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Quoting Activity and the Cost of Capital

Ioanid Rosu
HEC Paris
rosu@hec.fr (corresponding author)

Elvira Sojli
University of New South Wales
e.sojli@unsw.edu.au

Wing Wah Tham
University of New South Wales
w.tham@unsw.edu.au

Abstract

We study the quoting activity of market makers in relation to trading, liquidity, and expected returns. Empirically, we find larger quote-to-trade (QT) ratios in small, illiquid, or neglected firms, yet large QT ratios are associated with low expected returns. The last result is driven by quotes, not by trades. We propose a model of quoting activity consistent with these facts. In equilibrium, market makers monitor the market faster (and thus increase the QT ratio) in neglected, difficult-to-understand stocks. They also monitor faster when their clients are more precisely informed, which reduces mispricing and lowers expected returns.

I. Introduction

Information is related to a firm's cost of capital, which is important for firm shareholders and market participants alike.[1] In financial markets, information is incorporated into prices by market makers, who provide liquidity via quotes

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[1]See Diamond and Verrecchia (1991), Easley and O'Hara (2004), and Amihud, Mendelson, and Pedersen (2005) and references therein.

(or limit orders), and market takers, who demand liquidity via marketable orders and generate trades. A natural approach, then, is to study the relation between information and the cost of capital through the lens of quoting and trading. Quoting activity, in particular, has attracted the attention of exchanges and regulators because of its rapid increase in recent years.[2]

Quoting activity, however, has played a limited role in the academic literature on price discovery. The reason is that in many market-structure models, such as that of Glosten and Milgrom (1985), the market makers mechanically set their quotes at the expected asset value given the information contained in trades. In this setup, there is no expected price appreciation, and hence the expected return (cost of capital) is 0. Moreover, suppose we define the quote-to-trade (QT) ratio as the number of quote updates divided by the number of trades. Then, as market makers set their bid and ask quotes passively in response to trades, the QT ratio is always equal to 2 (or a higher constant, if one adds exogenous public news to the model). In contrast, we show empirically that the QT ratio exhibits various patterns across stocks, and we summarize these patterns as a list of new empirical stylized facts.

Our first stylized fact (SF1) is that the QT ratio is larger in stocks that are neglected or difficult to understand (with low analyst coverage, institutional ownership, trading volume, or volatility). To illustrate this result, Figure 1 shows the average number of analysts following a stock and the average trading volume for 10 portfolios sorted by the QT ratio. Firms with lower analyst coverage or lower trading volume have larger QT ratios than firms with higher analyst coverage or higher trading volume.

The second stylized empirical fact (SF2) is that the QT ratio has increased significantly over time, especially after the emergence of algorithmic and high-frequency trading (HFT) in 2003. This fact is documented by Hendershott, Jones, and Menkveld (2011) for their proxy of algorithmic trading, the message-to-trade ratio, but we show that the same pattern works for our QT ratio measure that uses quote updates at the best bid and ask.

The third stylized empirical fact (SF3) is that stocks with higher QT ratios tend to have lower expected returns (cost of capital). We regard this as our main result, and we call it the *QT effect.* This result is surprising because stocks with higher QT ratios are usually smaller and more illiquid (SF1), and thus one might expect them to have a higher cost of capital. Figure 2 illustrates the QT effect: Stocks with large QT ratios have low average returns, whether computed in excess of the risk-free rate or after risk adjusting with the Fama and French (1993) factors. Further empirical analysis using Fama–MacBeth regressions confirms the QT effect and verifies that it holds in different subsamples. The fourth stylized empirical fact (SF4) is that the QT effect appears to be driven by quotes and not by trades.

[2]Many exchanges have implemented limits on quoting activity. The London Stock Exchange was the first to introduce, in 2005, an "order management surcharge" based on the number of orders per trades submitted. Several exchanges followed: Euronext in 2007 and DirectEdge, Oslo Stock Exchange, Deutsche Börse, and Borsa Italiana in 2012. In 2014, the Markets in Financial Instruments Directive (MIFID-II/R) required trading venues to establish a maximum unexecuted order-to-transaction ratio as one of its controls to prevent disorderly trading conditions (see http://ec.europa.eu/finance/securities/docs/isd/mifid/rts/160518-rts-9_en.pdf).

FIGURE 1

Volume and Analyst Coverage for 10 QT Ratio Portfolios

Figure 1 shows the average U.S. dollar trading volume and the average number of analysts following a stock for 10 portfolios sorted on the quote-to-trade (QT) ratio. Portfolio 1 has the smallest QT ratio, and portfolio 10 has the largest QT ratio.

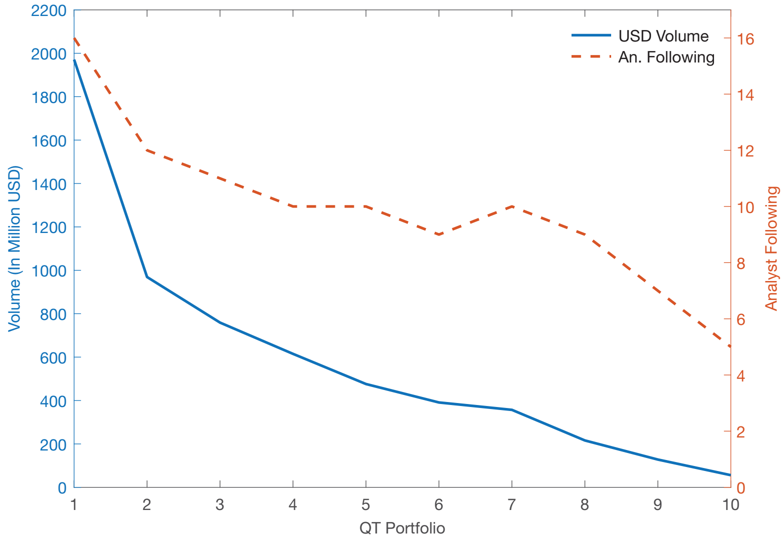
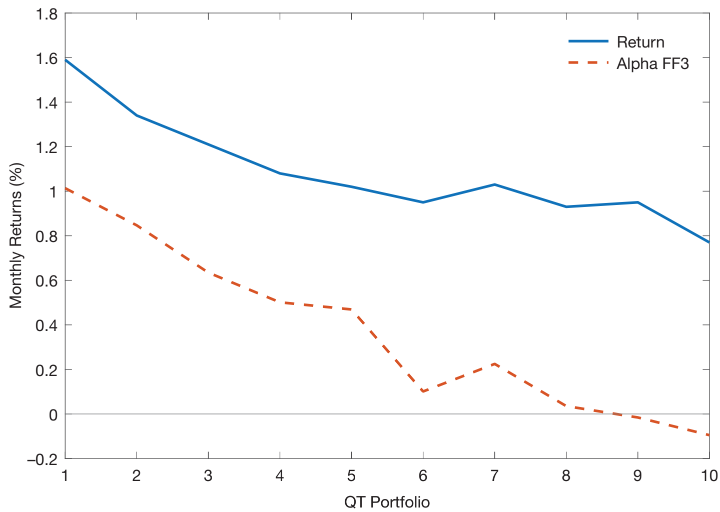


FIGURE 2

Excess Return and Alpha for 10 QT Ratio Portfolios

Figure 2 shows the average return in excess of the 1-month T-bill rate ("Return") and the alpha with respect to the Fama–French 3-factor model ("Alpha FF3") for 10 portfolios sorted on the quote-to-trade (QT) ratio. Portfolio 1 has the smallest QT ratio, and portfolio 10 has the largest QT ratio. Returns are computed monthly and presented in percentages.



To interpret our empirical findings, we construct a model that focuses on the quoting activity of market makers and its relation to the cost of capital. Our model extends the monopolistic dealer models of Ho and Stoll (1981) and Hendershott and Menkveld (2014), with two changes: First, the dealer learns about the value of the risky asset via costly monitoring (which generates quote changes). Second, the order flow is driven by risk-averse investors (that demand a positive risk premium). The dealer ("she") sets ask and bid quotes to maximize the expected profit, subject to a quadratic penalty in her inventory. She monitors the market by getting signals about the fundamental value according to a Poisson process with a frequency called the *monitoring rate*. There is one round of trading, after which the asset liquidates at a random fundamental value. Trading occurs at the first arrival of a Poisson process with a frequency normalized to 1.[3] Because the dealer optimally changes her quotes every time she receives a signal, her monitoring frequency is the same as her quoting frequency, or the *quote rate*.

In equilibrium, the dealer's quote rate is decreasing in the monitoring precision. Indeed, a small precision of the signals obtained from monitoring makes the dealer monitor more often (and increase her quote rate) in order not to stay far away from the fundamental value and incur a large expected inventory penalty. This is consistent with our SF1: The QT ratio (which is an empirical proxy for the quote rate) is higher in neglected, difficult-to-understand stocks, in which monitoring is expected to produce imprecise signals.

The dealer's quote rate is increasing in the monitoring cost. Indeed, when this cost is small, the dealer can afford to monitor more often in order to maintain the same precision. There is evidence that monitoring costs have decreased dramatically in recent times (see Hendershott et al. (2011)). This is consistent with our SF2: QT ratios have increased significantly over time, especially after the emergence of algorithmic trading and HFT.

We define the cost of capital in the model simply as the price discount, which is the difference between the dealer's value forecast and her midquote price (the midpoint between the bid and ask). A key determinant of the equilibrium price discount is the investor elasticity, which measures how aggressively investors trade in response to the dealer's pricing error. Consider an increase in investor elasticity, which happens if investors have more precise private signals or if they are less risk averse. Then, first, the dealer must monitor the market more often (hence, increase the quote rate) to reduce the pricing error because large errors would make aggressive investors cause large dealer inventories. Second, the dealer must reduce the pricing discount (hence, reduce the cost of capital) by keeping the midquote closer to her forecast. Intuitively, this reduction occurs because more informed or less risk-averse investors need a smaller compensation in the form of a smaller price discount. These facts together imply an inverse relation between the QT ratio and the cost of capital, which is consistent with our SF3.

The model generates two additional empirical predictions, which are borne out in the data. Our first prediction is that the number of market makers in a stock has an inverse relation to the stock's QT ratio. This is surprising because one might think

[3]Our results are robust if we extend our baseline model to multiple dealers (see Section 4 in the Supplementary Material) or to multiple trading rounds (see Section 5 in the Supplementary Material).

that a larger number of market makers generates more quoting activity. However, in our model, we interpret a larger number of market makers as a smaller inventory aversion for the representative dealer, and a less inventory-averse dealer can afford to monitor the stock less often and set a lower quote rate. An extension of the model to multiple dealers provides additional intuition for our first prediction: Because dealer quotes are public information, each dealer's monitoring exerts a positive externality on the others and thus leads to underinvestment in monitoring in equilibrium.[4]

Our second additional prediction is that the number of market makers in a stock has no relation to the stock's cost of capital. This prediction depends on the dealer being in the *neutral state*, meaning that her initial inventory is such that there is a 0 expected imbalance between the traders' buy and sell quantities.[5] Intuitively, in the neutral state, the price that balances the incoming order flow is affected only by the properties of the order flow and not by the characteristics of the dealer, including her inventory aversion (or the number of dealers if we consider the case of multiple dealers).

We also examine several alternative explanations for the QT effect. In particular, we study the role of frictions (e.g., tick size and impediments to arbitrage), institutional investors and governance, return reversals, and market-structure events (e.g., Regulation National Market System (Reg NMS)). Although our analysis supports some of these alternative explanations, they explain only part of the QT effect. Overall, our model provides a consistent explanation for several stylized empirical facts (SF1–SF4 and two additional predictions) that describe the market makers' quoting behavior and its relation with the cost of capital. Although alternative explanations for each individual stylized fact may exist, we note that our model provides a coherent explanation for all of these findings, based on the production of public information by market makers.

Related Literature

This article contributes to the literature on market making.[6] Our work is closest to that of Hendershott and Menkveld (2014). In their setup, the order flow is exogenously specified, and the equilibrium QT ratio is constant and equal to 2. Another related article is that by Easley and O'Hara (2004), which analyzes the relation between information and the cost of capital. One of their main findings is that more public information leads to a lower cost of capital.[7] In their rational-expectations equilibrium model, however, there are no quotes, and thus our results cannot be accommodated in their article. A related article is that by Foucault, Röell, and Sandas (2003), which, in its analysis of NASDAQ professional day traders (the

[4]In Section 4 in the Supplementary Material, we extend the model to N dealers and show directly that the aggregate quote rate is decreasing in N (see Corollary IA.4).

[5]In Section 5 in the Supplementary Material, we extend the model to multiple trading rounds and show that the neutral state is the long-term average state, regardless of the initial state.

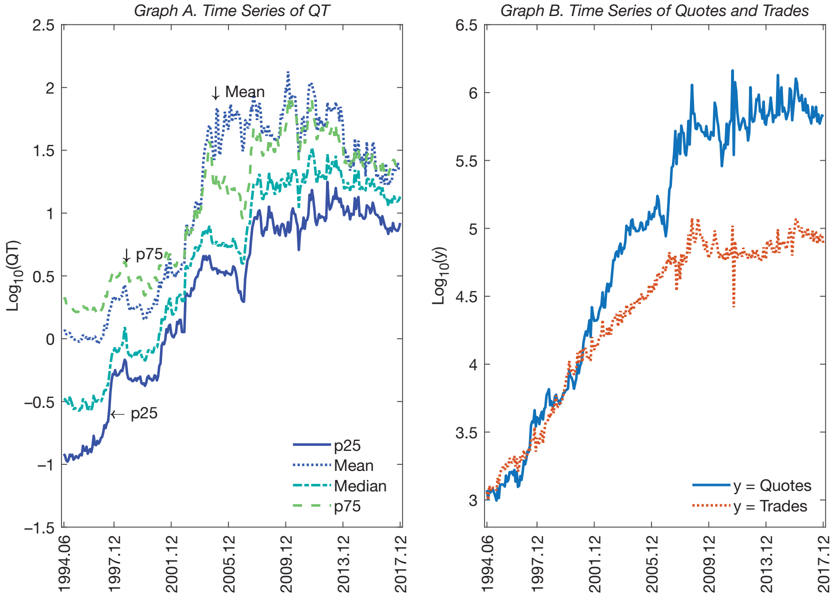
[6]See O'Hara (1995) and Hendershott and Menkveld (2014) and references therein.

[7]Easley and O'Hara (2004) show that the cost of capital is decreasing in the fraction of the public signals (which in their notation is equal to $1-\alpha$) and in the total number of signals (public or private). The intuition is that in both cases, the uninformed investors can learn better from prices and therefore view the stock as less risky and demand a lower cost of capital.

FIGURE 3

Time-Series Evolution of the QT Ratio

Figure 3 shows the base-10 logarithm of the time series of quotes, trades, and the quote-to-trade (QT) ratio $\mathrm{QT}_{i,t} = (N(\mathrm{QUOTES})_{i,t}) / (N(\mathrm{TRADES})_{i,t})$. Graph A shows the monthly time series of the cross-sectional mean, median, 25th percentile, and 75th percentile of the QT variable. Graph B shows the monthly average of the number of quote updates and the number of trades.



"Small Order Execution System (SOES) bandits"), shares a finding similar to ours: News monitoring by one dealer generates a positive externality on the other dealers. In their model, there is also a negative externality because the bandits may discover that some dealer quotes are stale after one dealer updates her quotes.

Our article has implications for the burgeoning literature on HFT.[8] The QT ratio is often connected to HFT by regulators, practitioners, and academics.[9] The recent dramatic increase in the QT ratio apparent in Figure 3 has been widely attributed to the emergence of algorithmic trading and HFT (see, e.g., Hendershott et al. (2011)). In our theoretical framework, this is consistent with a sharp decrease in dealer monitoring costs. Our main focus, however, is on the relation between the QT ratio and the cost of capital. Because the QT ratio is frequently used as a proxy for HFT, one may be tempted to attribute the QT effect to HFT activity. Hendershott et al. (2011) find that algorithmic trading has a positive effect on stock liquidity.

[8]See, for example, Menkveld (2016) and references therein.

[9]In practice, the QT ratio is typically defined with the numerator including not just the updates at the best quotes but all orders or messages. Exchanges such as NASDAQ classify HFT based on the QT ratio (see Brogaard, Hendershott, and Riordan (2014)). Among academics, the QT ratio is associated with the level of algorithmic trading (see Hendershott et al. (2011); Boehmer, Fong, and Wu (2018)), high-frequency trading (see, e.g., Conrad, Wahal, and Xiang (2015); Brogaard, Hendershott, and Riordan (2017)), and arbitrage activity (see Foucault, Kozhan, and Tham (2016)).

Therefore, it is plausible that stocks with higher HFT activity (and therefore higher QT ratios) are more liquid and thus have a lower cost of capital. This argument, however, is not consistent with our empirical SF1, which shows that a large QT ratio is typically found in illiquid, neglected stocks. Moreover, the argument does not explain why the QT effect also holds during 1994–2002, when HFT is not known to have had a significant impact in financial markets (see Section IV.D). We thus find the HFT explanation of the QT effect unlikely.

The remainder of the article is organized as follows: Section II describes the data and provides our main empirical results. Section III describes the model, solves for the equilibrium quote rate and cost of capital, and provides additional predictions. Section IV investigates alternative explanations of the QT effect. Section V concludes. All proofs are in the Appendix.

II. Quotes, Trades, and Returns

In this section, we construct our QT ratio (also called *QT*) measure and provide stylized facts on quotes, trades, and stock returns.

A. Data

To construct our QT ratio variable, we use the trades and quotes reported in the Trade and Quote database (TAQ) for the period June 1994–Dec. 2017.[10] Using TAQ data allows us to generate a long time series of the variable QT at the stock level in order to conduct asset pricing tests. We retain stocks listed on the NYSE, AMEX, and NASDAQ for which information is available in TAQ, CRSP, and Compustat data.

Our sample includes only common stocks (Common Stock Indicator Type = 0), common shares (share codes 10 and 11), and stocks not trading on a "when-issued" basis. Stocks that change primary exchange, ticker symbol, or CUSIP number are removed from the sample (Chordia, Roll, and Subrahmanyam (2000), Hasbrouck (2009)). To avoid illiquidity issues related to the price level, we also remove stocks that have a price lower than $2 and higher than $1,000 at the end of a month.[11] To avoid look-ahead bias, all filters are applied on a monthly basis and not on the whole sample. There are 10,670 individual stocks in the final sample.

All returns are calculated using bid–ask midpoint prices, following our definition of the price p_t (see Proposition 1) and to reduce market-microstructure noise effects on observed returns (see Asparouhova, Bessembinder, and Kalcheva (2010), (2013)).[12] All returns are adjusted for splits and cash distributions. We follow Shumway (1997) in using returns of −30% for the delisting month (delisting codes 500 and 520–584). Risk factors are from Wharton Research Data Services (WRDS) and Kenneth French's website for the period 1926–2017. The probability

[10]Our sample starts in June 1994 because TAQ reports opening and closing quotes but not intraday quotes for NASDAQ-listed stocks prior to this date.

[11]The results are quantitatively similar when removing stocks with a price lower than 5 and are available from the authors.

[12]Calculating returns from end-of-day prices does not change the results qualitatively. These results are available from the authors.

of informed trading (PIN) factor is from Sören Hvidkjaer's website and is available from 1984 to 2002. Table IA.1 in the Supplementary Material reports the definitions and the construction details for all variables, and Table IA.2 in the Supplementary Material provides the summary statistics.

We define QT as the monthly ratio of the number of quote updates at the best national price (National Best Bid Offer) to the number of trades. By *quote updates*, we refer only to changes either in the ask or bid prices and not to depth updates at the current quotes.[13] Specifically, we calculate the QT variable for stock i in month t as the following ratio:

$$\mathrm{QT}_{i,t} = \frac{N(\mathrm{QUOTES})_{i,t}}{N(\mathrm{TRADES})_{i,t}}, \tag{1}$$

where $N(\mathrm{QUOTES})_{i,t}$ is the number of quote updates in stock i during month t across all exchanges, and $N(\mathrm{TRADES})_{i,t}$ is the number of trades in stock i during month t.

B. Stock Characteristics and the Quote-to-Trade Ratio

In this section, we analyze the relation of the QT ratio with various firm-level characteristics. To alleviate concerns about the effect of market-wide events during our sample period, we use time fixed effects in our regressions. We also use stock fixed effects to control for unobservable time-invariant stock characteristics.

To get some perspective about the firms with different QT ratios, we report the average values of various firm-level characteristics in Table 1. Specifically, each month, we divide all stocks into decile portfolios based on their QT ratios during month t. The QT portfolio 1 has the lowest QT, and the QT portfolio 10 has the highest QT. For each QT decile at time t, we compute the cross-sectional mean characteristic for month t and report the time-series mean of the average cross-sectional characteristic.[14]

Column 5 of Table 1 shows that the average firm size, as measured by market capitalization, is decreasing in QT. The lowest-QT stocks (stocks in QT decile 1) have an average market capitalization of \$10.8 billion, whereas the highest-QT stocks (stocks in QT decile 10) have an average capitalization of \$0.8 billion. Column 7 shows that the average monthly trading volume decreases from \$1.97 billion for the lowest-QT stocks to \$0.06 billion for the highest-QT stocks. Columns 8–10 show the averages of three illiquidity measures: the quoted spread, the relative spread, and the Amihud (2002) illiquidity ratio (ILR). The highest-QT stocks are roughly 3 times more illiquid than the lowest-QT stocks. The lowest- QT stocks are almost 3 times as volatile as the highest-QT stocks, as shown in column 11.

Table 2 formally examines the relation of the QT ratio with various firm characteristics in a multivariate-regression setting. The dependent variable is the monthly QT ratio. We present the results from a panel regression with various

[13]The results are qualitatively similar if QT is defined by using both quote and depth updates in the numerator. Using only quotes, however, is more consistent with our theoretical model in Section III.A.

[14]The order of the different characteristics across QT portfolios remains unchanged when we compute the cross-sectional characteristics for two equal subsamples; see Table IA.3 in the Supplementary Material.

TABLE 1
Characteristics of QT Ratio Portfolios

Table 1 presents the monthly average characteristics for 10 quote-to-trade (QT) ratio portfolios constructed in month *t*. Portfolio 1 consists of stocks with the lowest QT ratios in month *t*, and portfolio 10 consists of stocks with the highest QT ratios. Each portfolio contains on average 290 stocks. Stocks priced below $2 or above $1,000 at the end of month *t* are removed. The sample period is June 1994–Dec. 2017. For each QT decile, we compute the cross-sectional mean characteristic for month *t*. The reported characteristics are computed as the time-series mean of the mean cross-sectional characteristic. Column 2 shows the QT level, columns 3 and 4 show the number of trades and quote updates in thousands, column 5 shows market capitalization (MCAP) ($millions), columns 6 and 7 show the share volume (in millions of shares) and USD volume traded ($millions), columns 8 and 9 show the quoted spread and relative spread (in % of the midquote), column 10 shows the Amihud illiquidity ratio (ILR) (in %), column 11 shows volatility (calculated as the absolute monthly return in %) (VOLAT), column 12 shows price (PRC), column 13 shows the average book-to-market value measured at the end of the previous calendar year (BM), column 14 shows the average number of analysts following the stock (ANF), and column 15 shows the average institutional ownership (INST).

QT		*N*(trades)	*N*(quotes)		VOLUME		SPREAD							
Portfolio	QT	(× 1,000)	(× 1,000)	MCAP	Shares	USD	Quoted	Relative	IRL	VOLAT	PRC	BM	ANF	INST
1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	1.4	156	280	10,764	84	1,971	0.118	1.21	2.09	4.01	16.1	0.64	16	0.51
2	3.1	65	356	5,555	24	969	0.142	1.41	2.90	3.29	19.6	0.63	12	0.51
3	4.5	47	377	4,571	16	759	0.158	1.50	3.41	3.02	23.1	0.63	11	0.51
4	5.9	36	376	3,812	12	615	0.178	1.59	3.76	2.84	25.7	0.62	10	0.52
5	7.5	27	349	3,045	9	476	0.206	1.73	4.58	2.73	27.8	0.63	10	0.51
6	9.6	20	313	2,826	7	391	0.244	1.88	6.04	2.58	28.9	0.67	9	0.49
7	13.1	14	259	3,308	7	357	0.232	1.74	5.30	2.12	28.9	0.73	10	0.50
8	19.2	8	207	2,069	4	216	0.245	1.64	4.01	1.75	29.0	0.73	9	0.50
9	34.4	5	160	1,425	3	128	0.285	1.71	4.53	1.59	28.7	0.76	7	0.46
10	177.3	2	137	826	1	56	0.403	2.11	7.34	1.43	30.3	0.99	5	0.39

specifications for fixed effects and with standard errors clustered at the stock and month level. Column 1 presents the results without any fixed effects. To control for unobservable time-invariant stock characteristics, we introduce stock fixed effect in column 2. To alleviate concerns about the effect of market-wide events during our sample period (e.g., Autoquote, Reg NMS, changes in the tick size), we use time fixed effects in column 3. Finally, the regression presented in column 4 includes both firm and time fixed effects because both play an important role in our analysis. All nonbinary variables have been standardized, demeaned, and divided by the standard deviation.

We find that the QT ratio is higher for stocks that have low analyst coverage, low institutional ownership, low trading volume, and low volatility.[15] Generally, these are stocks that are neglected by analysts or investors and are difficult to understand/evaluate (see Hong, Lim, and Stein (2000), Kumar (2009)).

TABLE 2

Determinants of the QT Ratio

Table 2 shows panel regressions of the quote-to-trade (QT) ratio on different stock characteristics. The dependent variable is the monthly QT. The independent variables are as follows: annual number of analysts following the stock (ANF), quarterly institutional ownership (INST), log-book-to-market as of the previous year-end (BM), and previous-month return (R1), as well as contemporaneous (monthly) variables of log-market capitalization (MCAP), price (PRC), trading volume (USDVOL) ($millions), Amihud illiquidity ratio (ILR), relative bid–ask spread (SPREAD), and idiosyncratic volatility (IVOLAT) (measured as the standard deviation of the residuals from a Fama and French (FF3) (1993) model regression of daily raw returns within each month, as in Ang, Hodrick, Xing, and Zhang (2009)). All nonbinary variables have been standardized, demeaned, and divided by the standard deviation. Time fixed effects (FE) are at the month-year level. Standard errors are double-clustered at the stock and month-year level.

	1	2	3	4
ANF	−0.05***	−0.04***	−0.01**	−0.02***
	(−5.07)	(−3.79)	(−2.55)	(−3.04)
INST	−0.06***	−0.11***	0.01**	−0.08***
	(−4.94)	(−7.84)	(2.06)	(−7.05)
BM	0.18***	0.17***	0.01	−0.01
	(2.93)	(2.73)	(0.36)	(−0.29)
R1	−0.01***	−0.01***	−0.01***	0.00
	(−4.44)	(−3.35)	(−2.66)	(−1.19)
MCAP	−0.02	0.00	0.03	0.00
	(−0.84)	(−0.12)	(1.45)	(−0.09)
PRC	0.07***	0.08***	0.02***	0.04***
	(5.83)	(5.99)	(3.01)	(4.69)
USDVOL	0.002	−0.02***	−0.01**	−0.02***
	(−0.63)	(−3.42)	(−2.37)	(−3.10)
ILR	0.02**	0.00	0.00	0.00
	(2.16)	(0.10)	(0.83)	(−0.21)
SPREAD	−0.06***	0.00	−0.04***	−0.02***
	(−8.97)	(−0.39)	(−6.34)	(−2.67)
IVOLAT	−0.04***	−0.02***	−0.01***	−0.01***
	(−6.02)	(−3.86)	(−5.81)	(−3.55)
Stock FE	No	Yes	No	Yes
Time FE	No	No	Yes	Yes
N	805,763	805,763	805,655	805,655
Adj.R^2	0.044	0.068	0.292	0.305

[15]Table IA.4 in the Supplementary Material shows that the results in Table 2 remain robust to the addition of two control variables: i) the number of registered NASDAQ market makers and ii) several time dummy variables related to market-wide events, previously subsumed by the time fixed effects.

Stylized Fact 1 (*SF1*). Neglected stocks (with low analyst coverage, institutional ownership, trading volume, and volatility) have higher QT ratios.

This result may appear puzzling, because in neglected stocks, one may expect a lower QT ratio because market makers have less precise information based on which to change their quotes. But in our theoretical model, a market maker with less precise information actually monitors more often to prevent getting a large inventory and therefore generates a higher QT ratio (see Section III.B.2).[16]

It is common practice among academics, practitioners, and regulators to associate QT with HFT activity (several examples are given in footnote 9). The results in Tables 1 and 2 suggest that using QT as a proxy for HFT activity must be done with caution. For instance, high-frequency traders are known to trade in larger and more liquid stocks (Hagströmer and Nordén (2013), Brogaard, Hagströmer, Nordén, and Riordan (2015)). In addition, high-frequency traders are more likely to trade in stocks with high institutional ownership if HFT activity stems from their anticipation of agency and proprietary algorithms of institutional investors, such as mutual funds and hedge funds (O'Hara (2015)). But SF1 shows that the QT ratio is actually lower in stocks with high institutional ownership. Thus, simply associating HFT activity with the QT ratio can be misleading.

C. Time Series of Quote-to-Trade Ratios

Graph A of Figure 3 shows the time series of the equally weighted base-10 logarithm of the monthly QT ratio over the sample period. We note the substantial increase in QT during this time. Graph B is similar to Graph A but displays the evolution of quotes and trades separately. Graph B shows that the increase in QT is driven by the explosion in quote updates. For example, in June 1994, the total number of quotes and the total number of trades are roughly equal to each other, at approximately 1.1 million each. In Aug. 2011, the peak month for both quotes and trades, the monthly number of quotes at the best price reached 1,445 million, whereas trades reached 104 million, an increase 10 times larger for quotes than for trades.[17]

Stylized Fact 2 (*SF2*). QT ratios have increased over time.

SF2 can be explained theoretically by a decrease in market-maker monitoring costs: When these costs are smaller, market makers monitor more often, and hence the QT ratio increases (see Section III.B.2). Both the empirical fact and its explanation are consistent with previous literature. Hendershott et al. (2011) study a change in the NYSE market structure in 2003 called *Autoquote* and argue that this change resulted in a decrease in monitoring costs among market participants and especially among algorithmic traders. At the same time, they document an increase

[16]One alternative view is that the QT ratio is driven by the exogenous arrival of public news. If a neglected stock is expected to have a low number of trades but a relatively large flow of news (e.g., coming from stock index changes), then we should also expect the stock to have a relatively high QT ratio, which is consistent with SF1. Because we do not incorporate exogenous news in our theoretical model, we leave an exploration of this alternative view to future research.

[17]The positive relation between quotes and trades is established in Skjeltorp, Sojli and Tham (2018).

TABLE 3

Risk-Adjusted Returns for QT Ratio Portfolios

Table 3 shows monthly returns (in percentage points) for various portfolios sorted on the quote-to-trade (QT) ratio. We form 10 portfolios based on the QT level in month t, and returns are calculated for each portfolio for month $t+1$. Column 1 shows the average monthly portfolio raw return in excess of the risk-free rate (r^e_{t+1}) for each portfolio at time $t+1$. Columns 2–7 report the risk-adjusted returns (alphas). The alphas reported in the table are the intercepts (risk-adjusted returns) obtained from regressions of returns on the risk factors. The monthly returns of the QT portfolios are risk-adjusted using several asset pricing models: the capital asset pricing model (CAPM), Fama and French (FF3) (1993) model, a model that adds the Pástor and Stambaugh (2003) traded liquidity factor (FF3+PS), a 5-factor model that adds a momentum factor (FF3+PS+MOM), the Fama and French (FF5) (2015) 5-factor model, and a model that adds the probability of informed trading (PIN) factor for the period June 1994–Dec. 2002 (FF4+PS+PIN). We show the alpha for the lowest- and highest-QT portfolios and the alpha for the difference in returns between the low and high portfolios. *, **, and *** indicate rejection of the null hypothesis that the risk-adjusted portfolio returns are significantly different from 0 at the 10%, 5%, and 1% levels, respectively.

	Risk-Adjusted Returns (%)						
	r^e_{t+1}	CAPM	FF3	FF3+PS	FF3+PS+MOM	FF5	FF3+PS+MOM+PIN
	1	2	3	4	5	6	7
α_1	1.59***	0.90*	1.05***	1.01***	1.64***	0.95***	1.66***
α_2	1.34***	0.91**	0.86***	0.85***	1.17***	0.59***	1.17***
α_3	1.21***	0.76*	0.67***	0.63***	0.97***	0.52***	0.98***
α_4	1.08***	0.62*	0.49***	0.50***	0.76***	0.34***	0.76***
α_5	1.02***	0.63*	0.47**	0.47**	0.67***	0.25***	0.67***
α_6	0.95***	0.30	0.08	0.10	0.32*	0.19**	0.31*
α_7	1.03***	0.58**	0.24	0.22	0.59***	0.21**	0.60***
α_8	0.93***	0.48***	0.06	0.04	0.32**	0.08	0.32**
α_9	0.95***	0.44	−0.01	−0.02	0.20	0.18**	0.18
α_{10}	0.77***	0.40***	−0.08	−0.10	0.08	0.01	0.06
α(QT1 − QT10)	0.83***	0.50	1.13***	1.11***	1.56***	0.94***	1.60***

in their proxy for algorithmic trading, which is close in spirit to our QT ratio.[18] Angel, Harris, and Spatt (2011) argue that the proliferation of algorithmic trading and HFT since 2003 has led to substantial increases in the number of both quotes and trades.

D. Quote-to-Trade Ratio and Stock Returns

In this section, we study the relation between QT ratios and average stock returns. We start with an investigation of abnormal expected returns to account for various risk factors through portfolio sorts and then examine other known cross-sectional return predictors through Fama–MacBeth regressions.

1. Univariate Analysis

First, we investigate the raw-return differential between the low- and high-QT stocks. For each time period, we sort stocks into decile portfolios based on their QT ratios for each month t. We then compute the return in excess of the risk-free rate for each of these portfolios for month $t+1$. Column 1 of Table 3 reports the excess returns for the 10 portfolios. The QT1 portfolio has a return of 1.59% per month, and QT10 has a return of 0.77%. The raw excess return of the long–short portfolio based on QT is 0.83% a month.

This raw-excess-return differential might be driven by compensation for known risk factors. Therefore, we test whether the return differential between the

[18] See Figure 1 in Hendershott et al. (2011). Their proxy for algorithmic trading is defined as the negative of dollar trading volume divided by the number of electronic messages (including electronic order submissions, cancellations, and trade reports but excluding specialist quoting or floor orders).

low- and high-QT stocks can be explained by the market, size, value, momentum, liquidity, profitability, and investment factors. Each month, all stocks are divided into portfolios sorted on QT at time t. Portfolio returns are the equally weighted average realized returns of the constituent stocks in each portfolio in month $t+1$.[19] We estimate individual portfolio loadings from the following regression:

$$r_{p,t+1} = \alpha_p + \sum_{j=1}^{J} \beta_{p,j} X_{j,t} + \varepsilon_{p,t+1}, \tag{2}$$

where $r_{p,t+1}$ is the return in excess of the risk-free rate for month $t+1$ of portfolio p constructed in month t based on the QT level, and $X_{j,t}$ is the set of J risk factors: excess market return (r_{MKT}), value (r_{HML}), size (r_{SMB}), the additional Fama and French (2015) factors: profitability (r_{RMW}) and investment (r_{CMA}),Pástor and Stambaugh (2003) liquidity (r_{LIQ}), momentum (r_{UMD}), and probability of informed trading (r_{PIN}). Table 3 reports the alphas obtained from the regression in equation (2).[20] We present results from several asset pricing models that include several risk factors: the capital asset pricing model (CAPM) (market), the Fama and French (FF3) (1993) model (market, size, value), FF3+PS (with the Pástor and Stambaugh (2003) traded liquidity factor), FF3+PS+MOM (with momentum), FF5 (with profitability and investment), and FF4+PS+PIN (with probability of informed trading).[21]

Columns 2–7 in Table 3 report the alphas for the 10 QT-sorted portfolios. We first focus on the full-sample analysis in columns 2–6. The low-QT portfolio (QT1) has a monthly alpha (α_1) that ranges between 0.90% and 1.64% across various asset pricing models, which is statistically different from 0. The high-QT portfolio alphas range from −0.10% to 0.40% but are statistically not different from 0 in all specifications, except the CAPM. This suggests that the high-QT portfolios are priced well by the factor models. However, the risk-adjusted return difference between the low-QT and high-QT portfolios is statistically different from 0 and varies between 0.50% and 1.56% per month across the different asset pricing models. Table IA.5 in the Supplementary Material shows that the differences between the low- and high-QT portfolio alphas are not sensitive to the number of formed portfolios.

Stylized Fact 3 (*SF3*). Higher QT ratios are associated with lower average stock returns in the cross section (the QT effect).

This result is puzzling when compared with SF1, which shows that the QT ratio is higher in neglected stocks and, in particular, in less traded or more illiquid stocks. In the literature, less traded or illiquid stocks also tend to have higher

[19]We also conduct the analysis using value-weighted portfolio returns, and the results do not change quantitatively.

[20]One can also estimate the individual portfolio loadings from rolling-window regressions to account for time-varying factor loadings. We construct time-series averages of the alphas obtained from 24-month rolling-window regressions and obtain quantitatively similar results. These results are available from the authors.

[21]The PIN factor from Sören Hvidkjaer's website is available only until 2002; therefore, we restrict our analysis in the last column of Table 3 to the period 1994–2002. This result is discussed in Section IV as part of the alternative-hypothesis analysis.

expected returns, which appears to contradict the QT effect. To address these issues, in the next section, we provide a multivariate analysis and control for other variables that are potentially important in the cross section of stock returns.

Table 3 also reveals an asymmetry in the QT effect. The profitability of the long–short strategy derives mainly from the long position (the performance of the low-QT portfolio QT1) rather than from the short position (the performance of the high-QT portfolio QT10). Therefore, short-selling constraints are not likely to impede the implementation of a strategy that exploits the main regularity in Table 3.

2. Fama–MacBeth Regressions

To control for other predictive variables of the cross section of returns, we estimate Fama–MacBeth (1973) cross-sectional regressions of monthly individual stock risk-adjusted returns on different firm characteristics, including the QT variable. In addition, the Fama–MacBeth procedure accounts for time fixed effects that could arise from market-wide events during our sample period.

We use individual stocks as test assets to avoid the possibility that tests may be sensitive to the portfolio grouping procedure. First, we estimate monthly rolling regressions to obtain individual stocks' risk-adjusted returns using a 48-month estimation window. We use a similar procedure as in Brennan, Chordia, and Subrahmanyam (1998) to obtain risk-adjusted returns:

$$r^a_{i,t} = r_{i,t} - \sum_{j=1}^{J} \hat{\beta}_{i,j,t-1} F_{j,t}, \tag{3}$$

where $r_{i,t}$ is the monthly return of stock i in excess of the risk-free rate, $\widehat{\beta}_{i,j,t-1}$ is the conditional beta estimated by a first-pass time-series regression of risk factor j estimated for stock i by a rolling time-series regression up to $t-1$, and $F_{j,t}$ is the realized value of risk factor j at time t. Then, we regress the risk-adjusted returns from equation (3) on lagged stock characteristics:

$$r^a_{i,t} = c_{0,t} + \sum_{m=1}^{M} c_{m,t} Z_{m,i,t-k} + e_{i,t}, \tag{4}$$

where $Z_{m,i,t-k}$ is the characteristic m for stock i at time $t-k$, and M is the total number of characteristics. We use $k=1$ month for all characteristics.[22] The procedure ensures unbiased estimates of the coefficients $c_{m,t}$, without the need to form portfolios, because errors in the estimation of the factor loadings are included in the dependent variable. The t-statistics are obtained using the Fama–MacBeth standard errors with Newey–West correction with 12 lags.

Table 4 reports the Fama–MacBeth (1973) coefficients for cross-sectional regressions of individual stock risk-adjusted returns on stock characteristics. We construct risk-adjusted returns using the Fama–French 3-factor model (market, size, and value), with the momentum and the Pástor and Stambaugh (2003) traded liquidity factor. Column 1 includes only the QT ratio. QT has a highly significant

[22]Table IA.6 in the Supplementary Material shows the estimation results where $k=2$ for all conditioning variables with the exception of the past return variables R1 and R212.

TABLE 4

Stock Returns and the QT Ratio

Table 4 reports the Fama–MacBeth (1973) coefficients from regressions of risk-adjusted monthly returns on firm characteristics. The dependent variable is the risk-adjusted return $r^a_{i,t} = r_{i,t} - \sum_{j=1}^{J} \beta_{i,j,t-1} F_{j,t}$, where the risk factors $F_{j,t}$ come from the FF3+PS+MOM model (market, size, value, momentum and the Pástor and Stambaugh (2003) traded liquidity factor). The firm characteristics are measured in month $t-1$. The characteristics included are as follows: quote-to-trade (QT) ratio (QT); number of quotes (QUOTE); number of trades (TRADE); relative bid–ask spread (SPREAD); Amihud illiquidity ratio (ILR); log-market capitalization (MCAP); book-to-market ratio (BM), calculated as the natural logarithm of the book value of equity divided by the market value of equity from the previous fiscal year; previous-month return (R1); cumulative return from month $t-2$ to $t-12$ (R212); idiosyncratic volatility (IVOLAT), measured as the standard deviation of the residuals from a Fama and French (FF3) (1993) model regression of daily raw returns within each month as in Ang et al. (2009); trading volume (USDVOL) ($millions); and price (PRC). All characteristics apart from returns are logged, and all coefficients are multiplied by 100. The standard errors are corrected by using the Newey–West method with 12 lags. t-statistics for the QT variable are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5
Constant	0.005***	0.004***	0.014***	0.012***	0.035***
$QT_{i,t-1}$	−0.172**	−0.199***	−0.251***	−0.261***	−0.156***
	(−2.23)	(−2.91)	(−3.61)	(−3.59)	(−3.85)
$SPREAD_{i,t-1}$		0.166***		0.074*	0.021
$ILR_{i,t-1}$			0.102***	0.081***	−0.008
$MCAP_{i,t-1}$					−0.136*
$BM_{i,t-1}$					0.032
$R1_{i,t-1}$					−3.350***
$R212_{i,t-1}$					0.084
$IVOLAT_{i,t-1}$					−9.525***
$USDVOL_{i,t-1}$					0.052
$PRC_{i,t-1}$					−0.345***
R^2	0.00	0.01	0.01	0.01	0.03
Time series (months)	278	278	278	278	278

and negative coefficient, implying that stocks with higher QT have lower next-month risk-adjusted returns. We thus again confirm the QT effect.

Because the QT effect might be driven by the correlation of QT with liquidity, we include two illiquidity proxies in the regression: the bid–ask spread (SPREAD) and the Amihud (2002) illiquidity ratio (ILR). Column 2 of Table 4 includes QT and SPREAD, column 3 includes QT and ILR, and column 4 includes QT and both SPREAD and ILR. The coefficients for both illiquidity proxies are positive and significant, consistent with higher illiquidity causing higher returns (see Amihud (2002)). However, the inclusion of these known illiquidity proxies does not reduce the effect of QT, which remains negative and significant in all specifications in columns 2–4.

In column 5 of Table 4, we introduce other firm characteristics that affect expected returns. With these additional control variables, the coefficient for QT remains negative and highly significant with a t-statistic of −3.85, whereas the illiquidity proxies SPREAD and ILR become both insignificant. The QT effect therefore is distinct from the known effects of other variables: spread, ILR, trading volume, and volatility. The coefficients of control variables are quantitatively similar to articles using a similar sample period (e.g., Hou and Loh (2016)). The results are quantitatively unchanged when introducing other control variables, such as short interest, institutional ownership, or analyst following, in Table IA.7 in the Supplementary Material. Furthermore, focusing on only the NASDAQ-listed subset or using excess returns, rather than risk-adjusted returns, does not alter the QT effect. Our results add to the literature that explores how trading activity and market structure are connected with asset returns (see Amihud and Mendelson (1986), Amihud (2002), Brennan and Subrahmanyam (1996), Chordia, Roll, and

TABLE 5

Quotes Versus Trades

Table 5 reports the Fama–MacBeth (1973) coefficients from regressions of risk-adjusted monthly returns on firm characteristics, including the number of quotes and trades. The dependent variable is the risk-adjusted return $r^a_{i,t} = r_{i,t} - \sum_{j=1}^{J} \beta_{i,j,t-1} F_{j,t}$, where the risk factors $F_{j,t}$ come from the FF3+PS+MOM model (market, size, value, momentum, and the Pástor and Stambaugh (2003) traded liquidity factor). The firm characteristics are measured in month $t-1$. The characteristics included are as follows: number of quotes (QUOTE); number of trades (TRADE); relative bid–ask spread (SPREAD); Amihud illiquidity ratio (ILR); market capitalization (MCAP); book-to-market ratio (BM), calculated as the natural logarithm of the book value of equity divided by the market value of equity from the previous fiscal year, previous-month return (R1); cumulative return from month $t-2$ to $t-12$ (R212); idiosyncratic volatility (IVOLAT), measured as the standard deviation of the residuals from an FF3 regression of daily raw returns within each month, as in Ang et al. (2009); dollar volume (USDVOL); and price (PRC). All characteristics apart from returns are logged, and all coefficients are multiplied by 100. The standard errors are corrected by using the Newey–West method with 12 lags. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	1	2	3	4	5	6
Constant	0.022***	0.021***	0.019***	0.020***	0.020***	0.021***
$QUOTE_{i,t-1}$	−0.320***	−0.337***	−0.290***	−0.313***	−0.130***	−0.154***
$TRADE_{i,t-1}$	0.175*	0.204**	0.235**	0.244**	−0.160	−0.134
$SPREAD_{i,t-1}$		0.023		0.011		−0.006
$ILR_{i,t-1}$			0.081**	0.064*		−0.003
$MCAP_{i,t-1}$					−0.159**	−0.143**
$BM_{i,t-1}$					0.023	0.026
$R1_{i,t-1}$					−3.496***	−3.418***
$R212_{i,t-1}$					0.069	0.073
$IVOLAT_{i,t-1}$					−7.348**	−8.466***
$USDVOL_{i,t-1}$					0.346***	0.322***
$PRC_{i,t-1}$					−0.573***	−0.534***
R^2	0.01	0.01	0.01	0.01	0.03	0.03
Time series (months)	278	278	278	278	278	278

Subrahmanyam (2002), Chordia et al. (2000), Easley, Hvidkjaer, and O'Hara (2002), and Duarte and Young (2009), among many others).

An important question is whether the QT effect is driven by the number of quotes or by the number of trades. We explore this question in Table 5. Column 1 shows that when conditioning on quotes and trades as separate explanatory variables, it is the number of quotes that matters most for risk-adjusted returns. This effect is economically and statistically large. Introducing other liquidity-based control variables in columns 2–4 does not affect the statistical significance of the number of trades and the number of quotes. Column 6 includes all firm characteristics, as well as liquidity measures as control variables, and shows that the predictive power of QT derives from quotes and not from trades.

Stylized Fact 4 (*SF4*). The QT predictability is driven by the number of quotes rather than the number of trades.

This result justifies our modeling choice in Section III to consider the trades as exogenous and focus instead on the quotes and how they result from the market makers' monitoring decisions.

III. Model of Quoting Activity

Our model is close in spirit to the dealer models of Ho and Stoll (1981) and Hendershott and Menkveld (2014). Because we are interested in the relation between quoting activity and the cost of capital, we make two key modifications. First, the dealer learns about the value of the risky asset via costly monitoring, which generates endogenous quote changes. Second, the order flow is generated by risk-averse investors, which causes a pricing discount in our model and thus generates a positive cost of capital.

A. Environment

The market consists of one risk-free asset and one risky asset. Trading in the risky asset takes place in a market exchange based on the mechanism described in the following subsection. There are two types of market participants: i) one monopolistic market maker called the *dealer* ("she"), who monitors the market and sets ask and bid quotes at which others trade, and ii) traders, who submit market orders.

Assets. The risk-free asset is used as the numeraire and has a 0 return. After trading takes place, the risky asset liquidates at a value v per share, called the *fundamental value or asset value.* The random variable v has a normal distribution $v \sim \mathcal{N}\left(v_0, \sigma_v^2\right)$, where σ_v is the *fundamental volatility.*

Trading. Trading occurs at the first arrival τ in a Poisson process with a frequency parameter normalized to 1. Upon observing the ask quote a and the bid quote b, traders submit at τ the following aggregate market orders:

$$
(5) \qquad \begin{aligned} Q^b &= \frac{k}{2}(v-a) + \ell - m + \varepsilon^b, \quad \text{with} \quad \varepsilon^b \overset{\text{IID}}{\sim} \mathcal{N}(0, \Sigma_L/2), \\ Q^s &= \frac{k}{2}(b-v) + \ell + m + \varepsilon^s, \quad \text{with} \quad \varepsilon^s \overset{\text{IID}}{\sim} \mathcal{N}(0, \Sigma_L/2), \end{aligned}
$$

where Q^b is the *buy demand* and Q^s is the *sell demand*. The numbers k, ℓ, m, and Σ_L are exogenous constants. Together, Q^b and Q^s are called the *traders' order flow.* The parameter k is the *investor elasticity*, ℓ is the *inelasticity parameter*, and m is the *imbalance parameter*. Hendershott and Menkveld (2014) use a similar reduced-form approach, except that they exogenously set the imbalance parameter m to 0. We endogenize the value of m and other parameters by providing microfoundations for the order flow, and we find that $m > 0$ when investors are risk averse and the asset is in positive net supply.

Order Flow Microfoundations. To get more intuition for equations (5), we provide microfoundations for the order flow. (For more details, see Section 2 in the Supplementary Material.) First, we assume that the risky asset has a positive net supply $M > 0$. There are two types of traders: i) liquidity traders, who submit inelastic aggregate buy order L^b and aggregate sell order L^s, where both L^b and L^s have independent and identically distributed (IID) normal distributions $\mathcal{N}(\ell_L, \Sigma_L/2)$, and ii) informed investors with constant absolute risk aversion (CARA) utility and coefficient of risk aversion $A > 0$. A mass one of informed investors starts with an initial endowment in the risky asset that is normally distributed as $\mathcal{N}\left(M, \sigma_M^2\right)$. To simplify notation, we redefine the asset value to be $v+u$, with u normally distributed as $\mathcal{N}(0, \Sigma_u)$. Investors observe the same signal v before trading and then trade on the exchange at the existing quotes. As a result, we show in Section 2 in the Supplementary Material that the aggregate order flow approaches the form in equation (5) when the endowment volatility σ_M is large.[23] Moreover, the investor elasticity k is proportional to the informed investors' signal precision $1/\Sigma_u$ and their risk tolerance $1/A$, whereas the imbalance parameter m is proportional to the net supply M.

Dealer Monitoring. The dealer monitors the market according to an independent Poisson process with a frequency parameter $q > 0$ called the *monitoring frequency* (or *monitoring rate*). Let t_n be the nth arrival of this process, and let $t_0 = 0$. Monitoring consists of the dealer receiving a signal s_n at each monitoring time t_n for $n \geq 0$:

$$s_n = v + \varepsilon_n, \quad \text{with } \varepsilon_n \overset{IID}{\sim} \left(0, \frac{1}{F(q)}\right). \tag{6}$$

In the rest of the article, we consider the initial signal s_0 at $t_0 = 0$ as the dealer's prior, whereas *monitoring* refers to the subsequent signals s_n with $n > 0$. Note that we allow the signal precision F to depend on the monitoring rate. Intuitively, if $F(q)$ is increasing in q, monitoring has increasing returns to scale: Monitoring more often produces more precise signals each time. The cost of monitoring at the rate q is $C(q)$, and it is paid only once, before monitoring begins at $t = 0$.

Dealer's Quotes and Objective. A quoting strategy for the dealer is a pair (a_t, b_t) of right-continuous functions in $t \geq 0$, where a_t is the ask quote at t, and b_t is the bid quote at t. Let x_0 be the dealer's initial inventory in the risky asset and x_{end} the inventory after trading. If Q^b is the aggregate buy market order and Q^s is the aggregate sell market order, the dealer's inventory after trading is as follows:

$$x_{\text{end}} = x_0 - Q^b + Q^s. \tag{7}$$

Denote by τ the random trading time, which is exponentially distributed with a parameter equal to 1. Then, for a given quoting strategy (a_t, b_t), the dealer's expected utility is equal to the expected profit minus the quadratic penalty in the inventory and minus the monitoring costs:

$$\mathrm{E}_0\left(x_0 v + \left((v - b_\tau)Q^s + (a_\tau - v)Q^b\right) - \gamma x_{\text{end}}^2 - C(q)\right), \tag{8}$$

where the parameter $\gamma > 0$ is the dealer's *inventory aversion*.[24]

Equilibrium Concept. Because the dealer is a monopolist market maker in our model, the structure of the game is simple. First, the dealer chooses a constant

[23] In Section 3 in the Supplementary Material, we show that the equilibrium is qualitatively similar if instead of aggregating the order flow over the whole population, we consider only the optimal orders from one individual trader selected at random from the population.

[24] This utility function is justified if the dealer either faces external funding constraints or is risk averse. The latter explanation is present in Hendershott and Menkveld ((2014), Section 3), where the dealer maximizes quadratic utility over nonstorable consumption. To solve for the equilibrium, they consider an approximation of the resulting objective function (see their equation (16)). This approximation coincides with our dealer's expected utility in equation (8) when $C(q) = 0$.

monitoring rate q. Second, in the trading game, the dealer chooses the quoting strategy (a_t, b_t) such that objective function (8) is maximized.

B. Equilibrium Quoting

We solve for the equilibrium in two steps. In the first step (Section III.B.1), we take the dealer's monitoring rate q as given and describe the optimal quoting behavior. In the second step (Section III.B.2), we determine the optimal monitoring rate q as the rate that maximizes the dealer's expected utility.

1. Optimal Quotes

We start by fixing the monitoring rate q. Consider the game described in Section III.A, with positive parameters $k, \ell, m, \Sigma_L, f, c, \gamma$. Also, let x_0 be the dealer's initial inventory. Define the following constants:

(9) $$h = \frac{\ell}{k}, \quad \delta = \frac{m}{k}\frac{1+2\gamma k}{1+\gamma k} + \frac{\gamma}{1+\gamma k} x_0.$$

Proposition 1 describes the optimal quoting strategy of the dealer, which is conditional on the dealer's value forecast w_t. In Section III.B.2, we describe the process for w_t, which is exogenous to the dealer once the initial monitoring decision is made.

Proposition 1. Suppose the dealer has initial inventory x_0 and her forecast at t is w_t. Then the dealer's optimal quotes at t are as follows:

(10) $$a_t = (w_t - \delta) + h, \quad b_t = (w_t - \delta) - h,$$

where h and are as in equation (9). The midquote price $p_t = (a_t + b_t)/2$ satisfies:

(11) $$p_t = w_t - \delta = w_t - \frac{m}{k}\frac{1+2\gamma k}{1+\gamma k} - \frac{\gamma}{1+\gamma k} x_0.$$

To get intuition for this result, suppose the imbalance parameter m is 0. Furthermore, consider first the particular case when the dealer is risk neutral: $\gamma = 0$. In that case, the dealer's inventory x_0 does not affect her strategy. Equation (10) implies that the dealer sets her quotes at equal distance around her forecast w_t. Hence, the ask quote is $a_t = w_t + h$, and the bid quote is $b_t = w_t - h$, where h is the constant half spread. The equilibrium value $h = \ell / k$ reflects two opposite concerns for the dealer. If she sets too large a spread, then investors (whose price elasticity is increasing in k) submit a smaller expected quantity at the quotes.[25] If she sets too small a spread, this decreases the part of the profit that comes from the inelastic part ℓ of traders' order flow.

When the dealer has positive inventory aversion ($\gamma > 0$), her initial inventory affects the optimal quotes. Indeed, according to equation (10), the quotes at t are equally spaced around an inventory-adjusted forecast $(w_t - \gamma x_0/(1+\gamma k))$. The effect of the dealer's inventory on the midquote price is the "price pressure"

[25]For example, equation (5) implies that the expected quantity traded at the ask is $\mathrm{E}_\tau(Q^b) = (k)/(2)(w_\tau - a_\tau) + \ell$, which is decreasing in a_τ.

mechanism identified by Hendershott and Menkveld (2014). To understand this phenomenon, suppose that the initial inventory is large and positive. To avoid the inventory penalty, the dealer must reduce the inventory. This implies that the dealer must lower the quotes to attract more buyers than sellers.

According to equation (11), the midquote price is also decreasing in the imbalance parameter m. To understand why, suppose the imbalance parameter m is large, yet the dealer sets the midquote price equal to her forecast (that is, $p_t = w_t$). The dealer then expects the sell demand to be much larger than the buy demand. Thus, in order to avoid inventory buildup and attract more buyers, she must lower her price well below her forecast.

2. Optimal Monitoring and the Quote Rate

Suppose the dealer monitors the market at the rate q, which means that at t_n, the nth arrival in a Poisson rate with a frequency q, she receives a signal s_n with precision $F(q)$. The next result describes the evolution of the dealer's forecast w_t that arises from monitoring.

Lemma 1. Let $n \geq 0$ and $t \in [t_n, t_{n+1})$. Then, the dealer's value forecast is the average current signal, $w_t = (s_0 + \cdots + s_n)/(n+1)$, and its precision is $1/\text{Var}(v - w_t) = (n+1)F(q)$.

Intuitively, the forecast changes only when there is a new signal, at the monitoring time t_n. The forecast is clearly the average signal. Because each signal has the same precision $F(q)$, the precision increases linearly with the number of monitoring times.

Proposition 1 implies that the dealer's equilibrium quotes change only when her forecast changes. Therefore, we interpret the monitoring rate q as the dealer's quote rate:

$$q = \text{Quote Rate}. \tag{12}$$

Thus far, the description of the equilibrium does not depend on a particular specification for the precision function $F(q)$ or the monitoring function $C(q)$.[26] Proposition 3.2.2, however, provides explicit formulas by assuming that

$$F(q) = f \ln(q+1), \quad C(q) = cq, \tag{13}$$

where $f > 0$ is a signal precision parameter and $c > 0$ is a monitoring cost parameter.[27]

Proposition 2. The dealer's optimal monitoring rate q satisfies the following:

[26]In Section 4.1 in the Supplementary Material, we show that the equilibrium remains essentially the same if we replace the monitoring process at rate q by a unique signal with precision $\widetilde{F}(q) = (qF(q))/(\ln(q+1))$.

[27]The results are qualitatively the same if we take $F(q) = f$ or $F(q) = fq$, but the formulas are less explicit. In the proof of Proposition 2, we describe the equilibrium conditions for general F and C.

(14) $$q^2 = \frac{k(1+k\gamma)}{fc}.$$

Corollary 1 uses the formula in equation (14) to generate some comparative statics for the quote rate.

Corollary 1. The quote rate q is increasing in investor elasticity k and inventory aversion γ, and it is decreasing in signal precision f and in monitoring cost c.

If investor elasticity k is larger, investors trade more aggressively on the pricing error, and the dealer increases her monitoring rate to prevent both adverse selection and large variation in inventory. To better understand the reasons behind this increase, we write equation (14) as a sum: $q^2 = k/(fc) + k^2\gamma/(fc)$. The first term (which does not depend on the dealer's inventory aversion γ) simply reflects that by increasing her monitoring rate, the dealer reduces the adverse selection that comes from trading with investors with superior information. The second term depends on the inventory aversion γ. If this parameter is larger, the dealer is relatively more concerned about her inventory than about her profit. She then increases her monitoring rate to stay closer to the fundamental value, such that her inventory is not expected to vary too much.

If the signal precision parameter f is smaller, the dealer gets noisier signals every time she monitors; hence, she must monitor the market more often in order to avoid getting a large inventory. As a result, in difficult-to-understand stocks where we expect dealers' signals to be noisier, the quote rate q should be larger. This is counterintuitive because one could think that the quote rate is actually smaller in difficult-to-understand stocks. This theoretical result is, however, consistent with our SF1 in Section II.B that the QT ratio is larger in neglected stocks (with low analyst coverage, institutional ownership, trading volume, and volatility).

If the monitoring cost c is smaller, the dealer can afford to monitor more often in order to maintain the same precision, which increases the quote rate. There is much evidence that monitoring costs have decreased dramatically in recent times (see Hendershott et al. (2011)). Therefore, according to Corollary 1, we should also expect a large increase in the QT ratio. This is consistent with our SF2 in Section II.C that documents a sharp rise in the QT ratio.

C. Pricing Discount and the Cost of Capital

In this section, we analyze the equilibrium cost of capital. We first define the *pricing discount* (or simply the *discount*) at t to be the difference between th dealer's forecast w_t and the midquote price p_t. According to Proposition 1, the equilibrium discount is always equal to the constant δ from equation (9). We compute the expected return at t using the midquote price: $(\mathrm{E}_t(v) - p_t)/p_t = (w_t - p_t)/p_t = \delta/(w_t - \delta)$. Therefore, the expected return is in one-to-one correspondence with the discount. We thus define the *cost of capital* r to be equal to the discount:[28]

[28]This is standard in 1-period models (e.g., Easley and O'Hara (2004)).

$$r = \delta = \frac{m}{k}\frac{1+2\gamma k}{1+\gamma k} + \frac{\gamma}{1+\gamma k}x_0. \tag{15}$$

Thus, the cost of capital depends on a state variable: the dealer's initial inventory x_0. In the rest of the article, we assume that $x_0 \geq 0$. Corollary 2 provides some comparative statics for the cost of capital.

Corollary 2. If $x_0 \geq 0$, then the cost of capital is increasing in the imbalance parameter m and decreasing in the investor elasticity k.

Intuitively, if the imbalance parameter m increases, the dealer expects the difference between the sell and buy demands to increase as well. To attract buyers, the dealer must lower the price and thus increase the discount. If the investor elasticity k increases, investors trade more aggressively when the price deviates from the fundamental value. To stop the inventory from accumulating too much in either direction, the dealer must raise the price closer to her forecast, which translates into a lower discount.

Corollary 3 connects the cost of capital to the equilibrium quote rate.

Corollary 3 (Quote Effect)**.** If $x_0 \geq 0$, then holding all parameters constant except for the investor elasticity k, there is an inverse relation between the discount (or cost of capital) and the quote rate.

The quote effect in our model is driven by investor elasticity. When k is larger, Corollary 1 shows that the quote rate q is also larger: Because traders are more sensitive to the quotes, in order to prevent large fluctuations in inventory, the dealer must monitor more often. At the same time, when k is larger, the discount is smaller: Because investors trade more intensely when the price differs from the fundamental value, in order to prevent an expected accumulation of inventory, the dealer must set the price closer to her forecast, which implies a lower discount and hence a lower cost of capital.

If we also consider the microfoundations for the order flow (see Section III.A), the investor elasticity k is larger when the investors have more precise information. Therefore, at a more fundamental level, the quote effect is driven by traders' information precision: More precise investors cause both a larger quote rate and a smaller cost of capital.

The quote effect is documented empirically in the cross section of stock returns by SF3 (see Section II.D).[29]

[29]One concern remains whether our theoretical explanation is systematic enough to justify the QT effect: It is possible that the pricing discount in any particular stock is just an idiosyncratic error that should vanish in the large cross section of stocks. We argue, however, that the price discount is likely to be driven by systematic variables. Indeed, Corollary 2 shows that a key determinant of the price discount is the investor elasticity k, which our microfoundations show to be determined by the precision of the informed investors' signals. If investors analyze multiple stocks, then their signal precision is likely to comove across stocks, which makes the investor elasticity systematic.

D. Neutral State

In this section, we describe the equilibrium when the dealer's initial inventory x_0 has a particular value:

$$x_{0,\text{neutral}} = \frac{m}{\gamma k}. \tag{16}$$

We call this value the *dealer's neutral inventory* (or *preferred inventory*), and we say that in this case, the system is in its neutral state.[30]

Corollary 4 shows that in the neutral state the dealer expects her inventory to stay the same; that is, the expected change in her inventory is 0.

Corollary 4. When the dealer's inventory is equal to its neutral value, the expected buy and sell quantities from equation (5) are equal. The equilibrium cost of capital (discount) is as follows:

$$\delta_{\text{neutral}} = \frac{2m}{k}. \tag{17}$$

The first statement of Corollary 4, that the traders' order flow is balanced in the neutral state, is in fact the reason behind our definition of neutral inventory in equation (16). The neutral inventory represents the dealer's bias in holding the risky asset, and mathematically, it is positive because the imbalance parameter m is positive. Intuitively, the neutral inventory is positive because the investors are risk averse, and the risky asset is in positive net supply (see the order flow microfoundations described in Section III.A). But the dealer also behaves approximately as a risk-averse investor because of the quadratic penalty in inventory (see footnote 24). Therefore, our model becomes essentially a risk-sharing problem, in which the dealer prefers to hold a positive inventory.

Formally, equations (16) and (17) imply that the neutral (or preferred) inventory $x_{0,\text{neutral}} \neq = m/(\gamma k)$ is positive and is equal to the product of the half discount $\delta_{\text{neutral}}/2 = m/k$ and the inverse inventory aversion $1/\gamma$. But the discount is a proxy for the expected return, and the inverse inventory aversion is a proxy for the number of market makers.

The dealer's preferred inventory is decreasing in γ because the dealer prefers to hold less of the risky asset when she is more inventory averse. The preferred inventory is increasing in the imbalance parameter m because the dealer can engage in more risk sharing when the risky asset is in higher supply. The preferred inventory is decreasing in the investor elasticity k because more aggressive investors hold relatively more of the risky asset and decrease the share left to the dealer.

A surprising consequence of Corollary 4 is that the discount (or cost of capital) in the neutral state is independent of the dealer's inventory aversion γ. One may indeed expect the discount to be larger if the dealer has a larger inventory aversion γ. But this is not the case in the neutral state because the neutral discount reflects

[30]In Section 5 in the Supplementary Material, we extend our model to multiple trading rounds, and we show that the neutral inventory is equal to the long-term average of the dealer's inventory, regardless of its initial value.

the dealer's desire to balance the order flow, and therefore only the coefficients of the order flow may affect the discount, not the dealer's characteristics, including the aversion parameter γ. In the multiple-trade model in Section 5 of the Supplementary Material, we see that the dealer's desire to balance the order flow (on average) arises as an equilibrium result because an imbalanced order flow would result in a permanent expected accumulation of inventory that would not be optimal.

E. Additional Predictions

In this section, we provide two additional predictions of our model. Corollary 1 implies that the dealer's optimal monitoring rate q is increasing in her inventory aversion γ. As a proxy for the inventory aversion γ of a dealer in a stock, we use $1/N$, where N is the number of market makers that provide liquidity in that stock. We expect that a larger number of intermediaries implies a smaller γ for the representative dealer. We obtain the following empirical prediction:

Prediction 1. The number of market makers in a stock has an inverse relation to the stock's QT ratio.

Intuitively, a larger number of market makers can be interpreted as a smaller inventory aversion γ of the aggregate market maker. But a less averse dealer monitors the stock less often because she is less concerned about accumulating inventory. Therefore, the resulting QT ratio is also smaller.

In Section 4 of the Supplementary Material, we provide an extension of the model to N dealers and show that the inventory aversion of a representative dealer is $1/N$ of the individual inventory aversion. In that extension, we also prove directly that the QT ratio is smaller in the N-dealer case (see Corollary IA.4). This result provides additional intuition to Prediction 1: Because the quotes are public information, each market maker's monitoring exerts a positive externality on the others and thus leads to underinvestment in monitoring in equilibrium.

We test this prediction in column 1 of Table IA.4 in the Supplementary Material. This augments column 4 of Table 2 with the number of registered market makers in a particular stock (MM) as an explanatory variable. This results in a smaller sample because the number of market makers is only available for NASDAQ-traded stocks. Nevertheless, we find that the number of market makers has a negative effect on the QT ratio. This is surprising because one may think that competition among market makers results in an increase of the QT ratio.

Corollary 4 implies that in the neutral state, when the traders' order flow is balanced, the dealer's discount (cost of capital) no longer depends on the dealer's inventory aversion γ. But the number of market makers is an empirical proxy for the (inverse) inventory aversion γ. We obtain the following empirical prediction:

Prediction 2. The number of market makers in a stock has no relation to the stock's expected return

Intuitively, when the dealer's initial inventory is in the neutral state (where the expected imbalance between buy and sell quantities is 0) the dealer wants only to balance the incoming order flow, and hence the pricing discount (or cost of capital) is affected only by the properties of the order flow and not by the characteristics of the dealer, including her inventory aversion (or the number of dealers if we consider the case of multiple dealers).[31]

We test this prediction in Table IA.8 in the Supplementary Material, which presents the results of Fama–MacBeth regressions similar to those in Table 4, but we include the number of registered market makers (MM) in a stock as an explanatory variable. Indeed, the introduction of the MM variable does not affect the QT effect. Moreover, all other explanatory variables have qualitatively similar magnitudes and levels of significance as in Table 4.

IV. Alternative Explanations of the QT Effect

In this section, we discuss several alternative explanations of the QT effect that involve various frictions (e.g., the tick size and impediments to arbitrage, institutional investors and governance, temporary price effects, and market structure changes).

A. Tick Size and Impediments to Arbitrage

Yao and Ye (2018) and Albuquerque, Song, and Yao (2021) provide a connection between an impediments-to-arbitrage hypothesis and the QT effect: First, Yao and Ye find that stocks with a larger tick size relative to price have higher QT ratios. Second, Albuquerque et al. (2021) find that an exogenous increase in tick size negatively affects stock prices and is associated with an increase in the cost of trading. Therefore, the QT effect might be driven in part by the effect of illiquidity related to the tick size. To investigate this alternative explanation, we follow two approaches: i) long–short portfolios double-sorted by QT and transaction cost proxy variables and ii) Fama–MacBeth (1973) regressions for high and low transaction cost levels.

To form the long–short portfolio alphas, we first sort stocks into terciles based on transaction-cost proxies (relative spread, Amihud illiquidity ratio, and turnover) and then create either three or five QT portfolios within each liquidity tercile. We examine the alpha from a strategy that, within each liquidity tercile, goes long in low-QT stocks and short in high-QT stocks. Then, if the illiquidity level explains the QT effect according to the impediments-to-arbitrage hypothesis, abnormal profits should concentrate in the most illiquid group, and the size of the risk-adjusted returns should be of the same magnitude as the cost of transacting in the U.S. equity

[31]This result depends on the system being initially in the neutral state, which we argue is a plausible assumption. Indeed, in an extension with multiple trading rounds, we show that the neutral inventory is equal to the long-term average of the dealer's inventory, regardless of its initial value (see Section 5 in the Supplementary Material).

TABLE 6

Risk-Adjusted Returns for QT Ratio Double-Sorted Portfolios

Table 6 shows the monthly alphas of a long–short strategy for various portfolios double-sorted on a variable of interest and the quote-to-trade (QT) ratio. The strategy longs low-QT stocks and shorts high-QT stocks within three levels of liquidity and institutional investors at the end of month *t*. We first assign all stocks to three portfolios based on their liquidity and institutional ownership levels. Then, we construct three or five portfolios based on the QT level within each liquidity and institutional ownership portfolio, and we long the low-QT portfolio and short the high-QT portfolio. The alphas reported in the table are the intercepts (risk-adjusted returns) obtained from regressions of returns on the risk factors. The monthly returns of the QT portfolios are risk-adjusted using a 5-factor asset pricing model including the Fama and French (FF3) (1993) model with the added Pástor and Stambaugh (2003) traded liquidity factor and momentum factor. All portfolio returns are equally weighted. Panels A–C report the long–short α for the liquidity portfolios with low, medium, and high relative bid–ask spreads, Amihud illiquidity ratio (ILR), and turnover, respectively. Panel D reports the long–short α for the institutional ownership level. *, **, and *** indicate rejection of the null hypothesis that the risk-adjusted portfolio returns are significantly different from 0 at the 10%, 5%, and 1% levels, respectively.

	3 × 3 Portfolios	3 × 5 Portfolios
Panel A. Relative Spread		
Low	0.27*	0.37**
	1.68	1.92
Medium	0.48***	0.63***
	2.77	2.96
High	0.89***	1.19***
	6.02	6.24
Panel B. ILR		
Low	0.17	0.23
	1.08	1.31
Medium	0.57***	0.78***
	3.50	3.79
High	0.83***	1.15***
	6.41	6.92
Panel C. Turnover		
Low	0.64***	0.82***
	6.02	6.23
Medium	0.55***	0.67***
	4.09	4.17
High	0.59***	0.86***
	3.53	4.02
Panel D. Institutional Investors		
Low	0.50***	0.72***
	3.50	3.99
Med	0.51***	0.65***
	3.52	3.67
High	0.36***	0.45***
	2.57	2.79

market. Moreover, abnormal returns for the other liquidity groups should not be statistically different from 0.

The results in Panels A and B of Table 6 provide support for the impediments-to-arbitrage hypothesis. The strongest QT effect occurs among the most illiquid stocks for relative spread and Amihud illiquidity ratio. The abnormal return for the most illiquid group is as high as over 100 basis points (bps) and as low as 17 bps for the most liquid group across the illiquidity proxies. The difference in abnormal returns across these illiquidity groups implies a difference in average transaction costs (impediment to trade) of 60 to 90 bps between the illiquid and liquid group of stocks. However, the results that the abnormal returns for other liquidity groups remain statistically and economically different from 0 suggest that impediments-to-arbitrage explain a proportion of the estimated economic effect of the inventory

TABLE 7

Stock Returns and Quote-to-Trade Ratio Across Subgroups

Table 7 reports the Fama–MacBeth (1973) coefficients from regressions of risk-adjusted monthly returns on firm characteristics for two levels of explanatory variables. The dependent variable is the risk-adjusted return $r^a_{i,t} = r_{i,t} - \sum_{j=1}^{J} \beta_{i,j,t-1} F_{j,t}$, where the risk factors $F_{j,t}$ come from the FF3+PS+MOM model (market, size, value, momentum, and the Pástor and Stambaugh (2003) traded liquidity factor). The sample is divided into two groups of high and low relative spread, Amihud illiquidity ratio (ILR), turnover, and institutional ownership (IO) based on sample median values for every time period. Panel A presents the results for low (below-median) levels, and Panel B presents the results for high (above-median) levels of the variables of interest. We exclude SPREAD from the regressions in columns 1 and 2 and ILR for columns 3 and 4. The characteristics included are as follows: quote-to-trade ratio (QT); relative bid–ask spread (SPREAD); ILR; log-market capitalization (MCAP); book-to-market ratio (BM), calculated as the natural logarithm of the book value of equity divided by the market value of equity from the previous fiscal year, previous-month return (R1); cumulative return from month $t-2$ to $t-12$ (R212); idiosyncratic volatility (IVOLAT), measured as the standard deviation of the residuals from a Fama and French (FF3) (1993) regression of daily raw returns within each month as in Ang et al. (2009); trading volume in (USDVOL) ($millions); and price (PRC). All characteristics apart from returns are logged, and all coefficients are multiplied by 100. The standard errors are corrected by using the Newey–West method with 12 lags. t-statistics for the QT variable are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Relative Spread		ILR		Turnover		IO	
	1	2	3	4	5	6	7	8
Panel A. Low								
Constant	0.033***	0.035***	0.032***	0.031***	0.040***	0.037***	0.043***	0.036***
$QT_{i,t-1}$	−0.194***	−0.191***	−0.179***	−0.189***	−0.159***	−0.161***	−0.184***	−0.193***
	(−2.65)	(−2.68)	(−2.72)	(−2.67)	(−4.17)	(−3.88)	(−4.40)	(−4.17)
$ILR_{i,t-1}$		−0.027				0.000		0.046*
$SPREAD_{i,t-1}$				−0.077		0.084***		0.025
$MCAP_{i,t-1}$	0.016	0.014	−0.005	0.001	−0.250***	−0.275***	−0.212***	−0.203***
$BM_{i,t-1}$	−0.012	−0.010	0.016	0.021	0.083	0.073	0.138	0.137
$R1_{i,t-1}$	−2.960***	−2.888***	−2.944**	−2.923**	−5.661***	−5.465***	−3.684***	−3.528***
$R212_{i,t-1}$	0.011	0.012	−0.040	−0.030	0.453**	0.465**	0.137	0.149
$IVOLAT_{i,t-1}$	−3.641	−2.937	−8.901*	−10.302*	−8.312*	−15.080***	−10.027**	−13.567***
$USDVOL_{i,t-1}$	−0.149	−0.173	−0.106*	−0.106	0.149**	0.193***	0.125***	0.172*
$PRC_{i,t-1}$	0.004	−0.003	−0.088*	−0.073	−0.262***	−0.250***	−0.461***	−0.429***
R^2	0.04	0.04	0.04	0.04	0.03	0.04	0.04	0.04
Time series (montds)	278	278	278	278	278	278	278	278
Panel B. High								
Constant	0.066***	0.064***	0.060***	0.061***	0.038***	0.030***	0.029***	0.036***
$QT_{i,t-1}$	−0.198***	−0.202***	−0.218***	−0.227***	−0.192**	−0.220***	−0.160**	−0.176**
	−4.841	−4.839	−4.153	−4.056	−2.213	−2.873	−2.333	−2.525
$ILR_{i,t-1}$		0.023			−0.013			−0.062**
$SPREAD_{i,t-1}$				−0.014		0.313		−0.132
$MCAP_{i,t-1}$	−0.356***	−0.352***	−0.349***	−0.350***	0.178	0.161	−0.059	−0.044

(continued on next page)

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TABLE 7 (continued)

Stock Returns and Quote-to-Trade Ratio Across Subgroups

	Relative Spread		ILR		Turnover		IO	
	1	2	3	4	5	6	7	8
Panel B. High (continued)								
$BM_{i,t-1}$	0.077	0.076	0.043	0.041	−0.017	−0.022	−0.053	−0.047
$R1_{i,t-1}$	−3.810***	−3.680***	−3.759***	−3.751***	−2.622***	−2.621***	−3.176***	−3.129***
$R212_{i,t-1}$	0.162	0.164*	0.185	0.195*	−0.060	−0.057	−0.029	−0.028
$IVOLAT_{i,t-1}$	−10.604***	−11.289***	−8.036**	−8.978*	−0.460*	−3.954	−2.342	−0.839
$USDVOL_{i,t-1}$	0.143***	0.160*	0.167***	0.156*	−0.297**	−0.254	−0.027	−0.109
$PRC_{i,t-1}$	−0.456***	−0.452***	−0.418***	−0.386***	−0.336*	−0.299	−0.178	−0.167
R^2	0.04	0.04	0.04	0.04	0.04	0.05	0.04	0.04
Time series (montds)	278	278	278	278	278	278	278	278

mechanism, but not all. The results on turnover (see Panel C of Table 6) show that the QT effect is quite strong across all turnover levels.[32]

In Table 7, we extend the univariate analysis to a multivariate analysis for stocks divided into two groups, depending on the median liquidity level in each month: one group with low liquidity and one group with high liquidity. Then, we reestimate the Fama–MacBeth regressions as in Table 4. Consistent with the impediments-to-arbitrage hypothesis, Table 7 shows that the QT effect diminishes when liquidity is high, but nevertheless, it remains statistically and economically significant for both subgroups.

Next, we perform a back-of-the-envelope calculation to estimate how large a transaction cost is needed to eliminate the QT alpha from Table 6. Consider the Amihud illiquidity ratio, which is a price-impact measure computed as a stock's absolute daily return divided by its daily trading volume. For stocks that exhibit the strongest QT effect, the average value of this ratio is 0.17 (i.e., a $1M trade triggers a 0.17% price impact). Given a 5-factor alpha of 0.83% in this group, it would take a trade of 0.83%/0.17% = $4.88 million to eliminate the profit over a single day. This is a substantial amount for the equity markets, where the average trade size is approximately $1 million. Moreover, Panel C of Table 6 shows that the QT effect is strong across stocks with different levels of trading turnover. Our results, therefore, suggest that the impediments-to-arbitrage hypothesis provides only a partial explanation for the QT effect.

B. Institutional Investors and Governance

Institutional investors as equity holders have become more active participants in the governance of modern corporations, whether by "voice" or by exit threat (see, e.g., Admati, Pfleiderer, and Zechner (1994), Maug (1998), and Gillan and Starks (2000). Good corporate governance in general increases firm value and reduces agency costs, leading to lower costs of capital (see, e.g., Becht, Franks, Mayer, and Rossi (2008); Brav, Jiang, Partnoy, and Thomas (2008)).

Albuquerque et al. (2021) find that long-term institutional investors tend to hold stocks with larger relative tick size and higher QT ratios. This suggests an alternative explanation of the QT effect where the QT ratio simply captures the proportion of institutional investors and level of corporate governance, which has an inverse relation with the cost of capital.

Thus, the QT effect should be stronger among stocks with lower institutional holdings and insignificant for stocks with higher institutional ownership. We test this hypothesis using both univariate and multivariate approaches. We construct institutional holdings of equity in firm i at the end of the year using 13F files. For the univariate analysis, we first sort stocks by institutional holdings and examine the alphas from a strategy that, within each institutional ownership tercile, goes long in low-QT stocks and short in high-QT stocks.

In Panel D of Table 6, we report the results for portfolios double-sorted on QT and institutional ownership. The results provide partial support for the institutional

[32]The results remain quantitatively similar when using other proxies for transaction costs, such as the quoted spread, number of trades, or dollar traded volume. We do not report these results for brevity, but they are available from the authors.

investors hypothesis. We find the strongest QT effect among stocks with the lowest institutional ownership. However, the alphas for all institutional ownership terciles are statistically significant. The abnormal return for stocks with the smallest institutional ownership is between 47 and 75 bps, and it is between 36 and 45 bps for the group with the most institutional investors. The difference in abnormal returns across these groups is consistent with the hypothesis that institutional investors play a role in reducing the cost of equity. Nevertheless, the abnormal returns across all institutional ownership groups remain statistically and economically significant. Thus, we find that institutional ownership dilutes but does not subsume the QT effect.

In columns 7 and 8 of Table 7, we show the estimated QT effect using Fama–MacBeth regressions across subsamples with high and low institutional ownership. Consistent with the univariate analysis, we find that the QT effect is partly mitigated by institutional ownership, decreasing by 20 bps between the samples with low and high institutional ownership. However, the QT effect remains statistically and economically significant. In additional analysis, column 2 of Table IA.7 in the Supplementary Material analyzes the QT effect while directly controlling for institutional ownership. Column 2 of Table IA.7 shows that the magnitude of the QT effect (in column 5 of Table 4) decreases with the inclusion of the institutional ownership variable by 0.013%, but QT remains highly statistically and economically significant.

C. Return Continuations and Reversals

In Section II.D.1, we consider only 1-month holding (portfolio rebalancing) periods. One could raise the concern that the QT effect is caused by temporary price effects. For example, suppose stocks with high or low realized returns attract HFT activity and get a temporary spike in the QT ratio. This type of explanation implies that the QT effect is only a short-term phenomenon. If that were the case, we would expect stocks to switch across QT portfolios and the alphas of a QT long–short strategy to decrease over longer holding periods.

To test the reversal hypothesis, we examine the average monthly risk-adjusted returns (alphas) of the QT long–short strategies for different holding and formation periods. We use the calendar-time overlapping-portfolio approach of Jegadeesh and Titman (1993) to calculate postperformance returns. We assign stocks into portfolios based on QT levels at four different formation periods and examine the average QT level for these portfolios in month $t+k$, keeping the portfolio constituents fixed for k months, where k ranges from 1 to 12 months. We use four formation periods; that is, we condition on different sets of information about QT: time t and the 3-, 6-, and 12-month moving average QT level.

Figure IA.1 in the Supplementary Material shows the long–short alphas from a 5-factor model (Fama–French 3-factor model plus momentum and liquidity) for strategies that long the low-QT portfolio and short the high-QT portfolio at different holding horizons and formation periods. The holding horizons reflect the number of months for which the portfolio constituents are kept fixed after the formation month (i.e., portfolios are rebalanced every k months). We construct the long–short strategies for 25 portfolios and examine four different formation periods.[33] The figure shows that the QT effect is very persistent. The 1-month formation and holding-period portfolio has the highest alpha of 1.00%. Overall, the long/short alphas after a year of both formation and holding periods are 0.50% per month and highly statistically significant.

D. Algorithmic Trading and Reg NMS

The emergence of algorithmic trading and the introduction of Reg NMS are two major events during the sample period that are likely to have important effects on the U.S. equity market structure.[34] Thus, to investigate whether our QT effect is robust to these market-structure changes, we verify the QT effect for the different subsamples defined by these two events.

We first consider the emergence of algorithmic trading. Because Hendershott et al. (2011) document the proliferation of algorithmic and electronic trading only after 2003, one might think that the QT effect should hold differently in the subsample from June 1994 to Dec. 2002 compared with the subsample from Jan. 2003 to Dec. 2017. Indeed, because the QT ratio is often used as a proxy for algorithmic trading and HFT (see footnote 9), one may argue that the QT effect is driven by the effect of algorithmic trading on the cost of capital. However, in the earlier subsample, the QT ratio is less likely to be related to algorithmic trading. Thus, if we find that the QT effect holds similarly in both subsamples, algorithmic trading is less likely to be an explanation for the QT effect.

Table IA.9 in the Supplementary Material shows the results of Fama–MacBeth regressions similar to those in Table 4 but performed over the two subsamples (June 1994–Dec. 2002 and Jan. 2003–Dec. 2017). The effect of the QT ratio on risk-adjusted returns is large and statistically significant in the pre- and post-2003 period, despite the reduction in power due to the lower number of time-series observations.

Additional evidence is shown in column 7 of Table 3. In this column, we report the alphas of 10 portfolios sorted on QT, where alpha is computed according to the standard risk factors plus a PIN factor. Because the PIN factor is available only until 2002, we are in effect computing the alphas during only the first part of our sample. We find that during this pre-algorithmic period, the effect of the QT ratio on risk-adjusted returns is strong and even larger than for the other columns in Table 3, which are computed using the whole sample.

Next, we investigate the introduction of Reg NMS, which transformed the market landscape by introducing more competition and led to unprecedented market fragmentation. Table IA.9 in the Supplementary Material shows the results of Fama–MacBeth regressions similar to those in Table 4 but performed over two different subsamples: June 1994–Dec. 2006 and Jan. 2007–Dec. 2017. The effect of QT on risk-adjusted returns is large and statistically significant in the pre- and post-2007 period.

[33]The results are robust to other factor model specifications and to the creation of more portfolios. These results are available from the authors.

[34]Table IA.4 in the Supplementary Material shows that the QT ratio increases significantly after both of these events.

In conclusion, Sections IV.C and Sections IV.D show that the QT effect holds at longer predictability horizons and is persistent throughout the sample.

V. Conclusion

This article studies the quoting activity of market makers and how the resulting QT ratio is related to liquidity, price discovery, and expected returns. Empirically, we find that the QT ratio is larger in neglected stocks, that is, in stocks with low analyst coverage, institutional ownership, trading volume, and volatility. Our main finding, the QT effect, is that stocks with higher QT ratios have lower average returns. Despite the fact that the QT ratio has increased significantly over time (especially since 2003), the QT effect is qualitatively unchanged across sample periods. Further analysis shows that the QT effect is driven by quotes and not by trades and is robust after controlling for other variables known to affect returns.

Because the quoting activity of market makers is clearly an important determinant of the QT ratio, we propose a model that incorporates i) the quoting activity that comes from the market makers' monitoring of the market and ii) the cost of capital that comes from risk-averse investors. The model is consistent with our stylized empirical findings and produces additional predictions that are borne out in the data: A larger number of market makers lowers the QT ratio but has no effect on expected returns. In our model, the QT effect is driven by investors' aggressiveness: For example, when investors are more precisely informed, market makers monitor faster and thus increase the QT ratio but at the same time reduce mispricing and lower expected returns. Although we rule out several likely alternative interpretations, we acknowledge that there could be other, nonmutually exclusive explanations for the surprising association between the QT ratio and the cost of capital.

Appendix. Proofs

Proof of Proposition 1. Fix the monitoring rate $q>0$. Let $\mathcal{I}_\tau$ be the dealer's information set just before trading at τ, and by E_τ denote the expectation operator conditional on $\mathcal{I}_\tau$. Let $w_\tau = \mathrm{E}_\tau(v)$ be the current dealer's forecast of the fundamental value, and $G_\tau = \mathrm{Var}(v - w_\tau)$ the variance of the forecast error. To simplify notation, in the remainder of this proof, we omit the subscript τ for the forecast w_τ and so on.

We compute the dealer's expected utility from quoting (a,b) at τ. If we define the following:

$$h = \frac{a-b}{2}, \quad \delta = w - \frac{a+b}{2}, \quad e = v - w, \tag{A-1}$$

the quoting strategy is equivalent to choosing (h,δ). Equation (5) implies that traders' buy and sell demands at t are given, respectively, by $Q^b = (k/2)(v-a) + \ell - m + \varepsilon^b$ and $Q^s = (k/2)(b-v) + \ell + m + \varepsilon^s$, with $\varepsilon^b, \varepsilon^s \sim \mathcal{N}(0, \Sigma_L/2)$. If x_0 is the dealer's initial inventory, the final inventory x_{end} satisfies $x_{\text{end}} = x_0 - Q^b + Q^s$, which translates into the following:

$$\text{(A-2)} \qquad x_{\text{end}} = x_0 - k\delta + 2m + \varepsilon, \qquad \varepsilon = -ke + \varepsilon^s - \varepsilon^b \overset{\text{IID}}{\sim} \mathcal{N}\left(0, k^2G + \Sigma_L\right).$$

Substituting Q^b and Q^s in the dealer's objective in equation (8), and ignoring monitoring costs, we get $\text{E}_\tau(x_0 v + (k/2)(a-v)^2 - (k/2)(v-b)^2 + (\ell - m)(a - v) + (\ell + m)(v-b) - \gamma x_{\text{end}}^2)$. We decompose $\text{E}_\tau(v-b)^2 = \text{E}_\tau(v - w + w - b)^2 = G + (w-b)^2$, and similarly $\text{E}_\tau(a-v)^2 = G + (a-w)^2$. Also, $\text{E}_\tau\left(x_{\text{end}}^2\right) = (x_0 - k\delta + 2m)^2 + \left(k^2G + \Sigma_L\right)$. Using the notation in equation (A-1), the dealer's maximization problem is equivalent to the following:

$$\text{(A-3)} \quad \max_{h,\delta} \left(x_0 w - kG - k\delta^2 - kh^2 + 2\ell h + 2m\delta - \gamma(x_0 - k\delta + 2m)^2 - \gamma\left(k^2G + \Sigma_L\right)\right).$$

The first-order condition in equation (A-3) with respect to h implies $h = \ell/k$, which shows that the optimal half spread satisfies equation (9). The first-order condition in equation (A-3) with respect to δ implies $\delta = \gamma x_0/(1+k\gamma) + (m/k)((1+2k\gamma)/(1+k\gamma))$, which shows that the optimal discount satisfies equation (9). The second-order conditions are satisfied for both h and δ. The maximum expected utility the dealer can achieve (ignoring monitoring costs) is as follows:

$$\text{(A-4)} \qquad U_{\max} = x_0 w + \frac{\ell^2}{k} - k(1+k\gamma)G - \gamma\Sigma_L + \frac{m^2 - 2\gamma k m x_0 - \gamma k x_0^2}{k(1+k\gamma)}.$$

Note that this formula is linear in the forecast w; hence, by the law of iterated expectations, it is time consistent and well defined as a value function. □

Proof of Lemma 1. In general, the forecast is the average signal with weights given by the precision of each signal. But the precision of each signal is the same: $1/\text{Var}(\varepsilon_0) = F(q)$. Hence, the forecast is the equal-weighted average signal: $w_t = v + (\varepsilon_0 + \cdots + \varepsilon_n)/(n+1)$. The variance of the forecast error is $\text{Var}(v - w_t) = \text{Var}((\varepsilon_0 + \cdots + \varepsilon_n)/(n+1)) = \text{Var}(\varepsilon_0)/(n+1)$; hence, the forecast precision is $1/\text{Var}(v - w_t) = (n+1)F(q)$. □

Proof of Proposition 2. Recall that we consider the initial signal s_0 as the dealer's prior, whereas the other signals s_n with $n > 0$ result from monitoring. Trading has frequency 1, and monitoring has frequency q. Hence, at each time before trading occurs, the probability that monitoring occurs before trading is $q/(q+1)$, whereas the probability that trading occurs before monitoring is $1/(q+1)$. Denote by n the event in which exactly n monitoring times occur before trading. The ex ante probability (before monitoring starts at $t = 0$) of event n is $(q/(q+1))^n(1/(q+1)) = q^n/(q+1)^{n+1}$. In that case, Lemma 1 implies that the forecast variance is $G_n = 1/((n+1)F(q))$. Thus, the ex ante expected forecast variance is:

(A-5) $$G(q) = \text{Var}(v - w_n) = \sum_{n=0}^{\infty} \frac{q^n}{(q+1)^{n+1}} \frac{1}{(n+1)F(q)} = \frac{\ln(q+1)}{qF(q)},$$

where the last equality comes from the Taylor series: $\ln(1-\alpha) = -\sum_{n=0}^{\infty} \alpha^{n+1}/(n+1)$, with $\alpha = q/(q+1)$. When $F(q) = f \ln(q+1)$, we get $G(q) = 1/(fq)$.

Consider general functions $G(q)$ and $C(q)$. Then, equation (A-4) from the proof of Proposition 1 implies that the dealer's maximum expected utility (accounting for the monitoring costs $C(q)$ is of the form $U_{\max} = D - k(1+k\gamma)G(q) - C(q)$, where D is a constant that does not depend on q. The first-order condition with respect to q is equivalent to $-k(1+k\gamma)G'(q) - C'(q) = 0$. Thus, the first-order condition for q is as follows:

(A-6) $$-\frac{C'(q)}{G'(q)} = k(k\gamma + 1).$$

The second-order condition for a maximum is $k(k\gamma+1)G''(q) + C''(q) > 0$, which is satisfied if the functions G and C are convex, with at least one of them strictly convex.

We now use the specification $F(q) = f \ln(q+1)$ and $C(q) = cq$ and compute the optimal q. Because $G(q) = 1/(fq)$, equation (A-6) implies that q satisfies $fcq^2 = k(k\gamma+1)$, which proves the first part of equation (14). Because G is strictly convex, the second-order condition is satisfied. One verifies that $F(q) = fq$ and $F(q) = f$ correspond, respectively, to $G(q) = \ln(q+1)/(fq^2)$ and $G(q) = \ln(q+1)/(fq)$, which are strictly convex functions as well. □

Proof of Corollary 1. By visual inspection of equation (14), it is clear that q is increasing in k and γ and decreasing in f and c. □

Proof of Corollary 2. Equation (15) implies that the cost of capital (discount) is equal to $(m/k)((1+2\gamma k)/(1+\gamma k)) + (\gamma/(1+\gamma k))x_0$. This is clearly increasing in m. The derivative with respect to k is $-(m(2\gamma^2k^2 + 2\gamma k + 1))/(k^2(1+\gamma k)^2) - ((\gamma^2/((1+\gamma k)^2))x_0$, which is negative if $x_0 \geq 0$. □

Proof of Corollary 3. Suppose we hold all parameters constant except for k. According to Corollary 2, the discount δ is decreasing in k. At the same time, the quote rate q is increasing in k (see Corollary 1). This proves the inverse relation between δ and q. □

Proof of Corollary 4. Equation (17) follows by simply substituting equation (16) in equation (15) and applying Proposition 1 to show that these values correspond to the equilibrium. It remains only to show that the neutral inventory

$x_0 = m/(\gamma k)$ indeed balances the expected order flow. We use the notation from the proof of Proposition 1. From equation (5), it follows that in equilibrium, $Q^b - Q^s = k(v - ((a+b)/2)) - 2m + \varepsilon^b - \varepsilon^s$. As $\mathrm{E}_\tau(v) = w$ and $w - (a+b)/2 = \delta$, we have $\mathrm{E}_\tau\left(Q^b - Q^s\right) = k\delta - 2m$. Thus, when δ is equal to its neutral value, $\delta_{\text{neutral}} = 2m/k$, the order flow is balanced (i.e., $\mathrm{E}_\tau\left(Q^b\right) = \mathrm{E}_\tau(Q^s)$). But equation (9) shows that x_0 and δ are in one-to-one correspondence. Thus, if δ is equal to its neutral value, x_0 is also equal to its neutral value. Hence, when $x_{0,\text{neutral}} = m/(\gamma k)$, the expected order flow is balanced, and this completes the proof. □

Supplementary Material

To view supplementary material for this article, please visit http://dx.doi.org/10.1017/S002210902000071X.

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