Coarse Pricing in QE Auctions*

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Abstract

This paper documents and studies the practice of coarse pricing by highly sophisticated institutions in an important market. Although the Fed explicitly sets the tick size of 1/256th in its QE-driven reverse auctions to purchase Treasury securities, the offer prices of primary dealers—the only direct participants—exhibit strong clustering on coarser grids. This coarse pricing has decreased over time but surged temporarily during March 2020. It grows when the offer-to-cover ratio is low, indicating a competitive constraint. Importantly, primary dealers with larger market shares price more finely, and laggard dealers employ coarse pricing especially when precise pricing is difficult. With regard to the Fed's purchase costs, coarsely priced offers have higher prices, conditional on winning the auction. This difference might reflect lower auction-winning chances of coarsely priced offers. The results are consistent with the notion that dealers' coarse pricing results from the information cost associated with pricing precision, as proposed by Grossman et al. (1997), but not with dealer collusion. Topmost dealers uniquely advance market efficiency in these multi-trillion-dollar operations of the Fed.

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1 Introduction

In March 2009, the Fed launched a large-scale purchase program of long-term Treasury securities, now marked as the beginning of its quantitative easing (QE) purchases of government bonds. After more than a decade of the Fed's QE, there is currently abundant and growing literature on its macroeconomic effects. Yet, we still know little about the market where these massive purchases take place. This is rather puzzling given the Fed's enormous purchase sizes and the role of the U.S. Treasury market as the "single most important financial market in the world" (Group of Thirty, 2021). To fill this gap, this paper closely examines offer-level data from the Fed's reverse auctions (hereafter called QE auctions) for Treasury security purchases,[1] and document that primary dealers (PDs) of the Federal Reserve Bank of New York (FRBNY)—the only direct participants in QE auctions—exhibit coarse pricing behavior.

Specifically, in QE auctions the Fed sets the uniform tick size of 1/256th (i.e., 0.390625 cents) per $100 par value for all target Treasury notes and bonds, although quotes of those securities are seldom posted at this level of fineness in secondary trading venues. Figure 1 demonstrates the existence of coarse pricing among (successful) offers in QE auctions, and perhaps more surprisingly, a striking difference between two PDs: Morgan Stanley (with the second largest market share in my sample of QE auctions) and Credit Suisse (with the seventh largest market share). Whereas Morgan Stanley's price endings are almost uniformly distributed, Credit Suisse's distribution displays a strong clustering of price endings on 0, 4/256, 8/256,. . . , 252/256 (i.e., 1/64ths).[2] Coarse pricing has been documented in various financial (and non-financial) markets,[3] but it is particularly surprising in this setting. First, Treasury securities are one of the world's most liquid and heavily researched asset classes. Second, PDs (and institutions indirectly participating in QE auctions) are highly sophisticated investors with expertise in fixed-income valuation. Third, in QE auctions there is no incentive to sacrifice pricing precision for execution priority; offers are treated equally as long as

[1]As discussed in Section 2, some of the reverse auctions in my sample period are better framed as traditional market operations rather than QE. However, for convenience, I use the term QE auctions to refer to all the Fed's reverse auctions of Treasury coupons.

[2]Note that Credit Suisse's smaller sample size can lead to greater variability in realized proportions of price endings, but not clustering on a specific subset of price endings.

[3]They include stock exchanges (Harris, 1991; Ikenberry and Weston, 2008; Bhattacharya et al., 2012), gold markets (Ball et al., 1985), future markets (Ap Gwilym et al., 1998a,b; Kuo et al., 2015), and particularly relevant to this research are dealer markets such as NASDAQ (Christie et al., 1994; Christie and Schultz, 1994, 1999) and municipal bond markets (Li, 2007; Griffin et al., 2023). Nikiforov and Pilotte (2017a,b, 2019) also document price-end clustering of Treasury coupon securities in the secondary market.

they are submitted by the QE auction closure.

This paper studies the causes and consequences of this previously undocumented practice in QE auctions. Market microstructure literature suggests two possible reasons. First, dealers' coarse pricing might work as a mechanism to coordinate among themselves, thereby extracting higher profits. A well-discussed example is NASDAQ market makers' avoidance of odd-eighth quotes, first documented by Christie and Schultz (1994). This practice was controversial especially because virtually no market makers deviated from the practice for *certain* stocks (Christie and Schultz, 1994). While disagreement exists about what caused this apparently anti-competitive practice,[4] it is a fact that this practice mechanically limited the minimum possible bid-ask spread to two eighths for the affected stocks. Nevertheless, this collusion view is inconsistent with the coarse pricing patterns observed in QE auctions. As suggested in Figure 1, top dealers, who by definition account for the bulk of transactions, engage in coarse pricing much less frequently, regardless of the Treasury security type.

An alternative view for dealers' coarse pricing is the "competitive theory of clustering" of Grossman et al. (1997), which was also proposed to explain the NASDAQ market maker behavior. According to this view, dealers, even when competing in the financial market, engage in coarse pricing due to information processing costs associated with increased pricing precision. Grossman et al. (1997, p. 25) state, "Finer units of trade allow for more accurate pricing. But this is a mixed blessing. It takes time and effort to obtain more precise valuations of assets," and as a result, "[t]he precise degree of coarseness chosen will depend on the balance between the benefits and costs of a finer grid." In the QE auction context, pricing precision's information costs can lead PDs to price on grids coarser than the Fed's 1/256ths grid, especially because secondary-market transactions are predominantly based on coarser grids (mainly 1/64ths or 1/128ths).

My results are consistent with the theory of Grossman et al. (1997). First, there exists a positive and strong association between the pricing fineness of (accepted) offers and the PD's market share in QE auctions. This result is expected if it is not costless for dealer banks to develop and employ sophisticated pricing technology tailored for this special QE market. (Note that the costs include not only capital investments but also, and perhaps more importantly, the attraction, retention, and deployment of human capital;

[4] Christie and Schultz (1994) interpret it as indicating implicit collusion, yet others point out institutional features limiting dealer competition (Demsetz, 1997; Kandel and Marx, 1997).

highly-skilled traders are a critical asset in high finance). Because the return from pricing technology increases with the investment size (Arrow, 1987; Peress, 2004), the cost-benefit tradeoff indicates a positive association between the market share and sophisticated pricing.

The estimated between-PD difference is economically sizable. This paper proposes a method to quantify PD-level pricing fineness in a manner that is directly interpretable and comparable. It infers the proportion at which a particular PD used each of the following four possible pricing grids—1/32nds, 1/64ths, 1/128ths, and 1/256ths. Because offered Treasury security types vary by PD and time, this method controls for this heterogeneity, estimating the proportions in case the PD prices a 'typical' security in QE auctions: off-the-run Treasury note maturing in 5–10 years. Take Figure 1 again. The estimated proportion of using the finest 1/256ths pricing grid is 94.9% for Morgan Stanley and 40.5% for Credit Suisse. More generally, according to my baseline specification, a one percentage point increase in QE auction market share translates into a 2.4 percentage point increase in the use of the finest 1/256ths grid.

Second, if the cost of increasing pricing precision drives dealers' coarse pricing, we should observe greater coarse pricing when it is more difficult—and therefore more costly—to precisely price the security (Ball et al., 1985; Grossman et al., 1997). I find a number of results in line with this prediction. First, coarse pricing is more pronounced for Treasury securities whose valuation is supposedly more difficult: those with longer remaining maturities (i.e., greater interest rate risk) and with high volatility. The second and perhaps more direct evidence is that offers for securities that are less finely priced in the secondary market are also priced less finely in QE auctions.[5] When a specific Treasury security's secondary-market prices are fine, it should be easier for PDs to price the security precisely in QE auctions—either because the fine secondary-market prices directly help them confidently price the security on a less coarse grid, or because fine prices in the secondary market indicate the intrinsic ease of precisely pricing the security. Moreover, I document that this effect is particularly large for non-top dealers.

Over time, PDs price more finely in QE auctions. This competition between PDs in upgrading pricing precision can be seen as direct micro-evidence of investor evolution in the adaptive markets view of Lo (2019). Notably, the Treasury security trading landscape has undergone remarkable changes during the

[5]Specifically, I collect daily closing ask prices of Treasury securities on the trading day preceding each QE auction.

analysis period. Joint Staff Report (2015) and Brainard (2018) indicate that in the 2010s dealers increasingly adopted fintech, such as systems for automated Treasury security trading, yet at different speeds.

The COVID-19 crisis period is, however, an exception to the trend toward greater pricing fineness. In massive Treasury purchase auctions of March 2020, pricing fineness temporarily plunged. This is a period in which the Treasury security market exhibited rare malfunctioning; in contrast to typical crisis episodes, the prices of long-term Treasury securities—arguably the world's safe haven—decreased in the wake of the COVID-19 crisis.[6] Yet, multivariate analysis indicates that the massive purchase sizes themselves, and the resulting low offer-to-cover ratios, contributed to the rise of coarse prices during this period. The inverse relationship between the offer-to-cover ratio and the prevalence of coarse pricing indicates the role of competition in curbing this phenomenon.

The last part of this paper investigates coarse pricing from the viewpoint of the Fed's QE operation costs. Admittedly, the lack of losing offer data limits the thoroughness of this analysis. My empirical approach is to compare the levels of offer prices among accepted offers for the same Treasury security in the same QE auction. The fixed-effects regressions show that *conditional on winning*, coarsely priced offers are more highly priced. Note that this does not necessarily mean that coarsely priced offers are generally more highly priced. To win a QE auction an offer needs to have a sufficiently *low* price. Consequently, higher prices, conditional on winning, can be observed as a result of a reduced probability of winning the auction. In any case, this exercise indicates that coarse pricing has cost implications for the Fed.

Two data limitations should be acknowledged. The first is that the offer-level data disclosed in accordance with the Dodd-Frank Act includes all *accepted* offers but not losing offers. This data curtailment precludes recovering some key structural parameters, such as dealers' marginal valuations (Boneva et al., 2020). In the context of this paper, this limitation's most direct consequence is that I can observe the pricing fineness of only winning offers, although the main interest lies in understanding how PDs price in general. This data curtailment can introduce a bias, as offers with different price-end fineness might have different auction-winning probabilities. The previous paragraph's finding suggests that coarsely priced offers have lower auction-winning probabilities. If this is the case, the extent of coarse pricing observed among *winning*

[6]The driver was investors dashing for cash, selling even safe Treasury securities to dealers at a massive scale (Duffie, 2020; He et al., 2022; Schrimpf et al., 2020; Vissing-Jorgensen, 2021).

offers should be regarded as a *lower* bound for dealers' actual use of coarse pricing, i.e., the extent of coarse pricing unconditional on the QE auction outcome.

Second, although QE auctions permit PDs to submit not only their own offers but also their clients' offers, the data do not flag client offers.[7] Consequently, the between-dealer variation might reflect different proportions of client offers. For example, the positive association between PD market share and pricing fineness can arise if client offers constitute a larger proportion for larger-market-share PDs *and* if client offers tend to be more finely priced. It appears highly unlikely that different client proportions solely explain the huge between-PD gap in pricing fineness.[8] Nevertheless, this issue should be kept in mind when interpreting the results concerning between-dealer differences.

This paper is policy-relevant. First, this paper sheds new light on the competition and microstructure of this important yet understudied market. In implementing QE-driven purchases, the Fed monitors "the performance of operations" and "the extent and concentration of dealer participation in operations" (Potter, 2013, p. 4). More broadly, there is an ongoing discussion about the optimal size—and "diversity"—of the Fed counterparties.[9] Based on the current primary dealer system, the Fed's market operations are solely intermediated by large Treasury security dealers designated as primary dealers. On one hand, Potter (2015) says that the system requires "established, regulated market participants" and "must be of an appropriate size to provide adequate execution capacity and competitive pricing." On the other hand, he also notes that "[s]taff time and resources are required to monitor and manage" relationships with counterparties.[10] This paper's results highlight the special role of topmost dealers in facilitating and enhancing price competition and market efficiency.

Second, the Fed's massive purchase scale means that coarse pricing can lead to substantial cost implications. In my sample period, the total amount of QE purchases of Treasury coupons is $3.92 trillion (with the average per auction being $4.12 billion). Then, one tick size change multiplied by the total purchase

[7] This is also the case of the proprietary U.K. QE auction data analyzed by Boneva et al. (2020).

[8] At the same time, I do not exclude the possibility that PDs' precise pricing capabilities are influenced by client offers. For example, finely priced offers from clients, or just receiving more client offers, might be helpful for the PD to increase the precision of its own offers.

[9] The "diversity" debate has emerged due to the increasing presence of non-dealers (most notably the so-called "principal trading firms") in the secondary market.

[10] The Fed's primary dealer pilot program (2013–2014), which temporarily allowed four relatively small dealers to participate in the Fed's operations, was one of the attempts to search for a better balance.

size amounts to $15.3 billion. The tick size is also economically significant in comparison to the Fed's transaction costs in QE auctions. Song and Zhu (2018) estimate that the weighted average cost (relative to the best ask price at auction closing) is merely 0.71 cents per $100 par value. This is roughly equivalent to two minimum ticks (0.78 cents per $100 par value).

This paper contributes to three strands of literature: First, this paper contributes to the literature on dealers' coarse pricing. In addition to the NASDAQ market maker behavior mentioned above, Li (2007) and Griffin et al. (2023) document that municipal bond dealers often price on a coarse grid (in eighths). Griffin et al. (2023) further show that dealers enjoy higher markups from such transactions. Note that the suspected mechanism here is the conflict of interest between well-informed sellers (dealers) and less-informed buyers (including retail customers) under decentralized bilateral transactions.[11] These market characteristics are quite different from QE auctions, where many PDs compete to sell more transparent Treasury securities. I show that in QE auctions dealers' coarse pricing is consistent with the theory of Grossman et al. (1997), in which they face a tradeoff between the pricing precision's cost and competitive advantage.

Second, this paper contributes to the emerging literature on the implementation mechanisms of QE. Song and Zhu (2018) study the Fed's preference in QE auctions and PDs' bidding behavior using the same data as this paper.[12] They first confirm that as the Fed's public disclosures suggest, the Fed prefers "cheap" Treasury securities, i.e., those whose secondary market prices are low relative to those implied by the yield-curve model. Song and Zhu (2018) then show that PDs extract higher profits when offering such securities. Boneva et al. (2020) analyze U.K. QE auction data containing both winning and losing offers. They structurally estimate U.K. primary dealers' marginal valuations of offered gilts, and show that these valuations are related to the interest rate risk and the regulatory capital requirements the dealers face. Laséen (2023) also uses comprehensive offer-level data in Sweden to study primary dealer behavior in those auctions.[13] This paper complements these papers in understanding price competition in QE auctions, taking cues from price-end patterns.

[11] The municipal bond market is unique among over-the-counter markets in that the participation of retail investors is high (see Bessembinder et al. (2020)).

[12] PDs' bidding behavior in Treasury issuance auctions is studied by Hortaçsu and Kastl (2012), Hortaçsu et al. (2018), and Allen et al. (2020).

[13] More broadly, the implementation cost of QE is also studied by D'Amico and King (2013) in the U.S., Breedon (2018) in the U.K., and Schlepper et al. (2020) in the Eurosystem. In addition, An and Song (2022) study the Fed's purchase prices in its agency MBS operations.

Third, this paper adds to the literature on the limited sophistication of sophisticated investors. Previous papers study institutional investors' herding (Wermers, 1999; Nofsinger and Sias, 1999; Griffin et al., 2003) and heuristic decisions (Akepanidtaworn et al., 2021; Wang, 2020) in stock trading.[14] This paper documents a manifestation of information processing constraints in the context in which it is arguably least expected—pricing of Treasury securities, the world's most heavily researched asset class, by the New York Fed's primary dealers, one of the most sophisticated and influential investor groups in the global economy (He et al., 2017; Goldberg, 2020).[15] Notably, pricing fineness of the market's most sophisticated investors is particularly interesting because it can even speak to the limit of market efficiency (Grossman and Stiglitz, 1980; Mondria et al., 2022).

2 Institutional background

2.1 Primary dealers

PDs are major dealers in U.S. Treasury securities designated by the FRBYNY as (sole) counterparties of the Fed's market operations. Most notably, PDs are allowed to submit competitive bids in Treasury issuance auctions (and profit from selling the purchased securities in the secondary market). A primary dealer status can also help the dealer attract large customers such as foreign central banks (Rennison and McLannahan, 2016). Their main requirements are as follows. First, PDs are expected to bid a certain amount in every Treasury issuance auction. Second, for other Fed operations (including QE operations), each PD is expected to participate "at levels commensurate with its size and presence in the market."[16] The last requirement is assisting the Fed to formulate monetary policy. During my sample period, the number of PDs changed

[14] Wang (2020) shows that institutional investors, like retail investors but to a lesser extent, exhibit the "round-number bias"—i.e., the tendency to submit orders with rounded price endings such as ".0"—in stock trading, and that this bias is lower for larger institutions. Note that his research question is fundamentally different from mine. Price-end clustering measured this way likely reflects traders' cognitive reference points (also see Bhattacharya et al. (2012), whose method Wang (2020) follows).

[15] Fleming et al. (2005) and Goldreich (2015) also study bounded rationality of PDs. They document evidence of sub-optimal bids in Treasury bill issuance auctions (until an auction rule change in 2004). One notable difference between their datasets and mine is that theirs are aggregated auction-level data, precluding PD-level analysis.

[16] The Fed's "Administration of Relationships with Primary Dealers" statement published on March 24, 2016 (`https://www.newyorkfed.org/markets/pridealers_policies.html`)

from 18 in 2010 to 24 in 2020.[17] Table 1 lists PDs in my sample period.

2.2 Phases of the Fed's QE

Table 2 lists major events among the Fed's QE purchases of Treasury securities. As shown in the last column, this paper divides the sample period into five sub-periods: *QE2* (August 17, 2010–September 20, 2020), *MEP* (September 21, 2011–December 11, 2012), *QE3* (December 12, 2012–October 29, 2014), *QE pause* (October 30, 2014–March 11, 2020), and *QE4* (March 12–June 29, 2020). Appendix A provides a summary of the history of the Fed's QE. Figure 2 shows the time series of the Fed's purchases of Treasury coupon securities.

The following clarifications will prove useful. First, the first sub-period (*QE2*) centers around, but is not limited to, the so-called "QE2" round, which was implemented from November 3, 2010 through June 22, 2011. Before and after the round, the Fed reinvested the proceeds of maturing securities into Treasury securities to maintain its balance sheet size. Those purchases are included in the *QE2* sub-period. Second, the *MEP* and *QE3* sub-periods exactly match the periods of the Maturity Extension Program (MEP) and the so-called "QE3," respectively. Third, the MEP was different from the other QE rounds in that the Fed financed the purchases of long-term Treasury securities by selling short-term securities (thereby not changing the aggregate bank reserves). Fourth, although the *QE pause* sub-period starts in October 2014, most of the purchases took place in August 2019 or thereafter. During this period, the Fed resumed reinvesting in Treasury securities to maintain a sufficient size of bank reserves. Lastly, the *QE4* sub-period covers QE purchases in response to the COVID-19 crisis (up to the sample conclusion of June 2020). Note that the primary purpose of the post-pandemic purchases was to tame the disruptions in the market (see Appendix A for more discussions).

2.3 Structure of QE auctions

The Desk of the FRBNY administers QE auctions, as in the case of other Fed market operations. Auction-level summary statistics are provided in Table 3. Details of the QE auction protocol vary from phase to phase, yet a typical timeline is as follows. First, the QE auction schedule for the next monthly cycle is

[17] The current and historical lists of PDs are available at `https://www.newyorkfed.org/markets/primarydealers`.

announced around the previous monthly cycle's end. The schedule lists the dates of auctions, together with their target maturity ranges (e.g., Treasury coupons with 4.5 to 7 years remaining to maturity) and expected purchase sizes.[18] Securities excluded from the auction, such as those scarce in the secondary market, are announced at the auction start. PDs are therefore well informed of which securities are included in the auction.

Second, on the auction date, PDs can submit up to nine offers per security. Each offer consists of price and quantity. Unlike Treasury issuance auctions, QE auctions are price-discriminatory; the offer price is the price at which the PD sells the security to the Fed if the offer is accepted. While PDs are the only direct participants, they can also place their clients' offers on their behalf. Both the minimum offer size and the price increment are set at $1 million. The tick size is 1/256th per $100 par value for all Treasury notes and bonds.

The Fed's QE auctions are multi-object auctions, as each auction accepts multiple Treasury securities within the target maturity range.[19] Therefore, the FRBNY adopts the following approach to rank offers for different securities. It first calculates the benchmark price for each auction-target security by applying its proprietary yield-curve model to secondary market prices (Sack, 2011). Then, offer prices normalized by their benchmark prices are directly comparable regardless of the differences in the offered securities. The FRBNY purchases from the offers with the lowest prices relative to the model-implied price until its desired total purchase amount is reached. Note that this protocol means that the Fed prefers securities whose market prices are below the prices implied by the Fed's model, i.e., "cheap" securities (Song and Zhu, 2018).

In my sample period, the median auction time is 45 minutes, and the auction close time ranges from 9:50 a.m. to 3:05 p.m., with 90.9% of them ending in the morning. It is exceedingly rare for an auction to end after 2 p.m. (1.6%).[20] The settlement is typically the next day, meaning that PDs can cover their short

[18]In early QE phases, the FRBNY disclosed the expected purchase *ranges*, while only the *maximum* purchase amounts are announced in later phases.

[19]In the average QE auction, 30.7 unique Treasury securities meet the basic eligibility criteria of QE auctions, with 3.8 of them being explicitly excluded for other reasons. Among the remaining 26.9 CUSIPs, 17.0 are purchased (Panel B of Table 3).

[20]More specifically, until 2019, the vast majority (95.9%) of QE auctions ended at 11:00 a.m. In the post-COVID-19 period, the Fed tended to hold multiple QE auctions (for different target maturities) at different times on the same day, resulting in more diverse auction close time.

positions anytime in the afternoon of the auction date.

Lastly, the FRBNY releases the auction result in three steps. First, immediately after each auction, the FRBNY releases quantity-related information, such as the total offered and accepted amounts and the purchased amount per security. Participating PDs are notified of their auction outcomes at this time. Second, the price-related information is disclosed at the end of each monthly auction cycle. The information is aggregated to the (purchased) security level. The disclosed items are the total offered and purchased amounts, the weighted average and highest accepted prices, and the proportion of accepted offers among the highest price offers. Lastly, about two years after the auction, the FRBNY releases disaggregated data on accepted offers, which is the primary dataset used in this study.

3 Data

The FRBNY publicly discloses all *accepted* offers of QE auctions after the enactment of the Dodd-Frank Wall Street Reform and Consumer Protection Act on July 21, 2010.[21] The offer-level data includes the Treasury CUSIP, offer price, offered amount, and the identity of the PD who submitted the offer. I retrieved all accepted offers for nominal Treasury notes and bonds.[22] My sample period spans from August 17, 2010 (the date of the first QE auction post-Dodd-Frank Act) to June 29, 2020 (the last auction date in 2020Q2). Treasury security information was obtained from TreasuryDirect.[23]

Table 4 reports the descriptive statistics of my sample offers. Security types dramatically vary over time. The vast majority of the purchased securities are off the run, with no on-the-run securities being purchased after the QE3 period. Also, the composition of remaining maturities varies strikingly over time. While 20–30 years account for 50.8% in the MEP period, 0–5 years is the majority (53.0%) in the QE4 period. These target security composition changes highlight the importance of controlling for security types in the empirical analysis. The bottom rows of Table 4 concern the market shares of PDs who submitted offers. The market share is based on trade amounts and calculated for each sub-period. Following Song and Zhu

[21] https://www.newyorkfed.org/markets/omo_transaction_data.html

[22] Therefore, my sample does not include Treasury bills or TIPS.

[23] https://www.treasurydirect.gov/instit/annceresult/annceresult_query.htm

(2018), I group PDs into top five PDs and non-top five PDs.[24]

4 Result

4.1 Setup

The market convention for quoting Treasury coupon securities is per \$100 par value, with the decimal part being a multiple of $1/32$ or a multiple of a fraction of $1/32$ (that is, $1/64$, $1/128$, or $1/256$).[25] In QE auctions, the tick size is set to one eight of $1/32$, i.e., $1/256$. Throughout the paper, a Treasury security prices' decimal part is denoted as $d/256$. That is, $d \in D = \{0, 1, 2, \ldots, 255\}$ and $d = 1$ means the price ending is $1/256$.

To analyze price-end clustering, which indicates dealers' use of coarser pricing grids, I divide D into four mutually exclusive subsets:

$$D = \{0, 1, 2, \ldots, 255\} = X_{32} \cup X_{64} \cup X_{128} \cup X_{256}, \text{where} \begin{cases} X_{32} = \{0, 8, 16, \ldots, 248\} \\ X_{64} = \{4, 12, 20, \ldots, 252\} \\ X_{128} = \{2, 6, 10, \ldots, 254\} \\ X_{256} = \{1, 3, 5, \ldots, 255\} \end{cases} \quad (1)$$

In words, each subset represents the possible *coarsest* pricing grid that the PD could have used to arrive at the particular d. For example, if $d \in X_{64}$, the possible coarsest pricing grid used by the dealer is $1/64$ths. This is because the dealer can arrive at $d \in X_{64}$ based on the pricing grid of $1/64$ths, $1/128$ths, or $1/256$ths, but not on the $1/32$nds grid. Note that only in the case of $d \in X_{256}$, the pricing grid used by the PD can be identified with certainty (to be $1/256$ths).

[24]The remaining results are robust to the use of alternative cut-off points, such as top four or top seven. Section 4.7 conducts detailed PD-level analysis.

[25]For example, given a \$1,000 face value, a price quote of \$101.09375 (= \$101 + 3/32) indicates that the bond's price is \$1,010.9375.

4.2 Testing price-end clustering on coarser grids in QE auctions

I follow Kuo et al. (2015) and Bhattacharya et al. (2018) to statistically test the existence of price-end clustering on coarser grids. Specifically, for each price ending $d \in D = \{0, 1, 2, \ldots, 255\}$, I calculate the percentage of offers with this price ending among all offers. To facilitate interpretation, this percentage is then subtracted by the expected percentage under the uniform priced-end distribution, which is $1/256 \times 100$ = 0.390625%. This outcome variable is regressed on the following variables:

$$Percent_d - 0.390625 = \alpha + \beta_1 D_{32} + \beta_2 D_{64} + \beta_3 D_{128} + \epsilon_{i,j}, \tag{2}$$

where D_{32}, D_{64}, and D_{128} take the value of one if the price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise.

The regression results are reported in Panel A of Table 5. Column 1, which pools all sample (winning) offers, shows strong price-end clustering on coarser grids. According to the constant, the percentage of a d in $X_{256} = \{1, 3, 5, \ldots, 255\}$ being selected is 0.177% (as it is 0.213 percentage points less than what is expected under the uniform distribution). This is due to clustering on grids coarser than 1/256ths; the three price-end type dummy variables are positive and statistically significant, meaning that price endings in D_{32}, D_{64}, and D_{128} are more likely to be selected. Based on Column 1, the probability of d in X_{32} being chosen is 0.177% + 0.839% = 1.016%. Likewise, the probabilities of a price ending in X_{64} and X_{128} are 0.719% and 0.340%. Importantly, the differences between D_{32} and D_{64} and between D_{64} and D_{128} are statistically significant. This result implies that PDs tend to use *all* of the coarse pricing grids, namely 1/32nds, 1/64ths, and 1/128ths.[26]

4.3 Estimating the proportions in which different pricing grids are used

The price-end clustering observed among accepted offers reflects dealers' use of coarse pricing grids. To directly gauge this behavior of dealers, I propose a method to infer the likelihoods that PDs employed the four possible pricing grids, based on the coefficients of Specification 2 (i.e., the observed price-end

[26] For example, if PDs used only the pricing grids of 1/128ths and 1/256ths, the coefficients of D_{32} and D_{64} should not be greater than that of D_{128}.

clustering). It is important to note that, given that my sample includes only *accepted* offers, the following inference is based on an implicit assumption that the price-end type is independent of the auction-winning probability.[27] If PDs always use the finest 1/256ths pricing grid (*grid-256ths*), then $\Pr[d \in X_{32}] = P[d \in X_{64}] = 12.5\%$, $\Pr[d \in X_{128}] = 25\%$, and $\Pr[d \in X_{256}] = 50\%$. I denote these conditional probabilities as $\phi_{32}^{grid\text{-}256ths}$, $\phi_{64}^{grid\text{-}256ths}$, $\phi_{128}^{grid\text{-}256ths}$, and $\phi_{256}^{grid\text{-}256ths}$, respectively. Table 6 summarizes these conditional probabilities for all the pricing grids.

Now, suppose that dealers use the 1/32nds pricing grid (*grid-32nds*) with probability λ_{32}, and the pricing grids of 1/64ths, 1/128ths, and 1/256ths with probabilities λ_{64}, λ_{128}, and λ_{256}, respectively. Then, the unconditional probabilities of price-end types are:

$$\phi_{32} = \lambda_{32} \times \phi_{32}^{grid\text{-}32nds} + \lambda_{64} \times \phi_{32}^{grid\text{-}64ths} + \lambda_{128} \times \phi_{32}^{grid\text{-}128ths} + \lambda_{256} \times \phi_{32}^{grid\text{-}256ths},$$
$$\phi_{64} = \lambda_{32} \times \phi_{64}^{grid\text{-}32nds} + \lambda_{64} \times \phi_{64}^{grid\text{-}64ths} + \lambda_{128} \times \phi_{64}^{grid\text{-}128ths} + \lambda_{256} \times \phi_{64}^{grid\text{-}256ths},$$
$$\phi_{128} = \lambda_{32} \times \phi_{128}^{grid\text{-}32nds} + \lambda_{64} \times \phi_{128}^{grid\text{-}64ths} + \lambda_{128} \times \phi_{128}^{grid\text{-}128ths} + \lambda_{256} \times \phi_{128}^{grid\text{-}256ths},$$
$$\phi_{256} = \lambda_{32} \times \phi_{256}^{grid\text{-}32nds} + \lambda_{64} \times \phi_{256}^{grid\text{-}64ths} + \lambda_{128} \times \phi_{256}^{grid\text{-}128ths} + \lambda_{256} \times \phi_{256}^{grid\text{-}256ths}.$$

The log-likelihood function can be defined as follows:

$$\ln \mathrm{L}(\lambda) = Fraction_{32} \times \ln \phi_{32} + Fraction_{64} \times \ln \phi_{64} + Fraction_{128} \times \ln \phi_{128} + Fraction_{256} \times \ln \phi_{256}, \quad (3)$$

where $Fraction_{32}$ is the observed fraction of $d \in X_{32}$, and $Fraction_{64}$, $Fraction_{128}$, and $Fraction_{256}$ are similarly defined.[28] I maximize this function to obtain the estimates of $\lambda = \{\lambda_{32}, \lambda_{64}, \lambda_{128}, \lambda_{256}\}$, with a constraint of each element of λ being between 0 and 1.

Panel B of Table 5 reports the predicted proportions in which the four pricing grids are used. The finest 1/256ths grid is predicted to be employed 45.4% of the time, and the coarsest 1/32nds grid 9.5% of the time. The rest is accounted for by the two pricing grids between these two extremes.

[27] As discussed later, I find some evidence suggesting that coarsely priced offers have a lower chance of winning a QE auction. If this is true, coarsely priced offers are underrepresented within the sample of accepted offers, leading to a downward bias in the predicted proportions of using coarse pricing grids. This potential sampling bias, arising from the data limitation, should be kept in mind.

[28] These ratios can be computed from the coefficients of Specification 2.

4.4 Price-end clustering by time and by PD

Table 5 also shows that price-end clustering in QE auctions greatly varies by time and the PD submitting the offer. In Columns 2–4, I repeat Specification 2 separately for each sub-period. There are two notable findings. First, PDs tend to price more finely over time. While the predicted proportion of the 1/256ths grid use is only 14.5% in the QE2 period, it accounts for more than 50% in the subsequent periods. Second, the predicted proportion of the coarsest 1/32nds grid use jumped to a much higher value than the earlier periods (21.2%) in the QE4 period. More specifically, Figure 3 illustrates that this surge in the coarsest pricing took place during the massive purchases of March 2020. The extent to which changing auction characteristics can explain these time-series patterns is examined in the next section.

The remaining columns of Table 5 show a stark difference in pricing fineness between top and non-top dealers. The last column of Panel A establishes the statistical significance, with the coefficients of all of D_{32}, D_{64}, and D_{128} being significantly lower for top dealers. Panel B also indicates that the difference is economically sizable; for instance, the predicted proportion of the 1/256ths grid use is 66.2% for top dealers and 26.3% for non-top dealers.

4.5 Determinants of coarse pricing in QE auctions

To analyze heterogeneity in coarse pricing, I regress the fineness of offer prices on security-, offer-, and auction-characteristics. The key idea is that the price-end type, X_{32}, X_{64}, X_{128}, or X_{256}, indicates the likelihood with which coarser pricing grids are used, with X_{32} being the highest and X_{256} the least. (To be precise, the probability of coarse pricing is zero if d is in X_{256}.) I therefore perform the ordered logit analysis with the dependent variable being *Price-end fineness*, which takes the value of one if the offer's price ending is in X_{32}, two if it is in X_{64}, three if it is in X_{128}, and four if it is in X_{256}. This analysis aims to uncover which factors increase (or decrease) the likelihood of precise pricing. Table 7 lists the definitions of variables used in this offer-level analysis. The descriptive statistics are provided in Table 8.

One key explanatory variable is *Cheapness*, which is included to analyze the effect of the Fed's algorithm in ranking offers. As explained in Section 2.3, the Fed's protocol prefers securities that are deemed undervalued based on the Fed's yield curve model. Although the model is not publicly disclosed, it is a standard cubic spline model (Sack, 2011), and Song and Zhu (2018) find that their yield curve estimation result—and the ensuing cheapness measure—can explain the Fed's purchase behavior. I thus estimate a cubic spline model following Song and Zhu (2018), and define *Cheapness* as the percentage difference between the yield-curve-implied price and the actual secondary-market price. The details of the yield curve estimation are summarized in Internet Appendix A.

Table 9 shows the estimation results. Panel A reports the coefficients and the marginal effects on the probability of *Price-end fineness* = 4, that is, $D_{256} = 1$.[29] The coefficient of *Top five* is positive and significant in all models. According to Model 1, the probability of the price ending being the finest type (i.e., $D_{256} = 1$) is 14.9 percentage points higher for top dealers' offers. This is sizable given that only 22.7% of sample offers have this finest price-end type (Table 8). Models 2 and 3 show that the marginal effect remains stable even when additional control variables are added.

In Model 1, *Cheapness* is negative and significant, meaning that prices are coarser when the Treasury security is deemed undervalued and therefore preferred by the Fed. Because strategic dealers can extract higher profits when delivering cheaper securities in QE auctions (Song and Zhu, 2018), those dealers might be using coarse pricing as a device to set a higher price for cheaper securities. However, the evidence is not consistent with this view.

First, Panel B further investigates this association by splitting the sample by *Top five* and reporting the marginal effect of *Cheapness* on all possible values of *Price-end fineness*. It shows that the marginal effects of *Cheapness* are generally more pronounced for non-top dealers. Strikingly, the marginal effect on the probability of *Price-end fineness* = 1 is 0.357 for those dealers, meaning that a one standard deviation change of *Cheapness* translates into an 8.50 percentage point increase in this probability. The stronger association for *non*-top dealers does not align well with the narrative that the effect of *Cheapness* is a result of dealers' deliberate coarse pricing for cheap securities. Instead, a more plausible explanation is that when the security is deemed undervalued by the Fed, it is more likely that even coarsely priced—or less sophisticatedly priced—offers can win the QE auction. (In Section 4.8, I show that coarsely priced offers are more highly priced among accepted offers.) This is because offers for cheap securities have an intrinsically higher chance

[29]The ordered logit model can derive marginal effects for each possible value of the outcome variable.

of winning a QE auction based on the Fed's algorithm to rank offers.

Second, the effect of *Cheapness* is sensitive to the inclusion of controls, with the coefficient even changing its sign. In particular, *Cheapness* is no longer negatively associated with *Price-end fineness* after controlling for three basic security types—on-the-run status, maturity, and Treasury bond dummy (Model 2 in Panel A of Table 9). On one hand, this result relates to the fact that *Cheapness* is highly positively correlated with remaining maturity.[30] On the other hand, this result is inconsistent with the view that dealers use coarse pricing deliberately and specifically for cheap securities. Rather, this result indicates that certain security types (most notably maturity) are associated with *both* pricing fineness and *Cheapness*.

Model 3 provides three additional insights. First, *Voaltility*, the standard deviation of the offered security in the five-day period leading up to the auction date, is negatively associated with pricing fineness. This finding is consistent with the hypothesis of Ball et al. (1985) and Grossman et al. (1997) that valuation uncertainty, and the resulting greater cost in precise pricing, drives coarse pricing.

Second, the result of *Offer-to-cover* suggests the role of competition in restricting coarse pricing. According to Model 3, one standard deviation increase in *Offer-to-cover* translates into a 1.99 percentage point increase in the probability of $D_{256} = 1$. Note that this is the effect after controlling for period dummies, and moreover, this result is not driven by massive post-COVID-19 purchases; the coefficient remains significant at the 1% level even if the QE4 period is dropped.

Third, pricing fineness is greater in later phases than in the first QE2 phase (the model's baseline period), and this is more evident after controlling for security- and auction-characteristics. In Model 1, the coefficient of *QE4* is not significant with a low marginal effect on the probability of $D_{256} = 1$ (a 3.8 percentage point increase). Yet, the variable is significant at the 1% level in Model 3, which controls for security- and auction-type variables. Most notably, *Volatility* is high and *Offer-to-cover* is low in the QE4 period, and these factors contributed to deteriorated pricing fineness in the post-pandemic QE operations.

[30] The correlation between *Cheapness* and remaining maturity in years is 0.754.

4.6 Pricing fineness in the secondary market for Treasury securities

I now turn my attention to the secondary market for Treasury securities with the purpose of better understanding the QE auction market's coarse pricing.

4.6.1 Trading venues and tick sizes

Since the launches of eSpeed and BrokerTec in 1999 (the latter of which started service in 2000), trades of on-the-run Treasuries have almost entirely moved to fully electronic systems (Mizrach and Neely, 2006). These markets now accommodate non-dealers, with the most significant non-dealer participants being the so-called principal trading firms (PDFs) (Harkrader and Puglia, 2020). However, once a security goes off-the-run, the trading volume plunges, and most of the trading migrates to more traditional voice-assisted systems (Barclay et al., 2006). Off-the-run trading is also characterized by high market fragmentation, as opposed to the on-the-run trading arena, where two platforms, BrokerTec and Dealerweb, dominate others (McPartland, 2018).

Tick sizes vary by transaction venue and maturity. The main electronic venues of on-the-run securities, such as BrokerTec and eSpeed (then acquired by Dealerweb), set the tick sizes of 1/128th for 2-, 3-, and 5-year notes and 1/64th for 7- and 10-year notes and 30-year bonds in the period investigated in this section.[31] Conversely, in the case of off-the-run trading on voice-assisted markets, it is customary, albeit not a rule, that brokers display tick sizes coarser than 1/256th (such as 1/64th and 1/128th), except for securities nearing maturity.

4.6.2 Pricing fineness in the secondary market for Treasury securities

To understand pricing fineness in the secondary market, I repeat the price-end clustering regression with secondary-market price data. For each Treasury security purchased in a QE auction, I obtained the security's daily closing ask price on the preceding trading day from Bloomberg.[32] The result of repeating

[31] These venues lowered the tick size of 2-year notes to 1/256th on November 19, 2018 (Fleming et al., 2022). Note, however, that the Fed purchased on-the-run securities only until August 2014.

[32] I do not use the CRSP Treasury data for studying price endings due to its apparent anomaly. For unknown reasons, the proportion of price endings in D_{128} doubled on March 7, 2012; while the average proportion was 23% for the preceding ten trading days, it jumped to 48% in the next ten trading days, and this was not a temporary phenomenon but a permanent shift. Bloomberg data does not exhibit such dramatic and puzzling price-end patterns.

Specification 2 with the secondary-market price data is reported in Table 10. According to Column 1 of Panel B, the predicted proportion of the 1/256ths grid use is 13.4%. The sub-period analysis reveals that this value remained virtually zero for the first three sub-periods (*QE2*, *MEP*, and *QE3*). The 1/64ths and 1/128ths grids account for a large fraction, and, there is little evidence of the coarsest 1/32nds grid use.[33]

Table 11 then estimates the ordered logit model of the determinants of pricing fineness of the secondary-market price data. Importantly, maturity exhibits a strong nagative association with pricing fineness, as was the case for QE auction offers. (*On-the-run* and *Bond* have the same signs, but they are not statistically significant in this secondary-market data analysis.) For example, relative to the baseline maturity of five to ten years, maturity of less than five years is associated with a 9.7 (18.6) percentage point higher probability of $D_{256}^{Secondary} = 1$ ($D_{128}^{Secondary} = 1$). To sum up, Table 11 suggests a link in pricing fineness between the secondary market and QE auctions.

4.6.3 Relating pricing fineness in the secondary market to that in QE auctions

To directly test the association, Table 12 regresses QE auction offers' *Price-end fineness* on the price-end type dummies of the security's secondary market price; $D_{256}^{Secondary}$ is a dummy variable taking the value of one if the price ending of the Treasury security's closing ask on the trading day preceding the QE auction is in X_{256}, and I similarly define $D_{32}^{Secondary}$, $D_{64}^{Secondary}$, and $D_{128}^{Secondary}$. Specifically, I estimate the ordered logit model with the baseline category being $D_{32}^{Secondary} = 1$. The coefficients show whether finer prices in the secondary market indicate finer offer prices in QE auctions (i.e., a higher *Price-end fineness*).

The positive coefficients of $D_{128}^{Secondary}$ and $D_{256}^{Secondary}$ in Column 1 confirm the association. They remain statistically significant even when security-type controls (*On-the-run*, $Maturity_{0\text{-}5}$, $Maturity_{10\text{-}20}$, $Maturity_{20\text{-}30}$, and *Bond*) are added (Column 4). To demonstrate the economic significance, Figure 4 plots the predicted probabilities according to the models of Columns 2 and 3 of Table 12. In particular, the predicted probabilities for the two extreme price-end types, X_{256} and X_{32}, greatly vary by the secondary-market price-end type for non-top dealers (Panel B of Figure 4). When $D_{32}^{Secondary} = 1$, the predicted probability of X_{256} is merely 11.5%. However, it jumps to 29.2% (i.e., a 153.9% increase) when $D_{256}^{Secondary} = 1$. On the other hand,

[33] Nikiforov and Pilotte (2017a) document a similar price-end distribution using tick-level data on Treasury notes.

the predicted probability of X_{32} drops from 42.8% to 19.1%.

These results strongly substantiate the costly nature of pricing precision as a driver of coarse pricing in QE auctions. There are two possible channels through which finer prices in the secondary market are associated with a lower cost of precise pricing for PDs. First, having fine secondary-market prices as inputs to the model makes it easier for dealers to confidently price securities on a fine grid. Second, securities with fine prices in the secondary market (e.g., short-maturity securities) are expected to be intrinsically easier to precisely price. That non-top dealers' pricing fineness is highly sensitive to the fineness of secondary market prices suggests that pricing easiness relaxes the limit of precise pricing that lagging PDs face.

4.7 Dealer-level analysis

4.7.1 PD-level pricing fineness

This section looks more closely at PD-level differences in coarse pricing. Pricing fineness varies by not only PD but also offered security type (Table 9). I thus quantify pricing fineness of each PD, after controlling for basic security characteristics. More specifically, I employ a variant of Specification 2, in which the right-hand side of the model includes dummy variables for three basic security characteristics—on-the-run status, remaining maturity, and Treasury note vs. bond—and PD $\times$ sub-period fixed effects. Appendix B explains more details about this method.[34] This approach allows for predicting the probabilities of price endings in X_{32}, X_{64}, X_{128}, and X_{256} for each PD in each sub-period in the case of offering 'typical' security in QE auctions, namely, off-the-run Treasury note maturing in 5–10 years. These predicted probabilities are then fed into the method of Section 4.3 to estimate the proportions in which different price grids were used. The summary statistics of the estimated PD-level proportions can be found in Table A.2 of Appendix B.

4.7.2 Pricing fineness and market share

PD-level analysis also points to a strong association between pricing fineness and market share. Figure 5 plots dealer market share and the predicted proportion of using the finest 1/256ths grid. Panel A of Table

[34] To include those dummy variables and fixed effects, the outcome variable, $Percent - 0.390625$, is calculated for each security type s, PD j, and sub-period t. Because this means that the ratios are calculated from different numbers of offers, the regression weights observations by the number of underlying offers.

13 shows that market share is significantly and positively associated with the use of the finest pricing grid for all the sub-periods other than *QE2*. The association becomes somewhat weaker but still remains, even if I use the predicted proportion of using the 1/128ths or 1/256ths grid (Columns 5–8).

In Column 1 of Panel B, which pools the four sub-periods, *Market share* is statistically and economically significant. The coefficient indicates that a one percentage point increase in *Market share* translates into a 2.4 percentage point increase in the finest 1/256ths grid use. Notably, this result is not driven by a few of the largest PDs, as it is robust to the exclusions of Goldman Sachs (Column 2) and Morgan Stanley (Column 3). In Column 4, I also remove small PDs (with less than 2% market share in the period). The result remains highly similar. Panel C shows that the coefficients of *Market share* remain similar even if the regressions are performed on the first differences.

Having established a strong positive association between pricing fineness and QE auction market share, I also ask whether pricing fineness is related to more primitive dealer characteristics such as balance sheet size, location, and experience. Internet Appendix B summarizes the data collection and the analysis result. Panel A of Table IA.4 shows that the use of the finest 1/256ths grid is positively associated with the balance sheet size and its use is lower for foreign PDs (i.e., PDs that are a subsidiary of a foreign-based financial group). However, these results are statistically significant only at the 10% level and become insignificant if the dependent variable is replaced with the probability of using the 128ths or 256ths grid (Panel B). Therefore, these variables' explanatory power is weak at best. In contrast, the market share remains highly significant even if PD-level controls are added. One interpretation is that the key driver of the between-PD variation in the tendency of precise pricing in QE auctions is their presence in this specific market, rather than their overall size or experience. At the same time, I note substantial measurement issues of my dealer-level variables; dealer size is measured infrequently and noisily,[35] and experience is only roughly measured.

[35] For most PDs, a separate balance sheet item for Treasury securities does not exist, and I simply analyze the balance sheet size.

4.8 Coarse pricing and the level of offer prices

Does coarse pricing relate to the *level* of offer prices, which ultimately determines the Fed's QE purchase costs? I examine this question by looking at differences in the level of prices *within* accepted offers for a given Treasury security in the QE auction. Specifically, I define *Price diff* as the percentage difference (in basis points) between the offer price and the lowest accepted offer price for the same security in the same QE auction, and run the following regression:

$$Price\ diff = \beta_1 D_{32} + \beta_2 D_{64} + \beta_3 D_{128} + \gamma + \epsilon_{i,j}, \tag{4}$$

where D_{32}, D_{64}, and D_{128} take the value of one if the (accepted) offer's price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise, and γ is CUSIP $\times$ QE-auction fixed effects. I measure *Price diff* only when multiple accepted offers exist for the security in the QE auction.[36] Absorbing between-security variation, γ ensures that D_{32}, D_{64}, and D_{128} compare *Price diff*—the offer price normalized by the lowest accepted offer for the security—for accepted offers with different price-end types *within* accepted offers for the same security in the same QE auction.

Panel A of Table 14 shows that the mean *Price diff*, which is winsorized at the 2.5% and 97.5%, is 3.6 basis points. This is fairly small, being less than the average bid-ask spread for my sample QE auction securities, 4.3 basis points (Table 8). This result is consistent with the claim of Song and Zhu (2018) that the QE auctions' operation costs are fairly moderate.

The regression results are documented in Panel B of Table 14. Column 1 is the result of estimating Specification 4, and it shows that (accepted) offers with coarse price endings have significantly higher prices compared to those with price endings in X_{256}. The differences are also economically significant. The coefficient of D_{32} (0.282) indicates that, relative to the mean value (3.61), (accepted) offers with the coarsest price endings have, on average, a 7.81% higher *Price diff*, which is the percentage difference between the offer's price and the minimum accepted offer price for the security in the QE auction.

[36]This restriction only slightly decreases the number of sample (accepted) offers: from 90,022 to 86,611. Conditional on having multiple accepted offers, the average (median) number of accepted offers for a Treasury security in a QE auction is 12.4 (10).

Therefore, coarsely priced offers on average have higher prices, *conditional on winning*. Note that this result does not necessarily mean that coarsely priced offers, unconditional on the QE auction outcome, are on average more highly-priced. For an offer to win a QE auction, its price needs to be sufficiently *low* relative to competing offers. Therefore, coarsely priced offers can have a higher average price conditional on winning simply because they have a lower chance of winning a QE auction in the neighborhood of the lowest acceptable price.

The remaining columns in Panel B of Table 14 show that *who* submits offers also matters. While the offer amount (*Ln(offer amount)*) has only an insignificant effect, *Top five*, the dummy for offers submitted by a top five dealer, is negative and significant at the 5% level in Columns 3 and 4.[37] Importantly, the inclusion of *Top five* materially lowers the effects of coarse pricing; the coefficients of D_{32} and D_{64} in Column 3 are slightly less than half of those in Column 1.

To summarize, Table 14 demonstrates that coarse pricing does indeed matter from the viewpoint of the Fed's QE operation costs. At the same time, prices are lower for accepted offers submitted by top dealers, and the association between pricing fineness and the offer price level is nearly halved when the top five dealer dummy is added to the right-hand side of the model. Therefore, the association partially reflects the fact that coarsely priced offers are more likely to come from non-top five dealers, whose accepted prices tend to be more highly priced.

5 Discussion of client offers

The positive association between market share and pricing fineness is consistent with the notion that larger-market-share PDs are more willing to seek precise pricing; the information processing costs of pricing precision can lead to increasing returns from pricing technology (Arrow, 1987; Peress, 2004). This section discusses how the existence of client offers can affect this interpretation.

In QE auctions non-PDs (such as hedge funds and money managers) are allowed to submit offers indirectly through PDs (Sack, 2011). Unfortunately, these client offers cannot be discerned in my data. Con-

[37] Note that in the presence of CUSIP × QE-auction fixed effects, any Treasury security-characteristic variables will be subsumed.

sequently, one concern is that the positive association between pricing fineness and market share might reflect different proportions of client offers *and* different extent of coarse pricing between PDs and clients. Consider a (seemingly more plausible) situation in which top PDs route more client offers due to their more extensive customer network. In such a case, in order for client offers alone to produce the positive association between PD market share and pricing fineness, clients must have a tendency to price more finely than PDs. There is one institutional reason to suspect this. In these primary dealer-intermediated markets, clients are aware that PDs can revise their own offers after observing client offers, possibly deliberately undercutting them (Hortaçsu and Kastl, 2012). As such, coarse pricing can be particularly costly for clients.

The observed between-PD variation, however, still rejects client offers as a sole explanation. Consider the MEP period as an example (Panel B of Figure 5). In this period, the estimated proportion of using the 1/256ths pricing grid reached 100% for Morgan Stanley, the market share leader. Of course, this should be the case only if *both* the PD (Morgan Stanley) and its clients always used the finest pricing grid. This result, however, is inconsistent with the assumption that clients tend to price more finely than PDs. Therefore, there must be at least *some* between-PD differences in the tendency of coarse pricing.[38]

6 Conclusion

This paper sheds new light on price competition in a massive, important, yet still understudied market: QE reverse auctions of Treasury securities. To my knowledge, this paper is the first to document dealers' practice of submitting coarsely priced offers in this market. As such, it complements the work of Song and Zhu (2018), who conduct auction theory-based analysis of dealer behavior in the Fed's QE auctions. On one hand, coarse pricing is on a downward trend. On the other hand, coarse pricing surged during the Fed's massive pandemic-driven purchases in March 2020. I also show that *conditional on winning a QE auction*, coarsely priced offers are more highly priced. Therefore, this practice has relevance for policymakers designing and monitoring this market.

The cross-sectional analysis of pricing fineness reveals that it varies by the ease of precisely pricing the

[38]Notably, this logic does not exclude the possibility that PDs *learn* from client offers; observing a larger number of client offers might help top PDs to price more finely than others.

security. Offer prices are more finely priced when valuation uncertainty is limited (e.g., low volatility) and when the security is finely priced in the secondary market prior to the auction. This paper also documents strong association between PD market share and pricing fineness—offers submitted by larger-market-share PDs are more finely priced. The relationship is economically significant; my benchmark specification indicates a one percentage point increase in market share translates into a 2.39 percentage point increase in the estimated proportion of using the finest 1/256ths grid. Collectively, my results are consistent with Grossman et al.'s (1997) theory that information costs of increasing pricing precision lead to coarse pricing of dealers. In contrast, I do not find evidence that coarse pricing works as a coordinating mechanism for PDs to maintain high spreads. Yet, the results do imply that competition plays a role in constraining coarse pricing.

This paper thus illustrates the special importance of the topmost dealers in the Fed's counterparty framework—they can uniquely facilitate price competition and market efficiency in Fed operations. Also, from a theoretical standpoint, this paper presents rare micro-level evidence that information processing costs can lead to a trade-off in pricing precision even among highly sophisticated investors.

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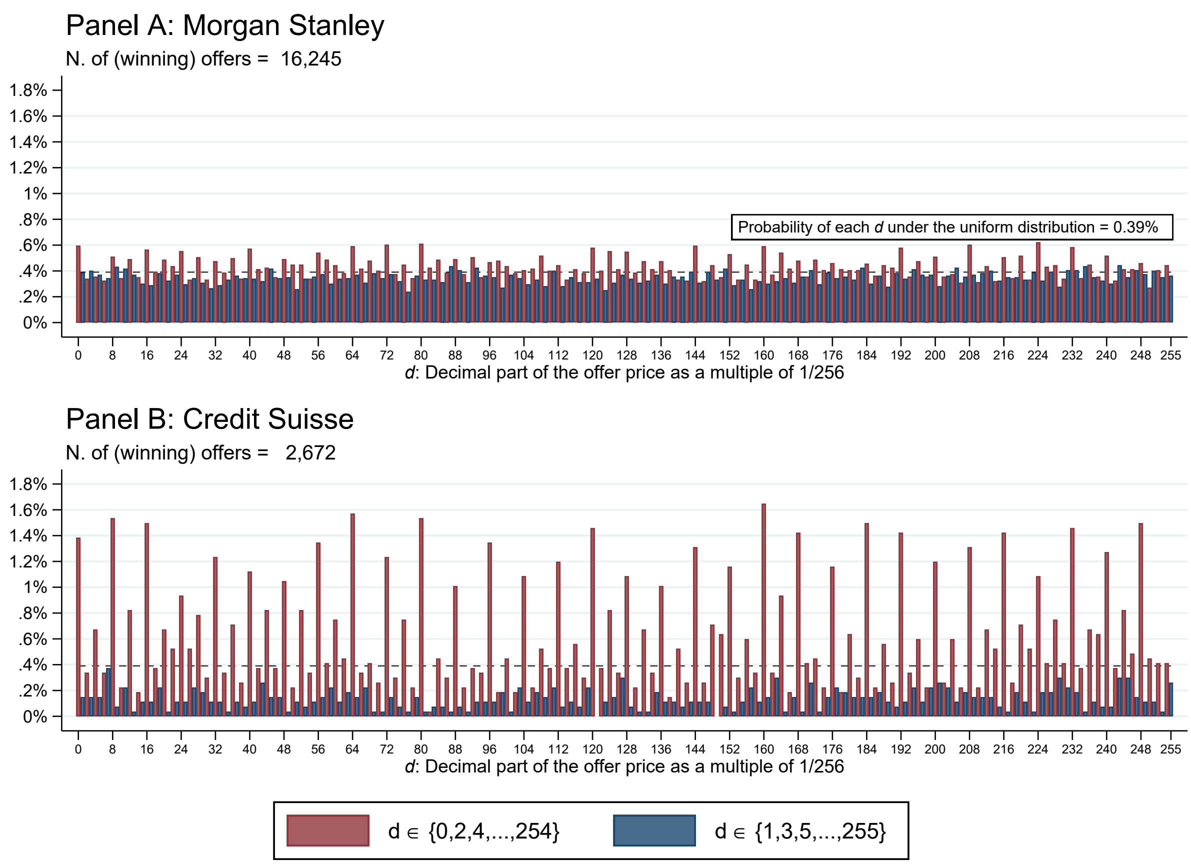
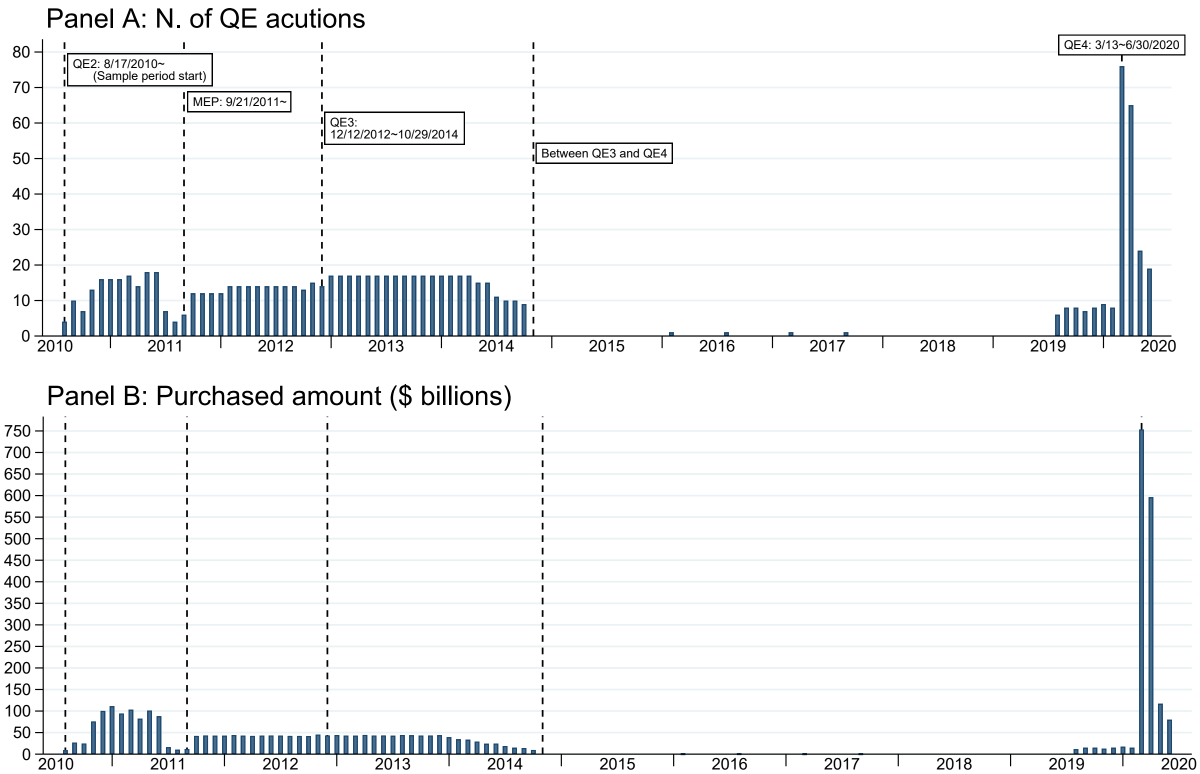
Figures

Figure 1: Price-end clustering of QE auction offers: Morgan Stanley vs. Credit Suisse



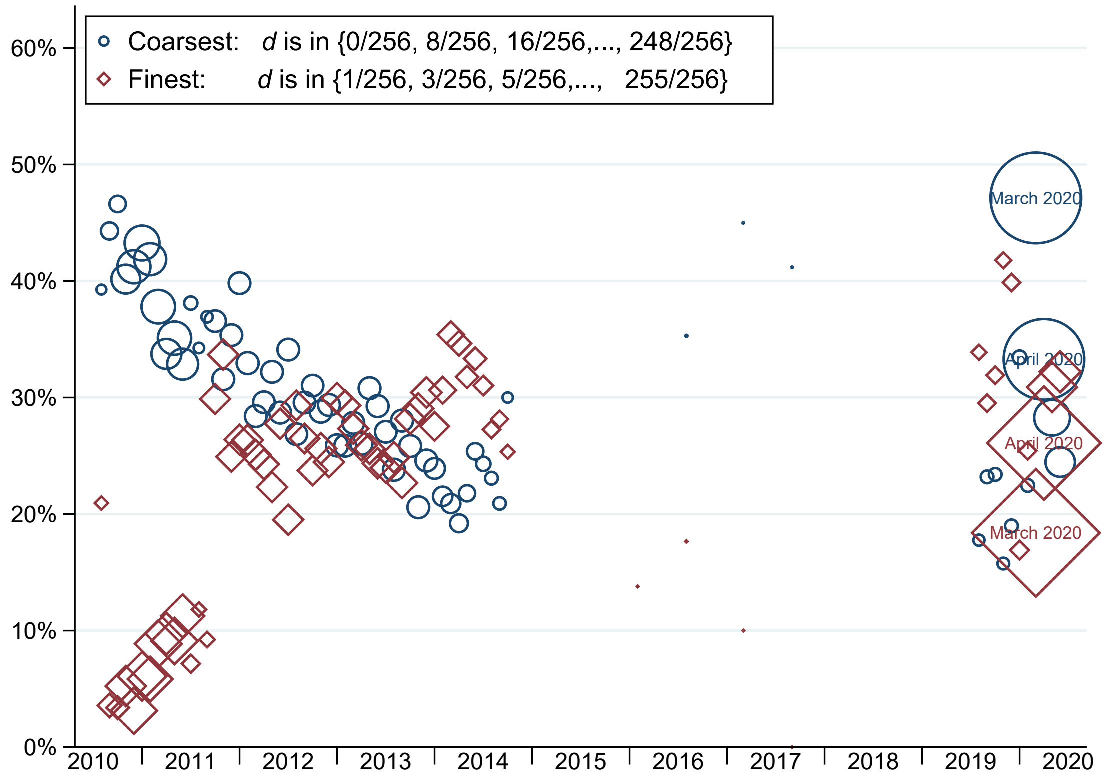
This figure shows the distributions of the decimal part of the offer price as a multiple of 1/256 (d). The sample is (winning) offers in QE auctions from August 17, 2010 to June 29, 2020. The data is obtained from the FRBNY.

Figure 2: QE operations of Treasury notes and bonds



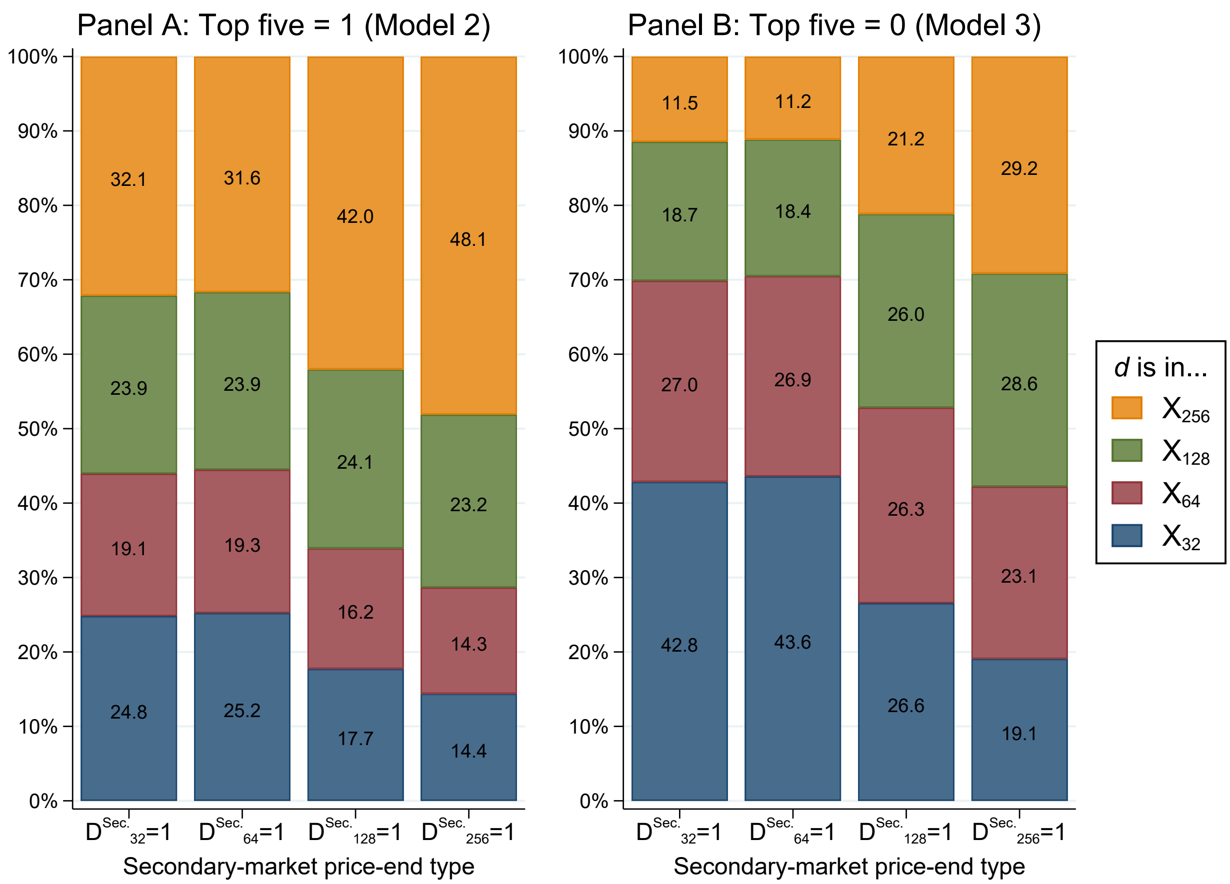
This figure shows the time series of the Fed's QE purchases of Treasury notes and bonds from August 17, 2010 to June 29, 2020. The data source is the Treasury securities operation results disclosed by the FRBNY at `https://www.newyorkfed.org/markets/desk-operations/treasury-securities`.

Figure 3: Price-end types of (successful) offers in QE auctions



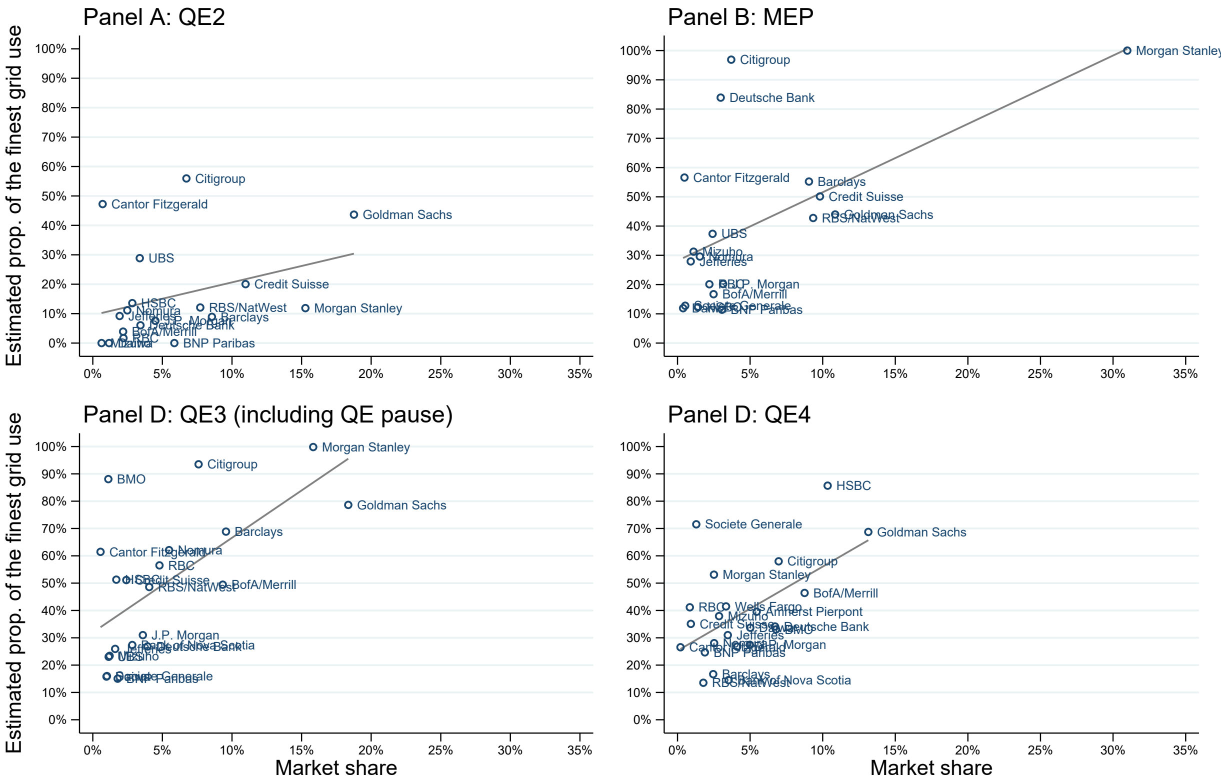
In this figure, successful offers in QE auctions are aggregated monthly, and each displayed symbol's size corresponds to the amount purchased in the month. For each month, the price-end types of (successful) offers are computed. The sample period is from August 17, 2010 to June 29, 2020.

Figure 4: Predicted probabilities of price-end types of QE auction offers based on Models 2 and 3 of Table 12



This figure shows the predicted probabilities of price-end types of QE auction offers based on Models 2 and 3 of Table 12. Model 2 uses the sample of $Top\ five = 1$, and Model 3 that of $Top\ five = 0$. The predicted probabilities are calculated for each of the four possible types of the secondary-market price ending: $D_{32}^{Secondary} = 1$, $D_{64}^{Secondary} = 1$, $D_{128}^{Secondary} = 1$, and $D_{256}^{Secondary} = 1$. $D_{32}^{Secondary}$ takes the value of one if the decimal part of the Treasury security's closing ask quote on the trading day preceding the QE auction is in X_{32}, and zero otherwise. $D_{64}^{Secondary} = 1$, $D_{128}^{Secondary} = 1$, and $D_{256}^{Secondary} = 1$ are similarly defined.

Figure 5: Market share and the predicted proportion of using the finest 1/256ths pricing grid



The x-axis measures the (traded amount-based) market share in QE auctions in the sub-period. The y-axis represents the estimated proportion of using the finest 1/256ths pricing grid. A PD is included in a panel only if it has at least 100 winning offers in the sub-period and if it was designated as a PD at the beginning of the sub-sample period. Each panel includes the fitted line.

Tables

Table 1: Primary dealer list

Name	Parent location	PD designation date (post-8/17/2010)	Amount sold ($ billions)	N. of offers accepted
Goldman Sachs	Domestic		595.787	8,612
Morgan Stanley	Domestic		503.859	16,245
Citigroup	Domestic		256.365	4,103
Barclays	Foreign		253.379	6,915
BofA/Merrill	Domestic		253.098	5,725
HSBC	Foreign		207.759	2,930
Credit Suisse	Foreign		190.467	2,672
RBS/NatWest	Foreign		187.855	2,820
Deutsche Bank	Foreign		186.736	4,112
J.P. Morgan	Domestic		167.096	2,836
BMO	Foreign	10/4/2011–	126.949	2,896
Nomura	Foreign		119.014	2,782
BNP Paribas	Foreign		114.229	11,117
Daiwa	Foreign		98.555	1,577
Jefferies	Domestic		90.034	1,903
Bank of Nova Scotia	Foreign	10/4/2011–	89.314	1,711
RBC	Foreign		88.638	1,610
Amherst Pierpont	Domestic	5/6/2019–	85.405	1,572
Mizuho	Foreign		67.256	1,637
TD	Foreign	2/11/2014–	66.321	424
Wells Fargo	Domestic	4/18/2016–	56.648	883
UBS	Foreign		56.207	1,607
Societe Generale	Foreign	2/2/2011–	36.135	1,531
Cantor Fitzgerald	Domestic		17.174	1,338
MF Global	Domestic	2/2/2011–10/31/2011	2.847	110
Pilot program primary dealers (July 2013–July 2014)				
Cabrera			0.477	162
G.X. Clarke			0.315	154
Loop			0.044	23
Mischler			0.023	15

Primary dealers during my sample period (2010Q3–2020Q2) are listed. Note that four dealers participated in the primary dealer pilot program in July 2013–July 2014. See Internet Appendix B.1 for data sources of the parent location and period as a primary dealer. The amount sold and the number of winning offers are based on my sample QE auctions of Treasury notes and bonds.

Table 2: Timeline of major events in the Fed's QE purchases of Treasury securities

Date	Event	Period
March 18, 2009	Announcement of "QE1" of Treasury securities: The Fed would purchase up to $300 billion of Treasury coupon securities in the next six months.	
March 25, 2009	Purchases of Treasury coupon securities began.	
October 29, 2009	QE1 ended.	
August 10, 2010	The FOMC announced the plan to reinvest proceeds of maturing Treasury securities, agency debt, and agency MBS in Treasury coupon securities.	
August 17, 2010	The Fed started disclosing detailed operation result data (roughly two years after the operation date).	*QE2*
November 3, 2010	Announcement of "QE2": The Fed would purchase $600 billion of Treasury coupon securities by June 2011.	
June 22, 2011	The FOMC announced the end of QE2 and the plan to reinvest proceeds of maturing debt in Treasury coupon securities.	
September 21, 2011	Announcement of the Maturity Extension Program: The Fed would purchase $400 billion of long-term Treasury securities (maturing in 6 to 30 years) based on proceeds from selling short-term ones (maturing in less than 6 years) by June 2012.	*MEP*
June 20, 2012	The termination date of the Maturity Extension Program was extended to December 2012. The Fed would continue the purchases of long-term Treasuries (and sales of short-term Treasuries) at the same pace.	
December 12, 2012	Announcement of "QE3" of Treasury securities: The Fed would continue the purchases of long-term Treasury securities, but unlike in the previous Maturity Extension Program, it would not match the purchase amounts with the proceeds from selling short-term securities.	*QE3*
October 29, 2014	QE3 ended. However, the Fed would continue reinvesting in Treasury coupon securities to maintain its balance sheet size at $4.5 trillion.	*QE pause*
June 14, 2017	The FOMC announced the intention of initiating the balance sheet normalization program (reducing reinvestment in Treasury securities) this year, if the economic condition allows.	
September 20, 2017	The FOMC announced the start of the balance sheet normalization program in October 2017.	
July 31, 2019	The balance sheet normalization program was concluded. The Fed would reinvest up to $20 billion per month in Treasury securities.	
March 12, 2020	Beginning of QE4" round: The Fed would purchase Treasury securities of various maturities to address highly unusual disruptions in Treasury financing markets associated with the coronavirus outbreak." The massive purchases started on March 13, 2020.	*QE4*
March 15, 2020	Announcement of QE4: The Fed would purchase at least $500 billion of Treasury securities "over coming months."	

Sources: Announcements and events listed on the website of the Federal Reserve.

Table 3: Descriptive statistics of QE auctions

Panel A: N. of QE auctions per auction date

Period	Mean number of QE auctions	Distribution of the number of QE auctions						
		1	2	3	4	5	6	Total
QE2	1.019	159	3	0	0	0	0	162
MEP	1.049	176	9	0	0	0	0	185
QE3	1.012	343	4	0	0	0	0	347
QE pause	1.017	58	1	0	0	0	0	59
QE4	2.493	39	9	4	4	5	12	73
Total	1.153	775	26	4	4	5	12	826

Panel B: N. of eligible, included, and purchased securities per QE auction

Period	N	Eligible securitis			Included securities			Purchased securities		
		Mean	S.d.	Median	Mean	S.d.	Median	Mean	S.d.	Median
QE2	165	27.4	6.08	28.0	25.2	5.28	26.0	13.2	5.20	13.0
MEP	194	19.1	4.11	19.0	16.5	4.54	17.0	13.6	4.02	14.0
QE3	351	22.2	3.07	22.0	18.3	2.76	19.0	12.9	4.64	13.0
QE pause	60	38.0	7.84	40.0	33.8	8.56	36.5	11.4	6.41	10.0
QE4	182	60.0	30.41	52.0	53.9	29.12	49.0	33.8	19.68	29.0
Total	952	30.7	20.42	24.0	26.9	19.23	20.0	17.0	12.61	14.0

Panel C: Submitted and purchased amounts per QE auction

Period	N	Submitted amount ($ milllions)			Accepted amount ($ millions)			Offer-to-cover ratio		
		Mean	S.d.	Median	Mean	S.d.	Median	Mean	S.d.	Median
QE2	165	20,641	8,481	20,949	5,182	2,414	6,260	4.996	4.212	3.899
MEP	194	9,223	4,914	6,486	3,193	1,406	2,512	2.838	0.599	2.774
QE3	351	8,004	4,250	5,870	2,264	1,268	1,575	3.775	1.373	3.521
QE pause	60	9,549	4,172	9,530	1,768	520	1,801	5.549	2.279	5.189
QE4	182	18,797	12,725	14,270	8,477	5,967	6,000	2.344	0.853	2.104
Total	952	12,603	9,227	10,426	4,116	3,797	3,000	3.634	2.301	3.159

Panel D: Winning offers and dealers per QE auction

Period	N	N. of winning offers			N. of winning dealers			Mean N. of winning offers per winning dealer		
		Mean	S.d.	Median	Mean	S.d.	Median	Mean	S.d.	Median
QE2	165	94.2	55.3	89	15.2	3.33	16	5.96	3.12	5.61
MEP	194	128.4	58.5	117	16.2	3.64	17	7.71	2.75	7.38
QE3	351	80.1	42.9	72	15.6	3.88	16	5.03	2.30	4.64
QE pause	60	30.9	23.8	24	11.0	4.33	11	2.65	1.35	2.16
QE4	169	115.8	66.0	110	19.3	4.09	20	5.66	2.59	5.13
Total	939	95.9	58.3	86	16.0	4.26	17	5.71	2.86	5.18

This table presents desctiptive statistics of QE auctions of Treasury notes and bonds held from August 17, 2010 to June 29, 2020. The sample period is divided into five sub-periods based on QE phases: *QE2* (8/17/2010–9/19/2011), *MEP* (9/23/2011–12/10/2012), *QE3* (12/13/2012–10/27/2014), *QE pause* (2/23/2016–3/3/2020), and *QE4* (3/13/2020–6/29/2020). Panel A reports the number of separate QE auctions (based on the Fed's operation ID) that the Fed conducted per QE auction date. Panels B–D report QE auction-level characteristics. The sample size for Panel D is slightly smaller because there were 13 instances in which two separate QE auctions targeting the same set of Treasury securities were held on the same date. Panel D treats those pairs of QE auctions as a single observations, because the publicly disclosed offer-level data does not indicate which of the two auctions each offer belongs to in such cases.

Table 4: Descriptive statistics of (accepted) offers in QE auctions

	QE2	MEP	QE3	QE pause	QE4	Total
N	15,549	24,912	28,126	1,857	19,578	90,022
Offer size ($ millions)						
Mean	55	24.9	28.3	57.1	78.8	43.5
S.d.	121.1	78.2	65.5	129.8	128.1	99.7
Min	1	1	1	1	1	1
Median	25	5	10	25	49	15
Max	5,008	1,875	1,500	2,150	4,749	5,008
On-the-runs vs. off-the-runs (%)						
Off-the-run	89.0	96.0	95.8	100.0	100.0	95.7
On-the-run	11.0	4.0	4.2	0.0	0.0	4.3
Remaining maturities (years; %)						
0–5	34.4	0.0	10.7	46.3	53.0	21.8
5–10	50.8	37.3	37.9	30.7	22.7	36.5
10–20	6.6	7.0	4.7	5.4	2.1	5.1
20–30	8.2	55.8	46.7	17.5	22.2	36.6
Security types (%)						
2Y notes	1.0	0.0	0.0	7.5	8.6	2.2
3Y notes	10.2	0.0	0.0	8.5	11.8	4.5
5Y notes	18.3	0.0	6.3	18.1	18.8	9.6
7Y notes	22.6	15.3	15.7	22.5	17.5	17.3
10Y notes	23.8	18.3	21.6	19.3	18.0	20.3
30Y bonds	24.0	66.4	56.5	24.0	25.2	46.2
Market share of the primary dealer (%)						
Top five dealers	33.6	57.0	56.1	31.1	37.4	47.9
Non-top five dealers	66.4	43.0	43.9	68.9	62.6	52.1

This table reports the types of the sample offers for QE auctions of Treasury notes and bonds from August 17, 2010 to June 29, 2020. Primary dealer market shares are measured based on the trade amount in QE auctions in the sub-period.

Table 5: Price-end clustering on coarser grids

Panel A: Regression results

	All	Sub-period					PD market share		
		QE2	MEP	QE3	QE pause	QE4	Top five	Non-top five	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(7) - (8)
D_{32}	0.839***	1.155***	0.794***	0.584***	0.571***	1.037***	0.493***	1.157***	-0.665***
	(0.017)	(0.024)	(0.020)	(0.017)	(0.052)	(0.048)	(0.012)	(0.023)	(0.026)
D_{64}	0.542***	0.872***	0.536***	0.492***	0.378***	0.374***	0.332***	0.735***	-0.403***
	(0.008)	(0.020)	(0.016)	(0.014)	(0.042)	(0.013)	(0.007)	(0.011)	(0.013)
D_{128}	0.163***	0.322***	0.093***	0.156***	0.196***	0.134***	0.117***	0.206***	-0.089***
	(0.004)	(0.011)	(0.007)	(0.008)	(0.025)	(0.007)	(0.005)	(0.005)	(0.007)
Constant	-0.213***	-0.334***	-0.189***	-0.174***	-0.168***	-0.210***	-0.132***	-0.288***	0.156***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.012)	(0.004)	(0.003)	(0.002)	(0.003)
N	256	256	256	256	256	256	256	256	
Adjusted R^2	0.980	0.967	0.956	0.937	0.542	0.910	0.954	0.981	
$D_{32} - D_{64}$	0.297***	0.282***	0.259***	0.093***	0.194***	0.663***	0.161***	0.423***	
	[265.535]	[79.976]	[107.412]	[18.534]	[9.090]	[181.815]	[154.367]	[264.990]	
$D_{64} - D_{128}$	0.378***	0.550***	0.443***	0.335***	0.182***	0.240***	0.215***	0.528***	
	[1977.001]	[578.012]	[684.574]	[467.250]	[15.948]	[296.327]	[866.277]	[1894.439]	

Panel B: Estimated proportions in which different pricing grids are used (%)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
grid-32nds	9.52	9.04	8.28	2.96	6.19	21.21	5.15	13.53
grid-64ths	24.22	35.2	28.36	21.47	11.63	15.36	13.76	33.82
grid-128ths	20.89	41.23	11.84	19.99	25.09	17.15	14.92	26.37
grid-256ths	45.38	14.53	51.53	55.58	57.08	46.28	66.17	26.28

C Panel A reports the results of estimating Specification 2. The dependent variable, $Percent_d - 0.390625$, is the percentage of offers with price endings being d among all offers, minus 0.390625. The right-hand side variables are D_{32}, D_{64}, and D_{128}, which take the value of one if the price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise. Column 1 uses all sample (winning) offers. In Columns 2–6, the ratios are calculated separately for each sub-period: *QE2*, *MEP*, *QE3*, *QE pause*, and *QE4*. Columns 7 and 8 repeat the analysis for offers of top five PDs and non-top five PDs, respectively. PDs are ranked based on trade amounts in QE auctions in each sub-period. Column 9 tests the differences in the coefficients between Columns 7 and 8. Heteroskedasticity-robust standard errors are reported in parentheses. At the bottom, differences between coefficients are tested and their F statistics are reported in bracket parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels. Panel B reports the predicted proportions in which PDs used the 1/32nds, 1/64ths, 1/128ths, and 1/256ths pricing grids, based on the method described in Section 4.3.

Table 6: Price-end type distributions conditional on a pricing grid used

	Conditional on using *grid-g* = …			
	grid-32*nds*	*grid*-64*ths*	*grid*-128*ths*	*grid*-256*ths*
$\phi_{32}^{grid\text{-}g} = \Pr[d \in X_{32} \mid grid\text{-}g]$	1	0.5	0.25	0.125
$\phi_{64}^{grid\text{-}g} = \Pr[d \in X_{32} \mid grid\text{-}g]$	0	0.5	0.25	0.125
$\phi_{128}^{grid\text{-}g} = \Pr[d \in X_{128} \mid grid\text{-}g]$	0	0	0.5	0.25
$\phi_{256}^{grid\text{-}g} = \Pr[d \in X_{256} \mid grid\text{-}g]$	0	0	0	0.5

This table summarizes the conditional probabilities of price ending d in X_{32}, X_{64}, X_{128}, and X_{256}, for each of the four pricing grids, *grid-32nds*, *grid-64ths*, *grid-128ths*, *grid-256ths*.

Table 7: Definitions of the variables for the analysis of the determinants of pricing fineness

Variable	Description	Data sources
D_{32}	A dummy variable that takes a value of one if the price ending is in $X_{32} = \{0/256, 8/256, 16/256, \ldots, 248/256\}$	FRBNY
D_{64}	A dummy variable that takes a value of one if the price ending is in $X_{64} = \{4/256, 12/256, 20/256, \ldots, 252/256\}$	FRBNY
D_{128}	A dummy variable that takes a value of one if the price ending is in $X_{128} = \{2/256, 6/256, 10/256, \ldots, 254/256\}$	FRBNY
D_{256}	A dummy variable that takes a value of one if the price ending is in $X_{256} = \{1/256, 3/256, 5/256, \ldots, 255/256\}$	FRBNY
$Topfive$	A dummy variable that takes the value of one if the PD is a top five dealer based on the trade amount in QE auctions in the sub-period	FRBNY
Cheapness	Yield-curve-implied price minus market mid-price, divided by market mid-price (based on the previous trading day's close price; in percent; winsorized at the 2.5% and 97.5%)	CRSP
On-the-run	A dummy variable that takes a value of one if the security is an on-the-run security	TreasuryDirect
$Maturity_{0\text{-}5}$	A dummy variable that takes a value of one if the remaining maturity is in (0,5) years	TreasuryDirect
$Maturity_{5\text{-}10}$	A dummy variable that takes a value of one if the remaining maturity is in [5,10) years	TreasuryDirect
$Maturity_{10\text{-}20}$	A dummy variable that takes a value of one if the remaining maturity is in [10,20) years	TreasuryDirect
$Maturity_{20\text{-}30}$	A dummy variable that takes a value of one if the remaining maturity is in [20,30) years	TreasuryDirect
Bond	A dummy variable that takes a value of one if the security is a Treasury bond	TreasuryDirect
Bid-ask	Bid-ask spread, divided by the mid quote (based on the previous trading day's end-of-the-day bid and ask quotes; in percent; winsorized at the 2.5% and 97.5% levels)	CRSP
Volatility	Standard deviation of the security's returns in the previous five trading days (percent; winsorized at the 1% and 99% levels)	CRSP
Ln(offer amount)	Natural logarithm of the amount of the offer	FRBNY
Ln(outstanding)	Natural logarithm of the publicly-held outstanding par value of the offered CUSIP	CRSP
Ln(total purchases)	Natural logarithm of the total purchase amount of the QE auction	FRBNY
Offer-to-cover	Offer-to-cover ratio of the QE auction (winsorized at the 2.5% and 97.5% levels)	FRBNY

This table lists the definitions and data sources of the variables used in the subsequent cross-sectional analysis of price-end fineness of QE auction offers.

Table 8: Descriptive statistics of the variables for the analysis of the determinants of pricing fineness

	Mean	S.d.	Min.	Median	Max.	N
D_{32}	0.325	0.468	0.000	0.000	1.000	90,022
D_{64}	0.230	0.421	0.000	0.000	1.000	90,022
D_{128}	0.218	0.413	0.000	0.000	1.000	90,022
D_{256}	0.227	0.419	0.000	0.000	1.000	90,022
$Topfive$	0.479	0.500	0.000	0.000	1.000	90,022
Cheapness	0.180	0.238	-0.251	0.101	0.723	89,964
On-the-run	0.043	0.204	0.000	0.000	1.000	90,022
$Maturity_{0\text{-}5}$	0.218	0.413	0.000	0.000	1.000	90,022
$Maturity_{5\text{-}10}$	0.365	0.481	0.000	0.000	1.000	90,022
$Maturity_{10\text{-}20}$	0.051	0.220	0.000	0.000	1.000	90,022
$Maturity_{20\text{-}30}$	0.366	0.482	0.000	0.000	1.000	90,022
Bond	0.462	0.499	0.000	0.000	1.000	90,022
Bid-ask	0.043	0.015	0.012	0.044	0.074	89,964
Volatility	0.552	0.455	0.027	0.434	2.079	89,281
Ln(offer amount)	23.153	1.782	20.723	23.431	29.242	90,022
Ln(outstanding)	24.013	0.620	21.409	24.122	25.041	85,974
Ln(total purchases)	22.023	0.797	19.052	22.032	23.942	90,022
Offer-to-cover	2.968	0.993	1.459	2.773	5.778	90,022

This table reports the descriptive statistics of the variables used in the subsequent cross-sectional analysis of price-end fineness of QE auction offers. See Table 7 for variable definitions. *Cheapness*, *Bid-ask*, *Volatility*, and *Offer-to-cover* are winsorized at the 2.5% and 97.5% levels.

Table 9: Ordered logit regression of the determinants of price-end fineness of QE auction offers

Panel A: Ordered logit regression of *Price-end fineness*						
	(1)		(2)		(3)	
	Coef.	Marg. eff.	Coef.	Marg. eff.	Coef.	Marg. eff.
Topfive	0.895***	0.149***	0.929***	0.151***	0.966***	0.156***
	(0.217)	(0.039)	(0.216)	(0.038)	(0.228)	(0.038)
Cheapness	-1.072***	-0.179***	0.429***	0.069***	0.252*	0.041*
	(0.226)	(0.029)	(0.142)	(0.021)	(0.138)	(0.022)
On-the-run			-0.385***	-0.062***	-0.532***	-0.086***
			(0.122)	(0.024)	(0.118)	(0.024)
$Maturity_{0\text{-}5}$			0.623***	0.117***	0.410***	0.072***
			(0.089)	(0.020)	(0.076)	(0.016)
$Maturity_{10\text{-}20}$			-0.419***	-0.063***	-0.405***	-0.059***
			(0.113)	(0.018)	(0.152)	(0.019)
$Maturity_{20\text{-}30}$			-0.456***	-0.068***	-0.139	-0.022
			(0.096)	(0.016)	(0.134)	(0.021)
Bond			-0.443**	-0.072**	-0.462**	-0.075***
			(0.219)	(0.030)	(0.201)	(0.027)
Bid-ask					0.484	0.078
					(0.657)	(0.105)
Volatility					-0.484***	-0.078***
					(0.104)	(0.017)
Ln(offer amount)					-0.066	-0.011
					(0.060)	(0.010)
Ln(outstanding)					-0.006	-0.001
					(0.039)	(0.006)
Ln(total purchases)					-0.012	-0.002
					(0.058)	(0.009)
Offer-to-cover					0.125***	0.020***
					(0.027)	(0.004)
MEP	0.476	0.070	0.919***	0.136***	0.900***	0.129***
	(0.309)	(0.052)	(0.261)	(0.050)	(0.227)	(0.043)
QE3	0.812***	0.132***	1.011***	0.153***	0.930***	0.134***
	(0.214)	(0.038)	(0.197)	(0.035)	(0.186)	(0.033)
QE pause	0.898***	0.149***	0.871***	0.127***	0.749***	0.103***
	(0.207)	(0.037)	(0.203)	(0.033)	(0.206)	(0.032)
QE4	0.270	0.038	0.238	0.029	0.613***	0.081***
	(0.193)	(0.028)	(0.172)	(0.022)	(0.212)	(0.031)
N	89,964		89,964		85,866	
Pseudo R^2	0.036		0.053		0.060	

(*Continued*)

Table 9: *Continued*

Panel B: The association of *Cheapness* and *Price-end fineness* for *Top five* = 1 and *Top five* = 0					
		Marginal effect of *Cheapness* on the probability of...			
	Coefficient	*Price-end fineness* $= 1$ ($\Longleftrightarrow D_{32} = 1$)	*Price-end fineness* $= 2$ ($\Longleftrightarrow D_{64} = 1$)	*Price-end fineness* $= 3$ ($\Longleftrightarrow D_{128} = 1$)	*Price-end fineness* $= 4$ ($\Longleftrightarrow D_{256} = 1$)
Sample: *Top five* = 1					
Cheapness	-0.633***	0.112**	0.038***	-0.013	-0.136***
	(0.210)	(0.044)	(0.011)	(0.016)	(0.040)
Period dummies	✓				
N	43,077				
Pseudo R^2	0.017				
Sample: *Top five* = 0					
Cheapness	-1.540***	0.357***	-0.026	-0.157***	-0.173***
	(0.207)	(0.045)	(0.018)	(0.032)	(0.032)
Period dummies	✓				
N	46,887				
Pseudo R^2	0.017				
Test of the difference in the marginal effects					
χ^2 statistics		17.33***	6.11**	22.92***	0.94

This table estimates the ordered logit model in which the dependent variable is *Price-end fineness*, which takes the value of one if $D_{32} = 1$, two if $D_{64} = 1$, three if $D_{128} = 1$, and four if $D_{256} = 1$. Panel A uses all sample (accepted) offers in QE auctions and reports the coefficients and marginal effects on the probability of *Price-end fineness* = 4 (i.e., $D_{256} = 1$). For the definitions of the variables, see Table 7. In Panel B, the sample is split by *Top five*. In addition to the coefficients, the table reports the marginal effects on the probabilities of *Price-end fineness* = 1, 2, 3, and 4. Standard errors are three-way clustered by CUSIP, auction date, and PD. They are reported in parentheses. Standard errors for marginal effects are obtained by using the delta method. At the bottom, the differences in the marginal effects between $Top\ five = 1$ and $Top\ five = 0$ are tested. To preferm this test, I pool the two sub-samples and run the ordered logit model in which the independent variables are *Top five*, *Cheapness*, the dummies for the sub-periods, the interaction term of *Top five* and *Cheapness*, and those of *Top five* and the sub-period dummies. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Table 10: Price-end clustering on coarser grids of secondary market prices

Panel A: Regression results

	All	Sub-period				
		QE2	MEP	QE3	QE pause	QE4
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{32}^{Secondary}$	1.159***	1.426***	1.465***	1.481***	0.848***	0.708***
	(0.017)	(0.045)	(0.030)	(0.031)	(0.067)	(0.025)
$D_{64}^{Secondary}$	1.173***	1.304***	1.513***	1.500***	0.748***	0.768***
	(0.015)	(0.043)	(0.034)	(0.038)	(0.059)	(0.025)
$D_{128}^{Secondary}$	0.187***	0.186***	0.074***	0.072***	0.350***	0.309***
	(0.005)	(0.013)	(0.007)	(0.006)	(0.030)	(0.010)
Constant	-0.338***	-0.388***	-0.391	-0.391	-0.287***	-0.262***
	(0.002)	(0.001)	(.)	(.)	(0.012)	(0.004)
N	256	256	256	256	256	256
Adjusted R^2	0.990	0.947	0.978	0.976	0.674	0.927
$D_{32}^{Secondary} - D_{64}^{Secondary}$	-0.014	0.122*	-0.048	-0.019	0.100	-0.059*
	[0.400]	[3.807]	[1.126]	[0.146]	[1.315]	[2.950]
$D_{64}^{Secondary} - D_{128}^{Secondary}$	0.986***	1.119***	1.439***	1.427***	0.399***	0.459***
	[4052.203]	[621.373]	[1693.223]	[1397.315]	[38.994]	[310.069]

Panel B: Estimated proportions in which different pricing grids are used (%)

grid-32*nds*	0.00	3.90	0.00	0.00	3.21	0.00
grid-64*ths*	62.66	71.60	90.56	90.75	25.51	27.46
grid-128*ths*	23.95	23.76	9.44	9.25	44.75	39.55
grid-256*ths*	13.38	0.74	0.00	0.00	26.53	32.99

Panel A tests the price-end clustering on coarser grids of my sample Treasury securities in the secondary market. For each Treasury security purchased in a QE auction, I obtain that security's closing ask price on the trading day preceding the QE auction from Bloomberg. The regression specifications are identical to Specification 2, except that this analysis uses not offer prices in QE auctions but secondary market prices. The dependent variable, $Percent_d^{Secondary} - 0.390625$, is the percentage of price endings being d, minus 0.390625. The right-hand side variables are $D_{32}^{Secondary}$, $D_{64}^{Secondary}$, and $D_{128}^{Secondary}$, which take the value of one if the price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise. Heteroskedasticity-robust standard errors are reported in parentheses. At the bottom, differences between coefficients are tested and their F statistics are reported in bracket parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels. Panel B reports the predicted proportions in which PDs used the 1/32nds, 1/64ths, 1/128ths, and 1/256ths pricing grids, based on the method described in Section 4.3.

Table 11: Ordered logit regression of the determinants of price-end fineness of secondary market prices

Dependent variable: $Price\text{-}end\ fineness^{Secondary}$

		Marginal effect on the probability of $Price\text{-}end\ fineness^{Secondary}$ =...			
	Coefficient	1 ($\Longleftrightarrow D_{32}^{Secondary} = 1$)	2 ($\Longleftrightarrow D_{64}^{Secondary} = 1$)	3 ($\Longleftrightarrow D_{128}^{Secondary} = 1$)	4 ($\Longleftrightarrow D_{256}^{Secondary} = 1$)
On-the-run	-0.179	0.034	-0.009	-0.015	-0.011
	(0.136)	(0.026)	(0.006)	(0.012)	(0.008)
$Maturity_{0\text{-}5}$	1.506***	-0.269***	-0.014	0.186***	0.097***
	(0.117)	(0.019)	(0.014)	(0.012)	(0.014)
$Maturity_{10\text{-}20}$	-0.345**	0.081**	-0.042**	-0.030**	-0.009**
	(0.145)	(0.034)	(0.019)	(0.012)	(0.004)
$Maturity_{20\text{-}30}$	-0.435***	0.102***	-0.055***	-0.036***	-0.011***
	(0.133)	(0.031)	(0.017)	(0.012)	(0.004)
Bond	-0.131	0.025	-0.006	-0.011	-0.008
	(0.135)	(0.026)	(0.006)	(0.012)	(0.008)
MEP	0.696***	-0.145***	0.059***	0.060***	0.026***
	(0.118)	(0.024)	(0.012)	(0.009)	(0.005)
QE3	0.556***	-0.116***	0.050***	0.047***	0.019***
	(0.118)	(0.024)	(0.013)	(0.009)	(0.004)
QE pause	1.177***	-0.238***	0.075***	0.109***	0.054***
	(0.177)	(0.035)	(0.013)	(0.017)	(0.011)
QE4	1.250***	-0.251***	0.075***	0.116***	0.059***
	(0.133)	(0.027)	(0.013)	(0.012)	(0.008)
N	15,872				
Pseudo R^2	0.114				

This table reports the result of estimating the ordered logit model of the price-end fineness of my sample Treasury securities in the secondary market. For each Treasury security purchased in a QE auction, I obtain that security's closing ask price on the trading day preceding the QE auction from Bloomberg. Therefore, the outcome variable, $Price\text{-}end\ fineness^{Secondary}$, is the price-end fineness of the secondary market price and takes the value of one if $D_{32}^{Secondary} = 1$, two if $D_{64}^{Secondary} = 1$, three if $D_{128}^{Secondary} = 1$, and four if $D_{256}^{Secondary} = 1$. The remaining columns show the marginal effects on the probabilities of $Price\text{-}end\ fineness^{Secondary}$ = 1, 2, 3, and 4. For the definitions of the explanatory variables, see Table 7. Standard errors are two-way clustered by CUSIP and auction date, and they are reported in parentheses. Standard errors for marginal effects are obtained by using the delta method. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Table 12: Ordered logit regression of the price-end fineness of QE auction offers on the price-end fineness of secondary market prices

Sample:	All	$Top\ five = 1$	$Top\ five = 0$	All	$Top\ five = 1$	$Top\ five = 0$
	(1)	(2)	(3)	(4)	(5)	(6)
$D_{64}^{Secondary}$	-0.017	-0.023	-0.030	-0.014	-0.027	-0.018
	(0.014)	(0.015)	(0.024)	(0.012)	(0.020)	(0.022)
$D_{128}^{Secondary}$	0.594***	0.440***	0.734***	0.114***	0.065	0.132**
	(0.075)	(0.096)	(0.093)	(0.042)	(0.062)	(0.058)
$D_{256}^{Secondary}$	0.904***	0.695***	1.164***	0.336***	0.214	0.468***
	(0.137)	(0.176)	(0.152)	(0.104)	(0.149)	(0.117)
Security-type controls				✓	✓	✓
Period dummies	✓	✓	✓	✓	✓	✓
N	90,022	43,096	46,926	90,022	43,096	46,926
Pseudo R^2	0.014	0.018	0.014	0.031	0.026	0.045

This table reports the coefficients of the ordered logit regressin in which the dependent variable is *Price-end fineness*, which takes the value of one if the QE auction offer's price ending is in X_{32}, two if it is in X_{64}, three if it is in X_{128}, and four if it is in X_{256}. $D_{64}^{Secondary}$ takes the value of one if the price ending of the Treasury security's closing ask on the trading day preceding the QE auction is in X_{64}, and zero otherwise. $D_{128}^{Secondary}$ and $D_{256}^{Secondary}$ are similarly defined. The secondary market price-end data come from Bloomberg. In Columns 4–6, the following scurity-type controls are included: *On-the-run*, $Maturity_{0\text{-}5}$, $Maturity_{10\text{-}20}$, $Maturity_{20\text{-}30}$, and *Bond*. Standard errors are three-way clustered by CUSIP, auction date, and PD. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Table 13: Market share and the predicted proportion of using fine pricing grids

Panel A: Sub-period analysis

Dependent var.:	*Pricing grid*$_{256}$				*Pricing grid*$_{128or256}$			
Period	QE2	MEP	QE3	QE4	QE2	MEP	QE3	QE4
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market share	1.006	2.395***	3.384***	2.970**	1.332	2.071***	2.158***	1.193
	(0.774)	(0.293)	(0.859)	(1.069)	(0.975)	(0.519)	(0.504)	(0.993)
Constant	15.166**	25.941***	32.692***	31.388***	45.762***	48.700***	67.630***	56.978***
	(6.143)	(6.623)	(6.919)	(6.336)	(6.024)	(6.825)	(5.084)	(5.479)
N	18	19	21	23	18	19	21	23
Adjusted R^2	0.031	0.326	0.363	0.244	0.110	0.266	0.305	0.044

Panel B: Pooled analysis in levels

Dependent var.:	*Pricing grid*$_{256}$				*Pricing grid*$_{128or256}$			
Sample	All	Excl. Goldman Sachs	Excl. Morgan Stanley	Excl. < 2% market share	All	Excl. Goldman Sachs	Excl. Morgan Stanley	Excl. < 2% market share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Market share	2.393***	2.431***	2.438***	2.402***	1.836***	1.703***	2.264***	1.665***
	(0.313)	(0.386)	(0.521)	(0.295)	(0.405)	(0.435)	(0.490)	(0.439)
Period dummies	✓	✓	✓	✓	✓	✓	✓	✓
N	81	77	77	55	81	77	77	55
Adjusted R^2	0.383	0.344	0.299	0.486	0.360	0.317	0.335	0.444

Panel C: Pooled analysis in first differences

Dependent var.:	Δ*Pricing grid*$_{256}$				Δ*Pricing grid*$_{128or256}$			
Sample	All	Excl. Goldman Sachs	Excl. Morgan Stanley	Excl. < 2% market share	All	Excl. Goldman Sachs	Excl. Morgan Stanley	Excl. < 2% market share
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ*Market share*	2.431***	2.413***	2.297**	2.574***	2.137***	2.284***	2.260***	1.908***
	(0.457)	(0.523)	(0.893)	(0.330)	(0.400)	(0.471)	(0.736)	(0.410)
Period dummies	✓	✓	✓	✓	✓	✓	✓	✓
N	63	60	60	38	63	60	60	38
Adjusted R^2	0.278	0.266	0.156	0.473	0.383	0.375	0.330	0.439

This table reports the results of the OLS regressions in which the dependent variable is the predicted proportion of using the finest 1/256ths pricing grid (*Price grid*$_{256}$) or that of using the pricing grids of either 1/128ths or 1/256ths (*Price grid*$_{128or256}$). A PD is included in the sample if it has at least 100 winning offers in the sub-period and if it was designated as a PD at the beginning of the sub-sample period. *Market share* is the trade amount-based market share of the PD in the sub-period. In Panel A, heteroskedasticity-robust standard errors are reported in parentheses. In Panels B and C, standard errors clustered for PD are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Table 14: Coarse pricing and the level of prices among accepted offers in QE auctions

Panel A: Summary statistics of ***Price diff***

	N	Mean	S.d.	Min	25%tile	Median	75%tile	Max
Price diff	86,611	3.61	3.93	0	0.81	2.62	4.82	18.50

Panel B: Regressions of ***Price diff***

	(1)	(2)	(3)	(4)
D_{32}	0.282*	0.278**	0.138	0.127
	(0.139)	(0.127)	(0.117)	(0.107)
D_{64}	0.247**	0.243**	0.119	0.108
	(0.117)	(0.108)	(0.110)	(0.100)
D_{128}	0.181**	0.178**	0.116*	0.109*
	(0.073)	(0.068)	(0.062)	(0.056)
Ln(offer amount)		0.035		0.050
		(0.052)		(0.045)
Top five			-0.415**	-0.431**
			(0.177)	(0.165)
CUSIP × QE auction FEs	✓	✓	✓	✓
N	86,611	86,611	86,611	86,611
Adjusted R^2	0.566	0.566	0.569	0.569
$D_{32} - D_{64}$	0.035	0.035	0.020	0.019
	[0.484]	[0.481]	[0.195]	[0.175]
$D_{64} - D_{128}$	0.066	0.066	0.002	-0.001
	[0.978]	[1.062]	[0.001]	[0.000]

Panel A shows the summary statistics of *Price diff*, which is the percentage difference (in basis points) between the offer price and the minimum accepted price of offers for the same security in the same QE auction. *Price diff* is defined only when there exist multiple winning offers for the security in the QE auction. This variable is winsorized at the 2.5% and 97.5%. Panel B reports the OLS regression results with the dependent variable *Price diff*. All the models include CUSIP × QE-auction fixed effects. D_{32}, D_{64}, and D_{128} take the value of one if the price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise. *Ln(Total assets)* is the natural logarithm of the offer amount. *Top five* takes the value of one if the PD is one of the top five dealers based on the trade amount in QE auctions in the sub-period, and zero otherwise. Standard errors are three-way clustered by CUSIP, auction date, and PD. They are reported in parentheses. At the bottom, differences between coefficients are tested and their F statistics are reported in bracket parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Appendices

Appendix A A brief history of the Fed's QE purchases of Treasury securities

Table 2 lists major events of the Fed's QE purchases of Treasury securities. The phases can be classified as follows. First, on March 18, 2009, the Fed announced the commencement of purchasing up to $300 billion of Treasury coupon securities. The purchases of this so-called "QE1" round began on March 25 and ended as planned six months later (on October 29).[39] The Fed then announced on August 10, 2010 that it would reinvest proceeds from maturing Treasury securities and other debt into Treasury coupon securities to maintain its balance sheet size. The Fed resumed Treasury coupon security purchases following the announcement.

Second, the "QE2" phase was announced on November 3, 2010. The announced purchase size of Treasury coupon securities was $600 billion. As planned, QE2 ended in June 2011, with the last purchase taking place on June 22. Proceeds from maturing debt continued to be reinvested into Treasury securities.

Third, the Maturity Extension Program (MEP) was announced on September 21, 2011.[40] While the MEP still purchased long-term Treasury securities, the MEP differed from the preceding programs in that it did not change the size of bank reserves—the purchases were funded by sales of shorter-term Treasury securities (maturing in less than 3 years). The original plan was to purchase $400 billion of long-term Treasury securities by June 2012. It was announced on June 20, 2012, however, that the Fed would continue the purchases (and sales of shorter-term Treasuries) at the same pace until December 2012.

Fourth, the Fed announced the replacement of the MEP with "QE3" on December 12, 2012. Like QE1 and QE2, QE3 did not entail sales of shorter-term Treasury securities. Unlike them, QE3 was open-ended as it specified the (initial) monthly purchase amount, $45 billion, but neither the total purchase size nor the termination date.[41] QE3 was concluded on October 29, 2014.

Fifth, in the years following the QE3 conclusion, purchases of Treasury coupon securities were sporadic and quite small. Moreover, purchases of long-term Treasuries were completely halted following the initia-

[39]The purchases of agency MBS and agency debt continued until March 2010.

[40]The MEP is also referred to as the "Operation Twist" after a similar program the Fed launched in 1961.

[41]The announcement says, "If the outlook for the labor market does not improve substantially, the Committee will continue its purchases of Treasury and agency mortgage-backed securities" (`https://www.federalreserve.gov/newsevents/pressreleases/monetary20121212a.htm`).

tion of the balance sheet normalization program in October 2017. The balance sheet normalization program was then concluded in August 2019, and the Fed resumed reinvesting proceeds of maturing securities in Treasury coupon securities (with the first purchase taking place on August 15, 2019). The reinvestment continued at the pace of roughly $15 billion per month until February 2020. The FOMC emphasized, however, that the purpose of Treasury security purchases during this period was to maintain a sufficient level of bank reserves, instead of restarting QE (Bernanke, 2022, pp. 248–252).

Lastly, the COVID-19 crisis led the Fed to launch massive operations in the Treasury market. On March 12, 2020, the Fed announced that, among other interventions, it would purchase Treasury securities of various maturities from the next day. The massive new round of QE, which this paper dubs "QE4," was announced on March 15. According to it, the Fed would purchase at least $500 billion of Treasury securities "over coming months." While previous QE rounds had the main policy objective of stimulating the economy through lowering long-term rates, that of QE4 was different. The March 12 announcement clarified that the purpose was "to address highly unusual disruptions in Treasury financing markets associated with the coronavirus outbreak."[42]

Appendix B Dealer-level estimation of the proportions of pricing grids used

To quantify the extent of coarse pricing for each PD while controlling for offered security heterogeneity, I employ a more elaborate version of Specification 2. The dependent variable, $Percent_{s,j,t,d} - 0.390625$, is the percentage of offers with price endings being d among all offers for security type s submitted by PD j during period t, minus 0.390625. More specifically, three basic Treasury security characteristics are taken into account: on-the-run status, remaining maturity, and Treasury note vs. bond. Therefore, the ratio is calculated for each possible combination of security type s, PD j, and period t. The full regression

[42] https://www.newyorkfed.org/markets/opolicy/operating_policy_200312a

specification is:

$$
\begin{aligned}
Percent_{s,j,t,d} - 0.390625 = {} & \beta_1 D_{32} + \beta_2 D_{64} + \beta_3 D_{128} + \beta_4 On\text{-}the\text{-}run_s + \beta_5 Maturity_{0\text{-}5Y} + \beta_6 Maturity_{10\text{-}20Y} \\
& + \beta_7 Maturity_{20\text{-}30Y} + \beta_8 Bond + (\beta_9 D_{32} + \beta_{10} D_{64} \beta_{11} D_{128}) \times On\text{-}the\text{-}run \\
& + (\beta_{12} D_{32} + \beta_{13} D_{64} + \beta_{14} D_{128}) \times Maturity_{0\text{-}5Y} \\
& + (\beta_{15} D_{32} + \beta_{16} D_{64} + \beta_{17} D_{128}) \times Maturity_{10\text{-}20Y} \\
& + (\beta_{18} D_{32} + \beta_{19} D_{64} + \beta_{20} D_{128}) \times Maturity_{20\text{-}30Y} \\
& + (\beta_{21} D_{32} + \beta_{22} D_{64} + \beta_{23} D_{128}) \times Bond \\
& + \gamma Z_{j,t} + (\delta D_{32} + \zeta D_{64} + \eta D_{128}) \times Z_{j,t} + \epsilon_{i,d},
\end{aligned}
\tag{5}
$$

where D_{32}, D_{64}, and D_{128} take the value of one if the cell's price ending d ($\in D = \{0, 1, 2, \ldots, 255\}$) belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise; $On\text{-}the\text{-}run_s$ is the dummy variable for on-the-run securities; $Maturity_{0\text{-}5Y}$, $Maturity_{10\text{-}20Y}$, and $Maturity_{20\text{-}30Y}$ are dummy variables for remaining maturities being in (0, 5), [10, 20), and [20, 30) years, respectively; *Bond* is the dummy variable for Treasury bonds; $Z_{j,t}$ is the fixed effects for PD × period. (In this PD-level analysis I merge the QE-pause period into the QE3 period due to its small sample size.) Since $Percent_{s,j,t,d}$'s are calculated from different numbers of offers, the regression weights the observations by the number of offers in the cell. The regression result is reported in Table A.1.

Based on Specification 5, the baseline security is an off-the-run Treasury note maturing in [5, 10) years, which is the most common security type in my sample of QE auction offers. Moreover, by combining the coefficients reported in Table A.1 with the coefficients of $Z_{j,t}$ and the interaction terms of $Z_{j,t}$ with D_{32}, D_{64}, and D_{128}, I can predict the price-end type distributions at the PD × period level in the case of offering the most common Treasury security type. These predicted PD × period-level values are then fed into the maximum likelihood procedure detailed in Section 4.3 for estimating the proportions in which the four pricing grids were used.

Table A.2 summarizes the estimated PD × period-level proportions in which the four pricing grids were used. There are two notable time-series patterns (which are in line with Table 5). First, PDs tend to price more finely over time. The median PD increases the use of the 1/256ths pricing grid from 15.6% in *QE2* to 29.6% in *MEP* and 48.5% in *QE3*. Second, the pricing fineness deteriorated in the QE4 period. The median probability of using the coarsest 1/32nds grid increased from 0% in *QE3* to 18.2%.

Table A.1: OLS estimation of Specification 5

	Coefficient	Standard error
D_{32}	1.132***	(0.037)
D_{64}	1.038***	(0.023)
D_{128}	0.492***	(0.013)
On-the-run	-0.062***	(0.020)
$Maturity_{0\text{-}5Y}$	0.054***	(0.012)
$Maturity_{10\text{-}20Y}$	-0.025**	(0.012)
$Maturity_{20\text{-}30Y}$	-0.027*	(0.015)
Bond	-0.029	(0.018)
On-the-run $\times D_{32}$	0.185*	(0.106)
On-the-run $\times D_{64}$	0.168	(0.106)
On-the-run $\times D_{128}$	0.071*	(0.042)
$Maturity_{0\text{-}5Y} \times D_{32}$	-0.440***	(0.073)
$Maturity_{10\text{-}20Y} \times D_{32}$	0.192**	(0.092)
$Maturity_{20\text{-}30Y} \times D_{32}$	0.109**	(0.053)
$Maturity_{0\text{-}5Y} \times D_{64}$	-0.165***	(0.039)
$Maturity_{10\text{-}20Y} \times D_{64}$	0.011	(0.077)
$Maturity_{20\text{-}30Y} \times D_{64}$	0.042	(0.058)
$Maturity_{0\text{-}5Y} \times D_{128}$	0.087***	(0.033)
$Maturity_{10\text{-}20Y} \times D_{128}$	-0.001	(0.030)
$Maturity_{20\text{-}30Y} \times D_{128}$	0.033	(0.034)
Bond $\times D_{32}$	0.415***	(0.093)
Bond $\times D_{64}$	0.074	(0.055)
Bond $\times D_{128}$	-0.130***	(0.024)
$Z_{j,t}$	✓	
$Z_{j,t} \times (\delta D_{32} + \zeta D_{64} + \eta D_{128})$	✓	
Number of observations...		
before weighting	161,024	
after weighting	23,045,632	
Adjusted R^2	0.324	

This table reports the OLS estimation of Specification 5. The dependent variable, $Percent_{s,j,t,d} - 0.390625$, is the percentage of offers with price endings being d among all offers for security type s submitted by PD j during period t, minus 0.390625. D_{32}, D_{64}, and D_{128} take the value of one if the price ending d belongs to X_{32}, X_{64}, and X_{128}, respectively, and zero otherwise. *On-the-run* takes the value of one if the offered Treasury security is on-the-run. $Maturity_{0\text{-}5Y}$, $Maturity_{10\text{-}20Y}$, and $Maturity_{20\text{-}30Y}$ are dummy variables for remaining maturities being in (0, 5), [10, 20), and [20, 30) years, respectively. *Bond* takes the value of one if the offered security is a Treasury bond and zero if it is a Treasury note. $Z_{j,t}$ is the fixed effects for PD × period. Given that the ratios are calculated from different numbers of offers, the OLS regression is weighted by the respective number of offers. Standard errors clustered by price ending (d) and PD (j) are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels.

Table A.2: Predicted proportions of using the 1/32nds, 1/64ths, 1/128ths, and 1/256ths pricing grids for each PD

	N	Mean	S.d.	Min	p25	Median	p75	Max
Panel A: Estimated proportion of using the 1/32nds grid								
QE2	19	8.70	8.40	0.00	3.83	5.54	13.11	35.78
MEP	21	10.29	14.95	0.00	0.00	6.50	15.11	62.80
QE3	23	3.44	6.47	0.00	0.00	0.00	4.52	20.64
QE4	23	18.87	10.82	0.00	9.54	18.15	25.25	47.89
Panel B: Estimated proportion of using the 1/64ths grid								
QE2	19	38.21	14.45	8.39	27.83	38.02	46.60	70.05
MEP	21	29.06	22.62	0.00	8.86	29.09	46.30	70.35
QE3	23	18.14	14.60	0.00	8.14	16.47	30.78	53.65
QE4	23	18.98	7.46	1.19	14.77	19.36	23.88	33.76
Panel C: Estimated proportion of using the 1/128ths grid								
QE2	19	32.75	12.82	13.51	25.38	30.53	39.11	63.52
MEP	21	21.01	9.21	0.00	15.95	22.00	25.52	40.21
QE3	23	29.74	15.21	0.93	19.49	31.94	35.50	72.98
QE4	23	17.88	10.98	0.00	11.35	16.54	23.35	45.42
Panel D: Estimated proportion of using the 1/256ths grid								
QE2	19	20.34	16.94	3.22	7.73	15.60	25.20	60.04
MEP	21	39.64	28.77	8.37	18.36	29.59	52.24	100.00
QE3	23	48.68	25.79	14.04	26.55	48.48	66.17	99.07
QE4	23	44.28	18.27	15.44	33.30	41.01	51.79	88.00

This table reports the estimated proportions of using the 1/32nds, 1/64ths, 1/128ths, and 1/256ths pricing grids, for each PD in each sub-period, in the case of offering an off-the-run Treasury note maturing in [5, 10) years. Therefore, N refers to the number of sample PDs in the sub-period. Note that in this analysis the QE3 period incorporates the QE-pause period due to a small sample size of the latter. A PD is included in the sample only if it has at least 100 winning offers in the sub-period. See text for the method of estimating these proportions.

Internet Appendix for "Coarse Pricing in QE Auctions"

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Internet Appendix A Fitting a Fed-style yield curve model

Song and Zhu (2018) estimate a yield curve model based on the Fed's public information. Unless stated otherwise, I replicate their method to the greatest extent possible. The model is a standard cubic spline model. There are two important choices to consider. First, some prefer setting a positive smoothness parameter, which effectively prioritizes curve smoothness at the expense of the model's fit. Following the baseline approach of Song and Zhu (2018), I set the smoothness parameter to zero. The second consideration is the number and location of knots. Again, I employ their choice: 2, 5, 10, 20, and 30 years.

Like Song and Zhu (2018), I exclude Treasury bills and on-the-run securities from the yield curve estimation. One difference between their sample selection and mine is the remaining maturity. Song and Zhu (2018) discard securities whose remaining maturities are less than one year. This selection makes sense in their setting; Treasury securities nearing maturity occasionally exhibit large, idiosyncratic price fluctuations, and during the period they examine, the Fed did not purchase any securities maturing in less than 1.5 years. In contrast, in my sample period, the shortest maturity purchased by the Fed was 32 days. I therefore set a minimum remaining maturity restriction of one month.

While Song and Zhu (2018) use the Fed's internal secondary-market price data (New Price Quote System), my data source is the CRSP Treasury data. For each QE auction, I estimate the yield curve using the daily closing mid price of the previous trading day. I then measure Treasury securities' cheapness by comparing the model-implied prices and their actual closing mid prices on the day of the yield curve estimation. Note that cheapness is measured even for on-the-run securities, which are not included in the yield curve estimation.

Internet Appendix B Dealer characteristics and coarse pricing

B.1 Data

Does the degree of pricing fineness relate to the PD's characteristics (other than QE auction market share)? To explore this question, I look at three dimensions of PD characteristics.

Location of the parent bank: First, I examine whether PDs have a foreign parent company or not, referring to the PD lists of He et al. (2017) and Giannone and Robotti (2022). *Foreign* takes the value of one if the PD has a foreign parent bank, and zero otherwise.

Number of years as a primary dealer: Second, To shed light on varying experiences of PDs in the Treasury market, I measure the number of years as a PD. One challenge is how to handle mergers & acquisitions, which have been pervasive from time to time in this industry. I thus checked the historical primary dealer lists of the FRBNY. Table IA.1 summarizes the designation dates of domestic PDs, and Table IA.2 those of foreign PDs. The identification of the designation date is particularly challenging for some foreign PDs. Therefore, for some foreign PDs, I assign both the baseline and earliest start dates. *Old* takes the value of one if the (baseline) PD designation date is earlier than the median date, and zero otherwise. The use of the earliest start dates, instead of the baseline dates, does not much change the result.

Balance sheet size: Third, I hand-collected each PD's balance sheet information from Form X-17A-5, as done by Gupta (2021). An advantage of using this form is that I can obtain balance sheet data of dealer subsidiaries, as opposed to the group-wide consolidated financial data reported in 10-Ks, etc. Note that this data is also available for foreign bank-affiliated PDs because they are still incorporated as a U.S. subsidiary, and large U.S. broker-dealers are mandated to file (audited) Form X-17A-5. I was able to locate all my sample PDs' Form X-17A-5, except for that of the Bank of Nova Scotia, although there exist some gap years and non-reported items for some PDs.[1] *Ln(Total assets)* is the natural logarithm of the total assets measured at the beginning of each sub-period.

[1]Ownership structures of PDs were examined using the National Information Center repository (`https://www.ffiec.gov/NPW`). See Avraham et al. (2012) for its details.

Table IA.1: Domestic primary dealers

Name	Period as a PD	Note
Amherst Pierpont	5/6/2019–	
BofA/Merrill	5/19/1960–	Merrill Lynch Government Securities was a primary dealer from 5/19/1960 to 2/11/2009. In 2009, Merrill Lynch was acquired by Bank of America, which also owned a primary dealer, Banc of America Securities. Banc of America Securities had roots in CRT Government Securities, which was designated as a primary dealer on 12/22/1987.
Cantor Fitzgerald	8/1/2006–	
Citigroup	5/19/1960–	Citigroup was created as a result of a merger between Citicorp and Travelers Group in 1998. Citicorp owned Citicorp Securities, which was designated as a primary dealer under the name of Citibank on 6/15/1961. Travelers Group owned Salomon Smith Barney, which had roots in Salomon Brothers. Salomon Brothers was designated as a primary dealer on 5/19/1960.
Goldman Sachs	12/4/1974–	
Jefferies	6/18/2009–	
JP Morgan	5/19/1960–	
MF Global	2/2/2011– 10/31/2011	MF Global filed for bankruptcy on 10/31/2011.
Morgan Stanley	2/1/1978–	
Wells Fargo	4/18/2016–	

This table summarizes domestic primary dealers during my sample period (2010Q3–2020Q2). The four (domestic) dealers that participated in the primary dealer pilot program for July 2013–July 2014 are not included. For domestic PDs, the period as a PD is the same whether the start date is based on the baseline or earliest one. See text for data sources.

Table IA.2: Primary dealers owned by foreign parent companies

Name	Period as a primary dealer: Baseline start date	Period as a primary dealer: Earliest start date	Note
Bank of Nova Scotia	10/4/2011–	10/4/2011–	
Barclays	12/7/1989–	12/7/1989–	Barclays De Zoete Wedd was designated as a primary dealer on 12/7/1989.
BMO	10/4/2011–	10/4/2011–	For a brief period (2/15/2000–3/31/2002), BMO Nesbitt, a subsidiary of BMO, was a primary dealer. Given the brevity of the period and the time gap, the start date is determined to be that of BMO.
BNP Paribas	5/1/1997–	5/1/1997–	Paribas was designated as a primary dealer on 5/1/1997. The name was changed to BNP Paribas on 9/15/2000 as a result of a merger.
Credit Suisse	12/23/1988–	5/19/1960–	On 12/23/1988, First Boston was merged into CS First Boston, which was established as a London-based joint venture of Credit Suisse and First Boston in 1978. CS Holding effectively controlled the new CS First Boston with a 44.5% equity stake. (Credit Suisse's ownership was further increased to 60% in 1990.) First Boston had been a primary dealer since 5/19/1960.
Daiwa	12/11/1986–	12/11/1986–	
Deutsche Bank	12/13/1990–	5/19/1960–	Deutsche Bank Government Securities was designated as a primary dealer on 12/13/1990. In 1999, Deutsche Bank acquired Bankers Trust, which had been a primary dealer since 5/19/1960. (Note that this acquisition occurred well after Deutsche Bank became a primary dealer.)
HSBC	12/2/1983–	9/29/1976–	Marine Midland Bank, whose majority equity stake was owned by the Hongkong and Shanghai Banking Corporation (current HSBC), acquired Carroll McEntee & McGinley on 12/2/1983. Carroll McEntee & McGinley had been a primary dealer since 9/29/1976.
Mizuho	12/28/1989–	2/13/1980–	Following Fuji Bank's acquisition, Kleinwort Benson Government Securities was renamed Fuji Securities on 12/28/1989. Kleinwort Benson was designated as a primary dealer on 2/13/1980. (Fuji Securities was renamed Mizuho Securities on 4/1/2002 due to a merger of its parent bank.)
Nomura	12/11/1986 –11/30/2007, 7/27/2009–	12/11/1986 –11/30/2007, 7/27/2009–	Nomura once quit as a primary dealer on 11/30/2007 and regained a primary dealer status on 7/27/2009. Given the brevity of the discontinuation period, the start date is considered to be the date on which Nomura was first designated as a primary dealer (12/11/1986).
RBC	7/8/2009–	7/8/2009–	
RBS/NatWest	3/6/2000–	7/31/1984–	On 3/6/2000, RBS acquired NatWest, which owned a primary dealer Greenwich Capital. Greenwich Capital had been a primary dealer since 7/31/1984, and it was acquired by NatWest in 1996.
Societe Generale	2/2/2011–	2/2/2011–	For a brief period (7/1/1999–10/31/2001), SG Cowen, a subsidiary of Societe Generale, was a primary dealer. Given the brevity of the period and the time gap, the start date is determined to be that of SG Americas.
TD	2/11/2014–	2/11/2014–	
UBS	12/7/1989–	6/24/1988–	UBS Securities was designated as a PD on 12/7/1989. In 1998, SBC and UBS merged, with the new entity name being UBS. Before the merger, UBS Securities, a subsidiary of UBS, had been a primary dealer since 12/7/1989. SBC also owned S. G. Warburg & Co., which had been a primary dealer since 6/24/1988, as a result of its acquisition in 1995.

This table summarizes primary dealers owned by foreign parent companies during my sample period (2010Q3–2020Q2). See text for data sources.

B.2 Result

Table IA.3 shows the correlation matrix of PD-level variables. The results of pooled regressions are reported in Table IA.4.

Table IA.3: Correlation matrix of PD-level variables

	Price grid$_{256}$	*Price grid*$_{128or256}$	*Market share*	*Ln(Total assets)*	*Foreign*	*Old*
Price grid$_{256}$	1					
Price grid$_{128or256}$	0.843*** [0.000] (81)	1				
Market share	0.457*** [0.000] (81)	0.428*** [0.000] (81)	1			
Ln(Total assets)	0.254** [0.030] (73)	0.271** [0.020] (73)	0.615*** [0.000] (73)	1		
Foreign	–0.300*** [0.006] (81)	–0.169 [0.132] (81)	–0.313*** [0.004] (81)	–0.158 [0.181] (73)	1	
Old	0.211* [0.059] (81)	0.076 [0.498] (81)	0.363*** [0.001] (81)	0.488*** [0.000] (73)	–0.343*** [0.002] (81)	1

This table presents the correlation matrix of PD-level variables, pooling the data from the four sub-periods. *Price grid*$_{256}$ is the predicted proportion of using the finest 1/256ths pricing grid, and *Price grid*$_{128or256}$ is that of using the pricing grid of either 1/128ths or 1/256ths. *Market share* is the trade amount-based market share of the PD in the sub-period. See Section B.1 for the definitions and data sources for the other variables. A PD is included in the sample only if it has at least 100 winning offers in the sub-period. The number of observations used for calculating the pair-wise correlation is shown in round brackets and p-values in square brackets.

Table IA.4: PD characteristics and the predicted proportions of using fine pricing grids

Panel A: Dependent variable: *Pricing grid*$_{256}$

	(1)	(2)	(3)	(4)	(5)
Market share	2.393***				2.084***
	(0.313)				(0.414)
Ln(Total assets)		7.513*			
		(4.112)			
Foreign			-16.004*		-8.603
			(7.958)		(7.469)
Old				12.025	1.492
				(7.330)	(5.738)
MEP	18.436***	17.370***	17.700***	17.689***	18.514***
	(4.625)	(5.909)	(5.991)	(5.999)	(4.790)
QE3	29.844***	29.541***	28.799***	28.769***	30.178***
	(5.301)	(6.276)	(5.437)	(5.505)	(5.385)
QE4	26.378***	28.257***	23.528***	24.874***	26.156***
	(5.230)	(6.796)	(4.825)	(4.981)	(5.367)
Constant	7.512	-169.328	30.495***	14.702***	13.731
	(5.202)	(106.113)	(7.406)	(4.574)	(9.768)
N	81	73	81	81	81
Adjusted R^2	0.383	0.223	0.232	0.191	0.397

Panel B: Dependent variable: *Pricing grid*$_{128 or 256}$

	(6)	(7)	(8)	(9)	(10)
Market share	1.836***				1.878***
	(0.405)				(0.490)
Ln(Total assets)		5.826			
		(3.386)			
Foreign			-8.062		-3.277
			(6.335)		(6.752)
Old				4.008	-3.981
				(5.772)	(5.357)
MEP	6.910	5.591	6.259	6.199	6.890
	(5.653)	(6.360)	(6.530)	(6.537)	(5.751)
QE3	26.165***	25.414***	25.129***	24.967***	26.096***
	(4.519)	(5.537)	(4.713)	(4.746)	(4.517)
QE4	11.204**	11.952**	9.027*	9.482**	10.812**
	(4.108)	(5.134)	(4.546)	(4.322)	(4.140)
Constant	42.982***	-93.763	58.037***	51.106***	46.745***
	(4.340)	(86.682)	(6.698)	(3.851)	(8.699)
N	81	73	81	81	81
Adjusted R^2	0.360	0.226	0.185	0.158	0.354

This table reports the results of the regressions in which the dependent variable is the predicted proportion of using the finest pricing grid of 1/256ths (*Price grid*$_{256}$) or that of using the pricing grids of either 1/128ths or 1/256ths (*Price grid*$_{128 or 256}$). A PD is included in the sample only if it has at least 100 winning offers in the sub-period. *Market share* is the trade amount-based market share of the PD in the sub-period. *MEP*, *QE3*, and *QE4* are indicator variables for the sub-periods. (*QE2* is the reference category.) See Section B.1 for the definitions and data sources for the other variables. Standard errors clustered for PD are reported in parentheses. ***, **, and * indicate significance at 1%, 5%, and 10% levels.