93)
Q2	0.51	0.84	0.52	0.42	0.55	0.04
	(2.35)	(2.64)	(1.45)	(1.19)	(1.43)	(0.11)
Q3	0.40	0.58	0.58	0.52	0.55	0.15
	(3.38)	(2.66)	(2.12)	(1.67)	(1.66)	(0.44)
Q4	0.31	0.53	0.49	0.81	0.84	0.53
	(1.81)	(2.50)	(1.85)	(2.58)	(2.41)	(1.45)
Q5 (High)	0.17	0.69	0.90	0.42	-0.35	-0.52
	(0.45)	(1.42)	(2.03)	(0.97)	(-0.73)	(-1.15)
Q5–Q1	-0.31	-0.24	-0.27	-0.98	-3.51	
	(-0.48)	(-0.32)	(-0.40)	(-1.49)	(-5.74)	
			B3. Three-factor Alpha			
Q1 (Low)	0.19	0.44	0.77	0.99	2.78	2.59
	(0.46)	(0.81)	(1.31)	(1.49)	(4.06)	(4.70)
Q2	0.37	0.45	0.02	0.03	0.22	-0.15
	(1.77)	(1.77)	(0.06)	(0.10)	(0.61)	(-0.45)
Q3	0.29	0.22	0.10	0.09	0.27	-0.02
	(2.68)	(1.54)	(0.59)	(0.37)	(0.87)	(-0.07)
Q4	0.17	0.18	0.05	0.38	0.52	0.35
	(1.04)	(1.37)	(0.31)	(1.51)	(1.63)	(0.98)
Q5 (High)	-0.11	0.12	0.29	-0.09	-0.78	-0.66
	(-0.34)	(0.36)	(0.95)	(-0.27)	(-1.82)	(-1.45)
Q5–Q1	-0.31	-0.32	-0.48	-1.08	-3.56	
	(-0.46)	(-0.42)	(-0.71)	(-1.60)	(-5.72)	
			B4. Four-factor Alpha			
Q1 (Low)	0.27	0.58	0.93	1.17	2.95	2.68
	(0.71)	(1.23)	(1.89)	(2.10)	(4.99)	(5.16)
Q2	0.39	0.49	0.08	0.10	0.29	-0.10
	(1.86)	(2.07)	(0.33)	(0.36)	(0.88)	(-0.30)
Q3	0.30	0.23	0.13	0.14	0.33	0.03
	(2.73)	(1.71)	(0.82)	(0.61)	(1.14)	(0.10)
Q4	0.17	0.19	0.09	0.43	0.57	0.40
	(1.05)	(1.45)	(0.55)	(1.83)	(1.86)	(1.14)
Q5 (High)	-0.09	0.14	0.34	-0.04	-0.74	-0.65
	(-0.28)	(0.41)	(1.19)	(-0.13)	(-1.75)	(-1.41)
Q5–Q1	-0.36	-0.44	-0.59	-1.21	-3.69	
	(-0.55)	(-0.60)	(-0.92)	(-1.94)	(-6.58)	

Table 28. Illiquidity Premium Based on Alternative Liquidity Measures

The table presents average monthly stock returns (in percentage) for quintiles sorted by the effective spread illiquidity measure (Panel A) or by the quoted spread illiquidity measure (Panel B). The sample contains ordinary common shares (share codes 10 or 11 in CRSP). At the beginning of each month *t*, stocks are sorted into quintiles based on the illiquidity measure of month *t* – 1. Quintile 1 (5) is the portfolio of stocks with the lowest (highest) illiquidity. We then calculate monthly equal-weighted quintile returns and report the time-series average. The table also reports alphas from CAPM, Fama-French (1993) three-factor, and Carhart (1997) four-factor regressions. The row "Q5–Q1" refers to the difference in monthly returns between quintile 5 and quintile 1. Robust *t*-statistics based on Newey-West (1987) corrected standard errors with twelve lags are reported in parentheses.

Illiquidity	Performance *t*			
Quintile *t* – 1	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
	Panel A. Pastor and Stambaugh (2003) Gamma			
Q1 (Liquid)	1.08	0.11	0.05	0.06
	(5.43)	(2.25)	(1.53)	(2.06)
Q2	1.15	0.13	-0.02	0.07
	(4.99)	(1.36)	(-0.62)	(1.88)
Q3	1.15	0.12	-0.12	0.05
	(4.63)	(0.92)	(-1.83)	(0.87)
Q4	1.12	0.13	-0.15	0.08
	(4.38)	(0.81)	(-1.59)	(0.85)
Q5 (Illiquid)	1.56	0.63	0.30	0.61
	(5.45)	(2.80)	(1.72)	(3.67)
Q5–Q1	0.48	0.51	0.25	0.54
	(2.36)	(2.50)	(1.40)	(3.12)
	Panel B. Effective Spread			
Q1 (Liquid)	0.93	0.14	0.15	0.16
	(2.25)	(1.81)	(2.41)	(2.77)
Q2	0.84	-0.10	-0.05	-0.03
	(1.61)	(-0.55)	(-0.75)	(-0.50)
Q3	0.92	-0.10	-0.04	0.02
	(1.54)	(-0.42)	(-0.27)	(0.23)
Q4	0.79	-0.11	-0.08	-0.04
	(1.49)	(-0.46)	(-0.38)	(-0.18)
Q5 (Illiquid)	0.85	0.16	0.19	0.25
	(1.78)	(0.48)	(0.58)	(0.80)
Q5–Q1	-0.08	0.02	0.04	0.09
	(-0.25)	(0.07)	(0.13)	(0.29)
	Panel C. Quoted Spread			
Q1 (Liquid)	0.93	0.16	0.16	0.17
	(2.31)	(2.09)	(2.75)	(2.89)
Q2	0.85	-0.09	-0.04	-0.02
	(1.63)	(-0.49)	(-0.58)	(-0.31)
Q3	0.92	-0.11	-0.04	0.03
	(1.53)	(-0.42)	(-0.27)	(0.25)
Q4	0.75	-0.15	-0.12	-0.07
	(1.41)	(-0.63)	(-0.58)	(-0.39)
Q5 (Illiquid)	0.88	0.18	0.21	0.27
	(1.81)	(0.53)	(0.62)	(0.84)
Q5–Q1	-0.05	0.03	0.05	0.10
	(-0.16)	(0.08)	(0.14)	(0.32)

Table IA.7 continued

Illiquidity Quintile $t-1$	Performance t			
	Return	Single-factor Alpha	Three-factor Alpha	Four-factor Alpha
		Panel D. Barardehi et al. (2021)		
Q1 (Liquid)	1.00	0.05	0.01	0.04
	(3.69)	(0.66)	(0.17)	(0.86)
Q2	1.14	0.07	-0.02	0.09
	(3.33)	(0.41)	(-0.25)	(1.59)
Q3	1.13	0.06	-0.08	0.11
	(3.12)	(0.31)	(-0.69)	(1.14)
Q4	1.12	0.166	0.04	0.30
	(3.28)	(0.74)	(0.22)	(2.03)
Q5 (Illiquid)	1.50	0.61	0.56	0.91
	(3.92)	(2.01)	(2.04)	(3.60)
Q5–Q1	0.49	0.56	0.55	0.86
	(1.74)	(1.98)	(2.00)	(3.34)

LIST OF REFERENCES

Admati, Anat R., and Paul Pfleiderer, 1988, A Theory of Intraday Patterns: Volume and Price Variability, *Review of Financial Studies* 1, 3–40.

Admati, Anat R., and Paul Pfleiderer, 1991, Sunshine Trading and Financial Market Equilibrium, *Review of Financial Studies* 4, 443–481.

Agarwal, Vikas, Paul Hanouna, Rabih Moussawi, and Christof Stahel, 2019, Do ETFs Increase the Commonality in Liquidity of Underlying Stocks? *Working Paper*, Georgia State University.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov and Haim Mendelson, 1986, "Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics* 17, 223–249.

Anand, Amber, Paul Irvine, Andy Puckett, and Kumar Venkataraman, 2012, "Performance of Institutional Trading Desks: An Analysis of Persistence in Trading Costs," *Review of Financial Studies* 25, 557–598.

Antoniewicz, Rochelle, and Heinrichs Jane, 2015 Understanding Exchange-Traded Funds: How ETFs Work. *Working Paper*, < https://www.ici.org/pdf/per20-05.pdf>.

Appel, Ian R, Todd A Gormley, and Donald B Keim, 2016, Passive investors, not passive owners, Journal of Financial Economics 121, 111–141.

Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, "Liquidity and Autocorrelations in Individual Stock Returns," *Journal of Finance* 61, 2365–2394.

Banz, Rolf, 1981. "The Relationship between Return and Market Value of Common Stocks," *Journal of Financial Economics* 9, 3–18.

Barardehi, Yashar, Dan Bernhardt, Thomas Ruchti, and Marc Weidenmier, 2021, "The Night and Day of Amihud's (2002) Liquidity Measure," *Review of Asset Pricing Studies*, forthcoming.

Barberis, Nicholas, Andrei Shleifer, and Jeffrey Wurgler, 2005, Comovement, *Journal of Financial Economics* 75, 283–317.

Beatty, Randolph P, and Jay R Ritter, 1986, Investment banking, reputation, and the underpricing of initial public offerings, *Journal of Financial Economics* 15, 213–232.

Ben-David, Itzhak, Francesco Franzoni, and Rabih Moussawi, 2018, Do ETFs increase volatility?, *Journal of Finance* 73, 2471–2535.

Beneish, Messod D, and Robert E Whaley, 1996, An anatomy of the “S&P game”: The effects of changing the rules, *Journal of Finance* 51, 1909–1930.

Benveniste, Lawrence M, and Paul A Spindt, 1989, How investment bankers determine the offer price and allocation of new issues, *Journal of financial Economics* 24, 343–361.

Ben-Rephael, Azi, Ohad Kadan, and Avi Wohl, 2015, “The Diminishing Liquidity Premium,” *Journal of Financial and Quantitative Analysis* 50, 197–229.

Bradley, Daniel J, and Bradford D Jordan, 2002, Partial adjustment to public information and ipo underpricing, *Journal of Financial and Quantitative Analysis* 37, 595–616.

Brennan, Michael, Sahn-Wook Huh, and Avanidhar Subrahmanyam, 2013, “An Analysis of the Amihud Illiquidity Premium,” *Review of Asset Pricing Studies* 3, 133–176.

Bogousslavsky, Vincent, and Dmitriy Muravyev. Should We Use Closing Prices? Institutional Price Pressure at the Close, *Working Paper*, Boston College.

Box, Travis, Ryan Davis, Richard Evans, and Andrew Lynch, 2020, Intraday Arbitrage Between ETFs and Their Underlying Portfolios, *Journal of Financial Economics* forthcoming.

Breen, W.J., Hodrick, L.S. and Korajczyk, R.A., 2002. Predicting equity liquidity. *Management Science*, 48(4), pp.470-483.

Busse, Jeffrey, Tarun Chordia, Lei Jiang, and Yuehua Tang, 2020, “Transaction Costs, Portfolio Characteristics, and Mutual Fund Performance,” *Management Science*, forthcoming.

Carhart, Mark, 1997, “On Persistence in Mutual Fund Performance,” *Journal of Finance* 52, 57–82.

Carter, Richard, and Steven Manaster, 1990, Initial public offerings and underwriter reputation, the *Journal of Finance* 45, 1045–1067.

Chang, Yen-Cheng, Harrison Hong, and Inessa Liskovich, 2014, Regression discontinuity and the price effects of stock market indexing, The *Review of Financial Studies* 28, 212–246.

Chen, Honghui, Gregory Noronha, and Vijay Singal, 2004, The price response to s& p 500 index additions and deletions: Evidence of asymmetry and a new explanation, The *Journal of Finance* 59, 1901–1930.

Chen, Honghui, Vijay Singal, and Robert F Whitelaw, 2016, Comovement revisited, *Journal of Financial Economics* 121, 624–644.

Chen, Hsiu-Lang, Narasimhan Jegadeesh, and Russ Wermers, 2000, “The Value of Active Mutual Fund Management,” *Journal of Financial and Quantitative Analysis* 35, 343–368.

Chen, Si, Allaudeen Hameed, Avanidhar Subrahmanyam, and Sheridan Titman, 2017, “Short-Term Reversals: The Effects of Past Returns and Institutional Exits,” *Journal of Financial and Quantitative Analysis* 52, 143–173.

Chernenko, Sergey, Josh Lerner, and Yao Zeng, 2017, Mutual funds as venture capitalists? evidence from unicorns, *Working Paper*.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, “Commonality in Liquidity,” *Journal of Financial Economics* 56, 3–28.

Coval, Joshua and Erik Stafford, 2007, “Asset Fire Sales (and Purchases) in Equity Markets,” *Journal of Financial Economics* 86, 479–512.

Coles, Jeffrey L., Davidson Heath, and Matthew Ringgenberg, 2017, On Index Investing, *Working paper,* University of Utah.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Cushing, David, and Ananth Madhavan, 2000, Stock returns and trading at the close, *Journal of Financial Markets* 3, 45–67.

Da, Zhi, and Sophie Shive, 2018, Exchange traded funds and asset return correlations, *European Financial Management* 24, 136–168.

Denis, Diane K, John J McConnell, Alexei V Ovtchinnikov, and Yun Yu, 2003, S&p 500 index additions and earnings expectations, *The Journal of Finance* 58, 1821–1840.

Dhillon, Upinder, and Herb Johnson, 1991, Changes in the standard and poor’s 500 list, *Journal of Business* pp. 75–85.

Drienko, Jozef, Tom Smith, and Anna von Reibnitz, 2019, “A Review of the Return-Illiquidity Relationship,” *Critical Finance Review* 8, 127–171.

Duffie, Darrell, 2010, Presidential address: Asset price dynamics with slow-moving capital, *Journal of Finance* 65, 1237–1267.

Easley, David and Maureen O’Hara, 1987, Price, trade size, and information in securities markets, *Journal of Financial Economics 19*, 69-90.

Elliott, William B, and Richard S Warr, 2003, Price pressure on the nyse and nasdaq: Evidence from s&p 500 index changes, *Financial Management* pp. 85–99.

Elton, Edwin J, Martin J Gruber, and Jeffrey A Busse, 2004, Are investors rational? choices among index funds, *The Journal of Finance* 59, 261–288.

Fama, Eugene and Kenneth French, 1992, “The Cross-section of Expected Stock Returns,” *Journal of Finance* 47, 427–465.

Fama, Eugene and Kenneth French, 1993, “Common Risk Factors in the Returns on Stocks and Bonds,” *Journal of Financial Economics* 33, 3–56.

Frazzini, Andrea, Ronen Israel, and Tobias Moskowitz, 2015, “Trading Costs of Asset Pricing Anomalies,” Working Paper, AQR Capital Management.

Frazzini, Andrea and Owen Lamont, 2008, “Dumb Money: Mutual Fund Flows and the Cross-Section of Stock Returns,” *Journal of Financial Economics* 88, 299–322.

Gao, Lei, Yufeng Han, Sophia Zhengzi Li, and Guofu Zhou, 2018, Market intraday momentum, *Journal of Financial Economics* 129, 394–414.

Gao, Xiaohui and Jay Ritter, 2010, “The Marketing of Seasoned Equity Offerings,” *Journal of Financial Economics* 97, 33–52.

Glosten, Larry R., and Larry E. Harris, 1988, Estimating the components of the bid/ask spread. *Journal of Financial Economics* 21, 123–142.

Glosten, Lawrence R, Suresh Nallareddy, and Yuan Zou, 2016, Etf activity and informational efficiency of underlying securities, *Working Paper*.

Goyenko, Ruslan, Craig Holden, and Charles Trzcinka, 2009, “Do Liquidity Measures Measure Liquidity?” *Journal of Financial Economics* 92, 153–181.

Greenwood, Robin, 2007, Excess comovement of stock returns: Evidence from cross-sectional variation in nikkei 225 weights, *The Review of Financial Studies* 21, 1153–1186.

Grossman, Sanford J., and Joseph E. Stiglitz, 1980, On the Impossibility of Informationally Efficient Markets. *The American Economic Review* 70, 393–408.

Harris, Lawrence, and Eitan Gurel, 1986, Price and volume effects associated with changes in the S&P 500 list: New evidence for the existence of price pressures, *the Journal of Finance* 41, 815– 829.

Harris, Larry and Andrea Amato, 2019, "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects: A Replication," *Critical Finance Review* 8, 173–202.

Harvey, Campbell, Yan Liu, and Heqing Zhu, 2016, "…and the Cross-Section of Expected Returns," *Review of Financial Studies* 29, 5–68.

Hasbrouck, J., 1991. Measuring the information content of stock trades. *Journal of Finance,* 46(1).

Ho, Thomas and Hans Stoll, 1981, Optimal dealer pricing under transactions and return uncertainty, *Journal of Financial Economics* 9, 47-73.

Hoberg, Gerard, 2007, The underwriter persistence phenomenon, *The Journal of Finance* 62, 1169– 1206.

Israeli, Doron, Charles M. C. Lee, and Suhas A. Sridharan, 2017, Is there a dark side to exchange traded funds? An information perspective, *Review of Accounting Studies* 22, 1048–1083.

Jegadeesh, Narasimhan, 1990, "Evidence of Predictable Behavior of Security Returns," *Journal of Finance* 45, 881–898.

Jegadeesh, Narasimhan and Sheridan Titman, 1993, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* 48, 65–92.

Kacperczyk, Marcin, Clemens Sialm, and Lu Zheng, 2008, "Unobserved Actions of Mutual Funds," *Review of Financial Studies* 21, 2379–2416.

Kasch, Maria, and Asani Sarkar, 2013, Is there an S&P 500 index effect?, *Working Paper*.

Kashyap, Anil K, Natalia Kovrijnykh, Jian Li, and Anna Pavlova, 2019, The benchmark inclusion subsidy, *Working Paper*.

Keim, Donald and Ananth Madhavan, 1997, "Transaction Costs and Investment Style: An Inter-exchange Analysis of Institutional Equity Trades," *Journal of Financial Economics* 46, 265–292.

Korajczk, Robert and Ronnie Sadka, 2004, "Are Momentum Profits Robust to Trading Costs?" *Journal of Finance* 59, 1039–1082.

Kwon, Sungjoung, Michelle Lowry, and Yiming Qian, forthcoming, Mutual fund investments in private firms, *Journal of Financial Economics*.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1335.

Lehmann, Bruce, 1990, “Fads, Martingales and Market Efficiency,” *Quarterly Journal of Economics* 105, 1–28.

Lettau, Martin, and Ananth Madhavan. 2018. Exchange-Traded Funds 101 for Economists.*Journal of Economic Perspectives*, 32 (1): 135-54.

Lesmond, David, Michael Schill, and Chunsheng Zhou, 2004, “The Illusory Nature of Momentum Profits,” *Journal of Financial Economics* 71, 349–380.

Liu, Xiaoding, and Jay R Ritter, 2011, Local underwriter oligopolies and ipo underpricing, *Journal of Financial Economics* 102, 579–601.

Lou, Dong, 2012, “A Flow-based Explanation for Return Predictability,” *Review of Financial Studies* 25, 3457–3489.

Lou, Xiaoxia and Tao Shu, 2017, “Price Impact or Trading Volume? Why is the Amihud (2002) Measure Priced?” *Review of Financial Studies* 30, 4481–4520.

Loughran, Tim, and Jay Ritter, 2004, Why has ipo underpricing changed over time?, *Financial management* pp. 5–37.

Lowry, Michelle, 2003, Why does ipo volume fluctuate so much?, *Journal of Financial Economics*,67, 3–40.

Lowry, Michelle, 2004, Is the ipo pricing process efficient?, *Journal of Financial Economics* 71, 3–26.

Lowry, Michelle, Micah S Officer, and G William Schwert, 2010, The variability of ipo initial returns, *The Journal of Finance* 65, 425–465.

Lowry, Michelle, and G William Schwert, 2002, Ipo market cycles: Bubbles or sequential learning?,*The Journal of Finance* 57, 1171–1200.

Lynch, Anthony W, and Richard R Mendenhall, 1997, New evidence on stock price effects associated with changes in the s&p 500 index, The *Journal of Business* 70, 351–383.

Madhavan, Ananth N, and Kewei Ming, 2003, The hidden costs of index rebalancing, The *Journal of Investing* 12, 29–35.

Mayhew, Stewart, Tim McCormick, and Chester S. Spatt, 2009, The Information Content of Market-on-Close Imbalances, the Specialist and NYSE Equity Prices, *Working paper,* NBER.

Nagel, Stefan, 2012, Evaporating Liquidity, *Review of Financial Studies* 25, 2005–2039.

McLean, R David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *The Journal of Finance* 71, 5–32.

Merton, Robert C, 1987, A simple model of capital market equilibrium with incomplete information, *The journal of finance* 42, 483–510.

Newey, Whitney and Kenneth West, 1987, "A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix," *Econometrica* 55, 703–708.

Pastor, Lubos and Robert Stambaugh, 2003, "Liquidity Risk and Expected Stock Returns," *Journal of Political Economy* 111, 642–685.

Pastor, Lubos and Pietro Veronesi, 2005, Rational ipo waves, *The Journal of Finance* 60, 1713–1757.

Patel, Nimesh, and Ivo Welch, 2017, Extended stock returns in response to s&p 500 index changes, *The Review of Asset Pricing Studies*.

Patton, Andrew and Brian Weller, 2020, "What You See Is Not What You Get: The Costs of Trading Market Anomalies," *Journal of Financial Economics* 137, 515–549.

Petajisto, Antti, 2011, The index premium and its hidden cost for index funds, *Journal of Empirical Finance* 18, 271–288.

Petersen, Mitchell A., 2009, Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22, 435–480.

Puckett, Andy and Xuemin Yan, 2011, "The Interim Trading Skills of Institutional Investors," *Journal of Finance* 66, 601–633.

Ritter, Jay R, 1984, The" hot issue" market of 1980, *Journal of Business* pp. 215–240.

Rock, Kevin, 1986, Why new issues are underpriced, *Journal of Financial Economics* 15, 187–212.

Schmidt, Cornelius, and Ru¨diger Fahlenbrach, 2017, Do exogenous changes in passive institutional ownership affect corporate governance and firm value?, *Journal of Financial Economics* 124, 285–306.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down?, *The Journal of Finance* 41, 579– 590.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *The Journal of Business* 75, 583–608.

Vayanos, Dimitri, 1998, "Transaction Costs and Asset Prices: A Dynamic Equilibrium Model," *Review of Financial Studies* 11, 1–58.