Open-Ended Treasury Purchases:

From Market Functioning to Financial Easing

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Open-Ended Treasury Purchases: From Market Functioning to Financial Easing

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Abstract

We exploit the Fed's Treasury purchases conducted from March 2020 to March 2022 to assess whether asset purchases can be tailored to accomplish different objectives: restoring market functioning and providing stimulus. We find that, on average, flow effects are significant in the market-functioning (MF) period (March-September 2020), while stock effects are strong in the QE period (September 2020-March 2022). In the MF period, the elevated frequency and size of the purchase operations allowed flow effects to greatly improve relative price deviations, especially at the long-end of the yield curve. But stock effects remained localized, thus not large enough to be stimulative. In contrast, in the QE period, stock effects were stimulative because cross-asset price impacts got larger as the Fed communication and implementation moved toward "traditional" QE, increasing purchases' predictability. Lower uncertainty about the expected size and duration of total purchases facilitated their impounding into prices. Overall, these findings suggest that communication and implementation can be used to tailor the goals of asset purchases.

Keywords: Monetary policy tools, quantitative easing, market-functioning asset purchases, communicated policy goals, asset purchases implementation.

Classification: E43, E44, E52, E58

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1 Introduction

Central banks employ large-scale asset purchases (LSAPs) for multiple purposes. One of the main purposes has been to provide monetary policy accommodation when the policy rate is at the effective lower bound (ELB). In addition, asset purchases have been used to restore smooth market functioning and support financial stability—in some cases at the same time as providing accommodation, and in some cases distinct from monetary policy decisions.[1] A fundamental unresolved question in the literature is how asset purchases can be tailored to accomplish different objectives, or, put another way, how the same open market operation can be used to achieve different results in different economic and market conditions. Recently, this question has been highly debated in policy and academic circles.[2]

The answer to the above question clearly depends on two crucial factors: (1) whether the LSAP's effects and transmission mechanism are affected by its communicated objective and (2) how the LSAP's design and implementation are adjusted to achieve different objectives. Our focus is to analyze these two key factors using the Treasury purchases conducted by the Federal Reserve from March 2020 to March 2022. This allows us to understand whether LSAPs can effectively serve a dual objective, that is, restore market functioning and provide monetary policy accommodation as needed; and tangentially, whether policymakers need to commit to each objective in advance.

The Fed's Treasury purchases of March 2020-2022 are particularly helpful to address this question because they were used to serve multiple objectives over time. According to the FOMC statements, their initial goal was to support smooth market functioning; later, the goal of fostering accommodative financial conditions was added as in previous QE.[3] As a result, over a few months, the purchases' implementation was greatly changed. The scale and pace of the Treasury operations, which initially peaked around $75 billion per day, was reduced to $80 billion per month as market functioning improved.

To understand whether this program's communicated objectives and implementation mattered, we estimate its flow and stock effects, both part of QE's supply chan-

1. For instance, see Bailey (2022).
2. See Logan (2023) and Duffie (2023).
3. Board of Governors of the Federal Reserve System (2020 a, b, c).

nel.[4] To this end, we use an approach similar to D'Amico and King (2013), which we modify to account for the differences between the 2020-2022 purchases and the Fed's first LSAP in 2008-2009. In particular, the latest round of Treasury purchases had several novel features: it was an open-ended rather than a fixed-size program, its goals shifted from supporting smooth market functioning to easing financial conditions, its implementation consisted of multiple purchase operations per day, and its operations' size pre-2021 was less predictable as it was contingent on market conditions.

We choose to study the program's flow and stock effects for the following reasons. Since stock effects measure the permanent price impact of total amounts purchased, they are predominately related to expectations of lower asset supply and hence easing financial conditions. As shown in D'Amico and King (2013), the key driver of the stock effect is the cross-price sensitivity of each security to the purchases of securities with similar maturity—the substitution effects—which in the aggregate move down entire sectors of the yield curve, providing monetary stimulus. In principle, substitution effects should be weak when markets are highly segmented. Therefore, it is reasonable to assume that stock effects would not be the main mechanism that restores market functioning.

In contrast, since flow effects measure the price impacts of ongoing purchase operations, where each operation's size is fairly predictable, we would expect these effects to be significant only when market functioning is poor. This is because, under limits to arbitrage, even perfectly anticipated changes in supply can have a temporary price impact (e.g., Lou, Yan, and Zhang (2013)). This implies that flow effects could be the predominant mechanism restoring smooth market functioning. Indeed, flow effects, by correcting relative price deviations from fundamental values, can simply smooth bumps in the yield curve without necessarily shifting down the entire curve.

To assess the importance of the communicated objective of the LSAPs, the estimation is conducted over the entire sample period, March 12, 2020 to March 9, 2022, and over two sub-periods: March 12–September 15, 2020, the period during which communications primarily emphasized a goal of smooth market functioning, and September 16, 2020–March 9, 2022, the period in which the communicated goals aligned more with traditional QE. We refer to the first period as the "market functioning" (MF) period, and the second period as the "QE" period, and we also check robustness to

4. Fleming et al. (2021), Duffie and Keane (2023), and Vissing-Jorgensen (2021) study the Fed's market-function purchases conducted in the spring of 2020. In contrast, we focus on the entire 2020-2022 LSAP program.

alternative definitions of those sub-periods.

We find that, in the QE period, the stock effect is about 10 times larger than in the MF period. In total, the supply channel alone reduced the 10-year equivalent yield by about 60 basis points. Nearly 54 basis points are due to the $1.2 trillion of Treasury purchases conducted in the QE period and only about 6 basis points are due to the $1.7 trillion of purchases conducted in the MF period. The strong stock effects in the QE period are solely due to the substitution effects, which are not activated at all in the MF period. In the MF period, stock effects remain very localized, and hence small in the aggregate, because only the price impact of individual purchases (as opposed to purchases of substitute securities) is significant. Overall, these findings suggest that the Treasury purchases were stimulative only in the QE period and that the program objective might matter.

Importantly, the results from 6-month rolling-window regressions indicate that the magnitude of the coefficient on substitute purchases starts increasing around September 2020 and becomes consistently larger from February 2021. September 2020 is when the FOMC announced that the goal of the purchases was to ease financial conditions. February 2021 is when the Fed began releasing auction calendars for the Treasury purchase operations at a monthly frequency. It is telling that the magnitude of the effect started increasing when the communicated goal changed, and became consistently larger when the increased transparency around auction dates/sectors/sizes reduced uncertainty about the expected size and duration of total purchases, facilitating their impounding into prices.

Hence, our findings suggest that it is not only the communicated goal of the purchases that matters, but also the design and implementation of the purchase operations. The increased predictability of the amounts purchased seem to amplify the stock effects, most likely by facilitating the expectation formation process. This contrasts with the flexibility in the scope and pace of purchases used to address the market dysfunction. Moreover, if the larger impact of the LSAPs in the QE period was due to the improved market conditions, which were essentially back to normal by June 2020,[5] the size of the coefficients on substitute purchases should have started rising around June 2020. But this is not the case.

Finally, the estimated size of the stock effects described above indicates that, on

5. As discussed in Logan (2020), by the beginning of June 2020, most measures of market functioning in the Treasury and MBS markets were back to pre-Covid levels.

average, $100bn of purchases would reduce the 10-year yield by 4.5 basis points, which is in line with previous average estimates of LSAP programs.[6] This suggests that there are no diminishing returns despite the size and length of the purchase program.[7]

When we estimate the flow effects, we find that they are much stronger in the MF period than in the QE period and they differ significantly across maturity sectors. In particular, the flow effects are much larger in the 20- to 30-year sector of the yield curve, which initially experienced the largest price dislocations. A typical operation ($7 bn) would reduce sector yields by one basis point, but at longer maturities its impact would be 7 times larger. However, in the period of elevated market stress, the flow effects are estimated to revert quickly—within a few days of the purchase operation—indicating that frequent and large operations were warranted to support market functioning in a consistent manner.

In the spring of 2020, the Fed, by purchasing securities at an aggressive pace daily, did not allow the flow effects to revert. To quantify their total average impact in the MF period, we apply the sector-level flow effect to each single security purchased over the first six months of the program, and obtain a counterfactual yield curve. That is, we estimate what the yield curve would have looked like in mid-September 2020 in the absence of daily purchase operations in each maturity sector. This curve indicates that in the 20- to 30-year sector, yields would have been about 75 basis points higher than they were in mid-March 2020. In the intermediate sectors, yields would have largely remained as high as they were in mid-March, rather than declining between 25 and 50 basis points by mid-September 2020. At maturities shorter than 2.5 years, the flow effects did not contribute much to the yield reduction that occurred by mid-September.

Overall, these findings indicate that, even if the stock effects were very small in the MF period, the flow effects restored a smooth yield curve, and hence market functioning, as they corrected price deviations by different amounts in each maturity sector. This, in turn, suggests that, when using LSAPs for market functioning purposes, frequent adjustments to the scope and pace of purchases can ensure that price

6. See Gagnon et al. (2010); Krishnamurthy and Vissing-Jorgensen (2011); D'Amico et al. (2012); Meaning and Zhu (2011); D'Amico and King (2013); McLaren, Banerjee, and Latto (2014); Eser and Schwaab (2016); Bonis, Ihrig, and Wei (2017); D'Amico and Seida (2023).

7. Since in the cross section, we do not control for purchases of MBS and corporate bonds with duration similar to the Treasuries purchased, it is possible that our estimated coefficients are upward biased. However, the duration of the MBS purchased (due to very small coupons) was much longer than the duration of the Treasuries purchased, hence the correlation of MBS and Treasury purchases across maturity buckets should be low; and corporate purchases were extremely small.

improvements are sustained. This flexibility, however, complicates the expectation formation process about the total amount that will be ultimately purchased and held in the Fed portfolio, making the permanent supply effect small.

Our study contributes to an emerging literature on the importance of the communicated rationale of a policy tool. In particular, Blot et al. (2022) examine two ECB bond purchase programs that mostly differed in their stated rationales. They find different effects between the purchases meant to ameliorate deflation risks and those meant to reduce financial market stress, hence conclude that a well-communicated rationale can influence the purchases' transmission to financial markets. Our findings suggest that it is not only the communicated goal of purchases that matters, but also the design and implementation of such purchases being aligned more closely to the goal. Moreover, we uncover how the relative importance of flow and stock effects changes with MF and QE purchases.

Somewhat relatedly, Haddad, Moreira, and Muir (2022) study the impact of implicit central bank promises to intervene in severely adverse states, and find that expectations of large interventions in those states of the world reduce tail risk. While we do not specifically investigate the value of the Fed's commitment to unlimited Treasury purchases during the Covid episode, state-contingent LSAP support may have played a role in the effects we document. That is, changing the goal and implementation of purchases over time, based on economic and market conditions, activated flow and stock effects in different ways. This suggests that committing in advance the entire purchase program to one specific objective might not be very valuable, as the state-contingent goal and implementation of the open-ended purchases seemed to activate different transmission mechanisms that help obtain the desired effects.

The rest of the paper is organized as follows. Section 2 describes how the studied purchase program differs from prior LSAPs. Section 3 discusses the rationale and basics for our approach. Section 4 focuses on the estimation of stock effects, while Section 5 focuses on flow effects. Finally, Section 6 offers concluding remarks.

2 Novel aspects of the 2020-22 LSAPs

From March 13, 2020 to March 9, 2022, the Fed purchased Treasury securities at an unprecedented pace. The initial goal of the purchases was to ensure smooth market functioning, but after a few months the goal shifted to easing financial conditions, the same goal of previous Fed LSAPs and QE in general.

Initially, the pandemic purchases were characterized by unprecedented scale and speed, deemed necessary to restore market functioning. In March 2020, *daily* Treasury purchases peaked at \$75 billion, which is equivalent to conducting the seven-month-long 2009 Treasury LSAP in only four days. Over the two years of the program, Treasury purchases totaled \$2.9 trillion.

Commitment and flexibility were key aspects of the pandemic purchases. Rather than specifying either the total amount of purchases, as in previous fixed-size programs, or a monthly pace, as in previous open-ended programs, the Fed committed to unlimited purchases, that is, "in the amount needed." Further, the size and maturity distribution of purchases were adjusted weekly and even daily when necessary, depending on market conditions. This made it difficult for market participants to forecast the quantities purchased in the early months of the purchase program.

In September 2020, the FOMC communicated an additional objective for the Treasury purchases: fostering "accommodative financial conditions." At the same time, the *monthly* pace of purchases stabilized to \$80bn. However, the language of the FOMC announcement related to asset purchases had already started shifting before September. In particular, the June 2020 FOMC statement indicated that, in addition to sustaining smooth market functioning, the purchases were intended "to support the flow of credit to households and businesses" and "thereby fostering effective transmission of monetary policy to broader financial conditions."

Hence, over a span of six months, the objective of the purchases transitioned from restoring and sustaining market functioning, to supporting the transmission mechanism of monetary policy, to fostering accommodative financial conditions.

Regarding the information available to investors about the Treasury purchase implementation, the initial announcements specified some key parameters of the program.[8] First, the Desk indicated that it would conduct purchases roughly in line with the composition of Treasury securities outstanding. Hence, it was clear from the beginning that the Desk did not intend to alter the average maturity of privately-owned Treasury debt. Second, the Desk specified that it would constrain the share of SOMA holdings of any one security to 70% of outstanding, with restrictions on purchase sizes per operation kicking in once SOMA holdings of a security reached 35% of outstand-

8. Federal Reserve Bank of New York (2020)

ing. Third, cheapest-to-deliver securities,[9] which in previous LSAPs were ineligible for purchase, became eligible between March 13, 2020 and April 17, 2020.

Overall, by examining the published guidelines, market participants could form expectations about purchase amounts at the CUSIP level. However, since at the height of the crisis, the operation calendar was not announced regularly and well in advance, it was harder than in previous programs to form expectations on the overall and individual quantities purchased. In March 2020, auction participants were informed by the end of each business day about the time/sector/size of the operations occurring the next day. By April 2020, the auction calendars covered a week of purchases; by mid-June 2020 they covered two weeks of purchases; and, in February 2021, the Desk moved to regularly released monthly calendars.

Finally, differently from previous LSAPs, there were up to seven operations per day, spread across the maturity sectors in which the Desk conducted its auctions. Thus, to investigate whether the purchase effects differ across maturity sectors, it is necessary to use high-frequency data. This enables us to compute price changes in the tight time window around each operation taking place in a specific maturity sector within a specific day.

2.1 Purchase operation mechanics

Some additional details about the mechanics of the Desk's purchase operations are necessary to better understand our empirical design and results. As in previous LSAP programs, the purchases were conducted by multiple-price auction.

From March 2020 to May 2021, the auctions were conducted in five separate maturity sectors: 0- to 2.25-year, 2.25- to 4.5-year, 4.5- to 7-year, 7- to 20-year, and 20- to 30-year. After May 2021, the number of sectors increased by one, as the longer-maturity sectors were divided in narrower ones: 7- to 10-year, 10- to 22.5-year, and 22.5- to 30-year. Auctions took place every day and settled on the following day. Typically, each auction would take place within a 15-minute window separated by 30-minute intervals from adjacent auctions. This allows us to isolate the daily price impact in each maturity sector by using intraday data.

9. Treasury futures contracts can be satisfied by delivering any of several Treasury securities within a specified maturity sector. The cheapest-to-deliver security for a given futures contract is the security that satisfies the futures contract specifications at the lowest cost, given market prices as well as the rules for converting among different eligible securities for a futures contract.

At the start of each auction, the Desk informed participants about specific issues that would be excluded from the operation. These exclusions could be due to the security's heightened scarcity value or very short maturities. Then, the Desk evaluated bids based on "their proximity to prevailing market prices at the close of the auction, as well as measures of relative value" from its proprietary model and decided at which price and how much of each CUSIP to purchase.[10]

Hence, ahead of each auction, market participants were not aware of the actual purchase distribution across CUSIPs that would prevail after the auction. It is the difference between expected and actual distribution of purchases that can trigger price reactions following the release of each auction's results. How pronounced and for how long these price reactions persist depend on the extent of limits to arbitrage.

3 Rationale and basics of our approach

3.1 Rationale

In theory, flow effects are the impact of actual purchase operations and therefore should be predominantly related to market functioning. Because the sectors of purchase operations are announced in advance and both the list of eligible CUSIPs and the total size of each operation are fairly predictable, one might expect that yields should not change significantly around actual purchases. However, within the list of eligible securities, the particular CUSIPs that will be purchased and the amount allocated to each CUSIP are not known in advance, so yield differentials could emerge after the auction between securities that are purchased in different amounts, included those that are not purchased at all despite being eligible.

In addition, under limits to arbitrage, even perfectly anticipated changes in supply could have effects on prices when they occur, as shown by Lou, Yan, and Zhang (2013) in the case of Treasury auctions and D'Amico and King (2013) in the case of Fed operations. This is because when dealers are risk averse, capital moves more slowly and markets are segmented. In this scenario, even small differences between the realized and expected distribution of purchases across securities can take a bit to be absorbed by investors, who will need to adjust their portfolios to these changes. However, in this case, flow effects are expected to reverse quickly and are shown to be

10. Federal Reserve Bank of New York (2020).

short lived.[11] How short lived will depend on the severity of the limits to arbitrage.

In contrast, stock effects are associated with the total change in the quantity and duration of Treasury securities that the Fed is expected to remove from the market. Therefore stock effects should be predominantly related to easing financial conditions and should be quite persistent. (The persistence of the effect will depend on how long the securities are expected to remain in the Fed portfolio at the time of purchase and, subsequently, on the announced strategy for QT.) Importantly, as shown in D'Amico and King (2013), stock effects mostly originate from substitution effects. In other words, what matters for having a significant stock effect is the cross-price sensitivity of each security to the purchase of securities with similar maturity.

Since this cross-price sensitivity depends on the degree of substitutability between the different securities, it measures the substitution effect, which determines the aggregate impact of QE on entire segments of the yield curve. These substitution effects tend to be weaker and occur more slowly when markets are highly disrupted, which is the main reason why we do not anticipate stock effects to be the key channel through which Treasury purchases restore market functioning. Finally, since stock effects are related to the cumulative Treasury supply shock, they tend to be much larger than flow effects.

3.2 Substitutes

In estimating the stock and flow effects, we follow an empirical design similar to D'Amico and King (2013), which we extend to account for the novel aspects of the pandemic purchases. Their granular approach exploits the cross-sectional variation in the individual prices and quantities of the securities bought by the Fed, and allows one to estimate the price sensitivity of each security to its own purchases and the purchases of substitute securities. For this reason, it is necessary to specify the "substitutes," which are a key element of the purchases' propagation mechanism.

For each security i in our sample, we partition the outstanding securities into buckets of substitutes, $S_n(i)$, consisting of other securities with very similar characteristics. The dollar amount of substitutes purchased for each security i in the n^{th} bucket is denoted by $Q_{i,n} \equiv \sum_{j \in S_n(i)} Q_j$, while $Q_{i,0}$ is the amount purchased of security i itself. We will refer to this as "own purchases," which allows us to analyze how localized

11. See e.g., D'Amico and King (2013) and Bernardini and De Nicola (2020).

supply effects are. If own purchases are the only ones that matter, then the price impact is extremely localized suggesting that the market is very segmented.

We consider three sets of substitutes (i.e., $n = 3$) and, as in preferred-habitat models, the degree of substitutability is based on the maturity distance of each Treasury security from security i, marked by the black vertical line in Figure 1. The "near" substitutes have the closest maturity distance from security i, shown in blue, the "far" substitutes have the farthest maturity distance from i, shown in green, and "mid" substitutes are in between, shown in orange. Specifically, substitutes are defined as a logistic function of the security's maturity, τ, to allow the bucket of substitutes to get wider as τ increases. This is important because there are fewer securities outstanding at the long end of the yield curve.[12]

[Figure 1 about here.]

Finally, since the Treasury market is very large, to better capture relative scarcity in the n^{th} maturity sector, we assume that the potential influence of quantities purchased in a given sector depends inversely on the nominal dollar amounts outstanding in that sector, $AO_{i,n}$ (D'Amico and King (2013)). Thus, we consider a normalized quantity variable $q_{i,t,n}$, where the normalization is a function of $AO_{i,n}$, which is dynamically updated to account for the Fed purchases and Treasury issuance. This is necessary because to correctly capture scarcity we need to consider only the amount outstanding remaining in the hands of private investors.

3.3 Subperiods

Since we are focused on understanding how the effects of LSAP vary based on the program objective (i.e., ensuring smooth market functioning versus fostering accommodative financial conditions), we estimate the stock and flow effects over two main subsample periods, and then extend the analysis to rolling sample periods.

The first subperiod, labeled the "market functioning" period and denoted "MFI", runs from 3/13/2020 to 9/15/2020. During this period, the primary goal of the Treasury purchases, as communicated by the FOMC, was to restore market functioning.[13]

12. First, we obtain the substitute bandwidth b for a given bucket (near, mid, or far) based on the time to maturity τ and a logistic distribution with location = 15 and scale = 4. See Appendix A.

13. See Logan (2020).

The second subperiod, labeled the "QE" period and denoted "QEI", runs from 9/16/2020 to 3/9/2022. During this period, the primary goal of the Treasury purchases communicated by the FOMC was fostering accommodative financial conditions. Moreover, by mid-September 2020, market functioning had greatly improved.

We also analyze an alternative specification, denoted "II." Instead of basing the sample breakpoint on the FOMC statements' language, we use the frequency of the Desk's auction calendars. Once the calendars were released at a regular monthly frequency as in previous QE programs, it must have been clear that the flexibility to adjust purchases on daily/weekly basis to market conditions was not anymore necessary. Thus, we choose February 2021 as an alternative date for the beginning of the QE period, when the auction calendars started being released monthly, specifying dates/sectors/sizes for the full month ahead. The amounts purchased in each of these subperiods are shown in Table A.1 in Appendix B.

Based on the rationales above, we start with analyzing the stock effects, which should be more relevant for understanding the overall easing provided by the Treasury purchases; and then, we transition to the analysis of the flow effects, as the initial purpose of the purchases was to improve market functioning. For both flow and stock effects, we examine their evolution in the market functioning period and in the QE period. Further, we address the persistence of each type of effect by estimating dynamic impulse responses.

4 Stock Effects

In this section, we focus on the stock effects, that is, the impact that the Fed purchases had on prices by permanently reducing the total amount of Treasury securities available to private investors. Of course, expectations of such effects should have been impounded into Treasury prices as soon as the market became aware of the Fed's intentions, before any purchases took place. Presumably, this mechanism should account for the largest share of the drop in Treasury yields. However, since the goal of the purchases was shifting over time and their monthly pace did not stabilize until February 2021, the expectation formation process related to these open-ended purchases could have been more complicated than in previous LSAPs.

In particular, the initial uncertainty due to the highly distressed market conditions and the flexible scope and pace of purchases might have caused fluctuations in expectations about the total amount and duration of the Treasury purchases. In other words, market participants may have kept updating their expectations based on the ongoing purchase operations and the evolving FOMC communication. However, these expectations become irrelevant once the total actual amounts and distribution of purchases are revealed. Thus, all else equal, the difference in price changes across two securities between the time the program was announced and the time it was concluded should depend only on the relative amount of each security that was actually purchased over the life of the program.

But, during the entire program, the quantities purchased by the Desk might have responded to price dislocations. This reverse causality is problematic. Hence, as in D'Amico and King (2013), we use two-stage least squares to estimate the stock effects and, at the first stage, we instrument the security-level purchases using the security's characteristics as of the day before the announcement, that is, March 12, 2020. Any security-level pre-announcement information used to form expectations about future quantities purchased cannot be endogenous to the post-announcement quantities purchased.

In particular, we estimate the following cross-sectional specification:

$$q_{i,0,T} = \gamma_0 + \gamma_1 FE_{i,t} + \gamma_2 \tau_{i,t} + \gamma_3 \tau_{i,t}^2 + \gamma_4 PO_{i,t} + \gamma_5 Off_{i,t} + \gamma_6 CTD_{i,t} + \gamma_7 PD_{i,t} + \varepsilon_i \quad (1)$$

$$q_{i,near,T} = \zeta_0 + \zeta_1 \overline{FE}_{i,t} + \zeta_2 \overline{\tau}_{i,t} + \zeta_3 \overline{\tau_{i,t}^2} + \zeta_4 \overline{PO}_{i,t} + \zeta_5 \overline{Off}_{i,t} + \zeta_6 \overline{CTD}_{i,t} + \zeta_7 \overline{PD}_{i,t} + \eta_i \quad (2)$$

$$\frac{\Delta P_{i,s,T}}{P_{i,t}} = \beta_0 q_{i,0,T}^{IV} + \beta_1 q_{i,near,T}^{IV} + \phi_0 + \phi_1 \tau_{i,t} + \phi_2 \tau_{i,t}^2 + \phi_3 \log(P_{i,t}) + \phi_4 FE_{i,t} + u_i \quad (3)$$

where t is the day before the announcement, T marks the day of the last purchase, and τ is maturity. β_0 and β_1 are the coefficients of interest. Specifically, β_0 measures the price sensitivity of each security to its own purchases, while β_1 reflects the cross-price sensitivity of that security to other Treasury securities' purchases. Since this cross-price sensitivity depends on the securities' degree of substitutability, it measures the substitution effect.

We control for maturity and maturity squared, which has a dual purpose. These terms not only help control for the duration-risk channel of QE purchases, but also account for possible secular changes in the slope and curvature of the yield curve resulting from varying macroeconomic conditions and new Treasury issuance from March 2020 to March 2022. (In the robustness section we assess whether these controls are indeed sufficient.) Since we expect prices and yield curve fitting errors (FE) to be mean-reverting, we include the initial price and the initial fitting error in the second stage, because their omission would bias the purchase coefficients β_0 and β_1.

The instrumental variables deserve a separate explanation. We chose a set of security characteristics that market participants could have used to form expectations about the distribution of Fed purchases, prior to their commencement. In many ways, the Desk's guidelines provided before the start of purchases, were similar to the guidelines from previous LSAP programs. Additionally, market participants could have looked to previous LSAPs for guidance in forming expectations. Thus, we rely on many of the same instruments used in D'Amico and King (2013), including maturity τ, maturity squared τ^2, percentage of amount outstanding held by the Fed PO, fitting error FE, and a dummy for far-off-the-run issues Off.

However, unlike previous LSAPs, the Desk explicitly allowed purchases of securities that were cheapest-to-deliver into futures contracts and notified the market of this on March 15, 2020. Given this directive, we include an indicator for the cheapest-to-deliver securities, CTD. More importantly, cognisant of the role of dealers' intermediation capacity during the Covid episode (e.g., Duffie (2023)), which was limited by their large Treasury inventories, it is reasonable to expect dealers to be more willing to offer the Fed securities that were clogging their balance sheets.[14] For this reason, we use as an instrument the net Treasury positions of primary dealers (PD) in each maturity range, as of the week before the start of purchases.[15]

It should be noted that while "own purchases" are instrumented using individual securities' characteristics, the "near purchases" are instrumented using a weighted average of the characteristics of all securities included in the basket of near substitutes. The construction of these weighted averages and each variable construction are discussed in Appendix C. And, since we have to instrument two endogenous variables (own and near purchases), the standard errors and p-values are generated using the wild bootstrap outlined in Davidson and MacKinnon (2010).

Finally, in the cross-section specification, we can include only the 195 CUSIPs that existed from March 2020 to March 2022 and accounted for about \$1.7tr of total purchases. Hence, because of the length of the purchase program, these stock effects do

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14. Since the Fed purchases depend on dealers' propositions at auctions, it is likely that the Fed would buy relatively more of the securities that were held by primary dealers in larger amounts.

15. The data are obtained from the Federal Reserve Bank of New York (FRBNY)'s Primary Dealer Statistics.

not include any securities with less than 2 years to maturity. The number of available observations implies that we have to drop the mid and far substitute purchases, which however can be included in the panel regressions used to estimate flow effects in the next section.

4.1 Results

We start with commenting briefly on the first-stage results, which are shown in Table A.4 in Appendix D.1, and then discuss in more detail the second-stage results, which are at the core of this study.

The most relevant aspect of the first-stage regressions is that we can explain a large share of the quantities purchased of near substitutes using the securities' characteristics as of the day before the announcement. In this case, the results are characterized by very high R^2 and F-statistics for both the MF and QE periods. The F-statistic are well above 10, the critical value suggested by Staiger and Stock (1997), or even above the higher refined values suggested by Stock and Yogo (2003) for strong instruments. However, the R^2 and F-statistic are lower in the case of own purchases, indicating that market participants were able to predict pretty well the distribution of purchases across maturity sectors, but not across individual securities. Interestingly, the instruments get much stronger in the QE periods relative to the MF periods, as investors learn to predict better a CUSIP's own and near-substitute purchases.[16]

Turning to the second-stage results, Table 1 summarizes the estimated stock effects over the full sample period (first column) and across the MF and QE periods, based on the two alternative criteria described in Section 3. A key finding is that the impact of the Fed purchases is 10 times bigger in the QE period than in the MF period, as the coefficient on the purchases of near substitutes—the key driver of the aggregate supply effects—is not statistically significant in the MF period. This suggests that the communicated goal of the program matters, as only in the QE period the persistent substitution effect is activated. However, these results could be in part driven by the improved market conditions, but later we show that this does not seem to be the case. Further, the coefficient on own purchases is positive and statistically significant only in the MF period, when market functioning is poor, in line with theories of market segmentation.

16. It should be noted that when we estimate the stock effects in each subperiod, the first-stage needs to be re-estimated using IV observed as of the day before each subperiod.

[Table 1 about here.]

In the QEI period, the coefficient of 0.197 on near-substitute purchases implies that, on average, purchasing 1% of the privately-held stock of a security's substitutes increased its return by about 0.197%; for a representative ten-year security with a duration of nine years, this translates into a yield decrease of about 4.5 basis points per $100 billion of purchases.[17] This implies that the total amount purchased during the QEI period ($1.2tr) reduced the equivalent 10-year yield by nearly 54 basis points.

In the MFI period, the coefficient of 0.019 on own purchases implies that, on average, purchasing 1% of the privately-held stock of a certain security increased its return by about 0.019%; for a representative 10-year security with a duration of nine years, this translates into a yield decrease of about 0.4 basis points per $100bn purchased, that is, a yield impact 10 times smaller than that found in the QE period. This implies that the total amount purchased during the MF period ($1.7 tr) reduced the yields by a mere 7 basis points. Hence, overall, the total amount of Treasury purchased ($2.9tr) is estimated to have reduced yields by about 60 basis points only through the supply channel. That is, our estimates do not include the impact of the duration-risk, signaling, and liquidity channels.[18]

To verify the robustness of our key finding to the choice of the MF and QE periods, we re-estimate Equation 3 over multiple subperiods, in which the end date is fixed at March 9, 2022 but the start date changes from March 2020 to February 2021, one week at a time.[19] Figure 2 shows the evolution of the coefficients for the own and near-substitute purchases over the different subperiods, along with 95% confidence bands. It should be noted that as we move along the horizontal axis the length of the sample period is getting shorter. It is clear that, as long as the later part of the sample period is included in the analysis, the coefficients of the substitute purchases are always positive and significant. Actually, as soon as the first month of purchases

17. This effect is obtained by multiplying the significant coefficient on near-substitute purchases, 0.197, by the average near-substitute percentage purchased in the QE period, 11.67%. We convert this average return of 2.30% into a 10-year equivalent yield by dividing by 9, the duration of the 10-year benchmark note.

18. The signaling channel works through changes in the expected path of the policy rate induced by QE. The duration-risk channel affects term premiums by changing the amount of aggregate duration risk held by private investors. The liquidity channel also works through risk premiums, as the ongoing asset demand from the central bank improves trading opportunities and reduces liquidity risk.

19. This exercise requires the re-estimation of the first stages with instruments observed as of the day before the beginning of each sub-sample.

is excluded from the sample, the estimated coefficient starts increasing, and it peaks at 0.4 once the first 3 months of purchases are excluded from the sample.

Finally, once June 2020 gets out of the sample period, the coefficient stabilizes toward its average level of 0.2 estimated in the QEI and QEII periods. As shown in the speech of Logan (2020), by the beginning of June measures of market functioning in the Treasury and MBS markets had uniformly improved and were practically back to their pre-Covid levels. This seems to suggest that better market functioning might be as important as the communicated goal of the purchases for the magnitude and significance of the stock effects. To try to disentangle the contribution of these two factors, rather than keeping the end date of the sample period fixed at March 9, 2022, we use rolling samples. In this way, the entire QE period is not contained in all sub-samples.

[Figure 2 about here.]

In particular, we use 6-month rolling windows starting in March 13, 2020, with the last sub-sample starting in May 6, 2021 (rather September 9, 2021, which marks exactly 6 months until the purchases' end). We use this end date because, by then, all securities in our cross-section are far off-the-run, and therefore we would lose one of the IVs if we kept rolling the window further.

Figure 3 plots the coefficients for the own and near-substitute purchases from the rolling-window regressions, along with 95% confidence bands. The estimated pattern of the near-substitute coefficient indicates that its magnitude starts converging toward its average value of 0.2 once February 2021 enters into the sample. As shown in the last row of Table 2, this is the month in which the auction calendars for the Treasury purchase operations started being released one month in advance (marking the beginning of our QEII period). That is, starting on February 12, 2021, market participants had knowledge of the dates/sectors/sizes of each operation earlier, which should have reduced the uncertainty about the expected maturity distribution of future purchases, facilitating the impounding of these expectations into prices. A better impounding of the expected size and maturity of purchases into prices is key to significant stock effects.

[Figure 3 about here.]

Other factors might have contributed to a better predictability of the size and maturity of future purchases. In May 2021, the maturity sectors of the purchase operations became narrower and the intended maturity distribution across these sectors was released to the public, further removing uncertainty. Moreover, the maturity distribution of purchases shifted by 3% towards the 7-30-year sector to adjust to Treasury issuance, further corroborating the Desk's initial guidance about replicating the maturity distribution of the Treasury debt outstanding.

[Table 2 about here.]

Further, it is possible that the lower frequency of the auction calendar releases has a signaling effect: it signals commitment to QE and therefore a more persistent supply shock. Releasing the auction calendars monthly, as in previous QE programs, reduced the optionality of adjusting frequently the size and sectors of purchases to market conditions, indicating that indeed the main goal of the purchases shifted toward providing monetary policy accommodation rather than supporting market functioning. In this respect, it is telling that the magnitude of the near-substitute coefficient does not get larger soon after the September-2020 FOMC, when the purchases' goal became easing financial conditions, but it gets larger soon after February 2021, when the purchase implementation aligned more closely with such goal.

These findings are very important because they seem to suggest that it is not only the communicated goal of the purchases that matters, but also the design and implementation of such purchases being adjusted to the goal. The increased transparency and predictability of the amounts purchased seem to amplify the stock effects, most likely by facilitating the expectation formation process and its impounding into prices. This, though, contrasts with the flexibility in the scope and pace of purchases needed to address market dysfunctions. If the purchases' flexibility made it harder to predict the size and persistence of asset supply shocks, then it should not be surprising that in the market functioning periods (MFI and II) we do not find any statistically and economically significant stock effects.

Last but not the least, it is also telling that the change in the magnitude of the near-substitute coefficient does not occur soon after June 2020, when market functioning is effectively back to normal, indicating that the improved market environment is not the main driver of the larger stock effects. As shown in Figure 3, stock effects did not pick up until 2021, suggesting that a better predictability of the supply shocks and their persistence is the key driver of the substitution effects that lead to a larger supply effect.

4.2 Robustness

4.2.1 Security-level liquidity

In order to examine how our results vary with a security's liquidity characteristics, we allow the second-stage coefficients to differ across security groups. In particular, we divide the sample by maturity and vintage. The small number of observations makes running separate regressions on each of these groups problematic, hence we interact $q_{i,0,T}$ and $q_{i,near,T}$ with dummy variables that divide the sample into mutually exclusive subsamples—short vs. long maturities and near-on-the-run vs. far-off-the-run securities. To distinguish longer and shorter maturities, we split the sample at the middle of the yield curve, 15 years. To distinguish securities by vintage, we split the sample into securities that are more than five issues off-the-run (far-off-the-run) and those that are less than six issues off-the-run (near-on-the-run). We retain the same first stage specification. The tables summarizing the results of this robustness exercise are in Appendix D.2.

In Table A.5, it is possible to note that the positively significant coefficient on own purchases in the MFI period is due to securities with less than 15 years to maturity; while, the coefficients for on- and off-the-run securities show no major differences. The same patterns are also present in the MFII period (Table A.7).

In Table A.6, it can be noted that the effect of near-substitute purchases is much larger in securities with less than 15 years to maturity and far off-the-runs. Interestingly, in the QEI period the coefficient on own purchases is never significant across any cut of the data, which should be the case in normal market conditions.

Finally, the results shown in Table A.8 indicate that in the later QEII period, once markets conditions were back to normal, all the effects become more homogeneous across all cuts of the data. Only the coefficient on near on-the-run becomes much larger, but this result should be taken with a grain of salt, as in the QEII period there were few near-on-the-runs left in the sample.

4.2.2 Treasury issuance

Considering that we analyze Treasury purchases that took place over the course of two years, one might be concerned about variation in other risk factors that could have affected the yield curve over such long period. In the specification for the stock effects (equation 3), we assume that the maturity-dependent yield-curve movements are sufficiently smooth to be well approximated by a second order polynomial in maturity, τ. These terms account for possible secular changes in the slope and curvature factors during our period that could have resulted from macroeconomic conditions and new Treasury issuance.

[Figure 4 about here.]

In particular, as shown in Figure 4, due to the fiscal response to the pandemic, Treasury issuance was very large, both in absolute terms and relative to the pace of the Fed purchases. And, the issuance process was not necessarily smooth and predictable as in the past, given the high uncertainty about the pandemic, which required fast and evolving fiscal stimulus. For instance, in the May 2020 Quarterly Refunding Announcement (U.S. Department of the Treasury (2020)), the Treasury indicated that "borrowing estimate is $3,055 billion higher than announced in February 2020;" a huge unplanned increase in the Treasury supply.

If the second order polynomial in maturity is not sufficient to control in the cross section for the issuance's effect on the yield curve, it is possible that our estimates of the stock effects are downward biased. To verify whether this is the case, we augment the specification of the stock effect in equation 3 with the CUSIP-level issuance that took place over our sample period. As shown in table A.9 in Appendix D.3, each security's issuance is not statistically significant and does not affect any of the estimated coefficients in our baseline, reported in table 1. This indicates that maturity and maturity squared are indeed sufficient to control for one of the most important risk factors that could have potentially offset the impact of the Fed purchases.

5 Flow Effects

In this section, we focus on estimating the average price impact of each Treasury purchase operation conducted by the Desk between March 2020 and March 2022. Hence, we have tracked, for each outstanding Treasury security, the amount purchased at each operation. This provides us with a very large panel, as 402 distinct securities were purchased at least once across 467 operations.[20]

Differently from D'Amico and King (2013), we also estimate the flow effects specific to each maturity sector. This is of interest due to the dash-for-cash that took place during the Covid crisis, when foreign and domestic investors very quickly sold a large amount of off-the-run long-term Treasury securities (Duffie (2020)). As a result, the long end of the yield curve experienced relatively larger price dislocations, measured for instance by the yield curve fitting errors shown in Figure 5 for March 13, 2020. These dislocations at the longer end of the yield curve also took longer to dissipate, suggesting a differential program impact.

[Figure 5 about here.]

Overall, Figure 5 illustrates that each maturity sector experienced a different degree of market dysfunction, which implies that flow effects could differ across sectors, and we account for this heterogeneity. Importantly, having estimates of the sector-specific price sensitivities to changes in quantities can be helpful for future purchase programs, including Treasury buybacks.

5.1 Panel regression specification

To estimate flow effects specific to each maturity sector, it is necessary to use intraday data. We compute price changes in a tight time window (w) around each operation taking place in a specific maturity sector within a specific day (from t to $t+w$). For each operation, the Desk provides data on the par value purchase amounts by CUSIP, as well as the time window within which those purchases took place. We rely on Refinitiv for intraday quotes from the Tradeweb platform, where all primary dealers trade Treasury securities. To mitigate the impact of microstructure noise, we take the average price in the 15-minute windows just before and after each operation.

Our flow-effect regressions take the following form:

$$\frac{\Delta P_{i,t,t+w}}{P_{i,t}} = \beta_0 q^0_{i,t,t+w} + \beta_1 q^{near}_{i,t,t+w} + \beta_2 q^{mid}_{i,t,t+w} + \beta_3 q^{far}_{i,t,t+w} + cusip_i + \epsilon_{i,t,t+w}, \quad (4)$$

20. We consider only nominal Treasury coupon securities, although the Desk also purchased TIPS in separate auctions.

where, similarly to the stock effects' specification, β_0 and β_n (with n=1, 2, 3) are the coefficients of interest. But here, the large number of observations allow us to consider all three buckets of substitutes defined in Section 3 (i.e., near, mid, and far). This is possible despite the fact that we include in the estimation only securities that were eligible for purchase during an operation, to avoid having too many "own purchases" equal zero. Further, by sharpening the focus on a narrow time window around each operation, we eliminate other confounding factors influencing prices, therefore we just control for CUSIP fixed effects, and we minimize the risk of reverse causality, hence we do not need to use the IV approach.

5.2 Results

Table 3 summarizes the flow-effect results for the full period (3/13/2020-3/9/2022), and across the different subperiods: MFI, QEI, MFII, and QEII.

We find that the coefficients on near- and mid-substitute purchases are positive and statistically significant only during the MFI and MFII periods, and they get smaller in magnitude as the degree of substitutability decreases (i.e., the maturity distance increases), in line with the hypothesis of market segmentation. In the QE period, the coefficients on far-substitute purchases are the only statistically significant ones. This is precisely what should be observed if market functioning improves and supply effects are transmitted along the yield curve rather than remaining highly localized.

Overall, the flow effects are much stronger in the MF period than in the QE period. For instance, the return coefficient of 0.134 in response to a 1% reduction in the amount outstanding of near substitutes (\$12bn) implies that, in the MFI period, a typical operation of about \$7bn reduced 10-year equivalent yield by 1bp. This is at least seven times bigger than the impact implied by the same coefficient in the QE period.[21] However, as we show later, the finding that the flow effect is almost absent in the QE period is not robust across maturity sectors, which stresses the importance of estimating sector-specific flow effects.

In Table 4, we report the results specific to the five auction maturity sectors used by the Desk for its operations. We begin with focusing on the period in which markets were extremely dysfunctional and therefore auctions were most frequent, that is, from

21. The concurrent study of Bernardini and De Nicola (2020), which investigates the flow effects of purchases by the Bank of Italy, also finds that the yield impact was the largest in times of heightened market stress.

March 13, 2020 to April 17, 2020. It is evident that the significance and magnitude of the estimated coefficients vary greatly across sectors. The coefficients are positive and statistically significant in the 2.25- to 4.5-year, 4.5- to 7-year, and 20- to 30-year maturity sectors. The magnitude of all the coefficients is the the largest in the 20- to 30-year sector, which was the most disrupted. Hence, these results indicate that, at the height of the crisis, the purchase operations were particularly helpful at the long end of the yield curve. However, some of the coefficients in the 7- to 20-year sector are negative but, as we show later, this is most likely due to the fact that the sector was too wide and scarcely populated.

[Table 3 about here.]

[Table 4 about here.]

As shown in Table 5, in the 20- to 30-year sector, the return coefficient of 0.456 in response to a 1% reduction in the amount outstanding of near substitutes of that sector ($6bn) implies that, in the MFI period, a typical operation of about $3.5bn reduced the 10-year equivalent yield by 3bp. This is an impact 7 times larger than that obtained for the average maturity sector in the MFI period, shown in Table 3.

[Table 5 about here.]

[Table 6 about here.]

By comparing the results for the MFII period, summarized in Table 6, to those for the MFI period reported in Tables 4 and 5, it is possible to see that, as market conditions improve, most coefficients become smaller and the coefficient on own purchases loses statistical significance, in line again with theory of market segmentation. This is true across nearly all maturity sectors but more so in the 20- to 30-year sector.

5.3 Persistence of the flow effects in the MF period

Next, we investigate the persistence of the flow effects. To do this, for each maturity sector, we estimate impulse response functions (IRFs) by regressing the cumulative percentage price change of each security on its own, near, mid and far substitute purchases at time t, while also controlling for the subsequent cumulative purchases up until the end of day 1, the end of day 2, and so on, up to 10 days from the initial purchase. Specifically, we run the following high-frequency regressions, with N going up to 10:

$$\frac{\Delta P_{i,t,t+N}}{P_{i,t}} = \beta_0 q^0_{i,t,t+1} + \beta_1 q^{near}_{i,t,t+1} + \beta_2 q^{mid}_{i,t,t+1} + \beta_3 q^{far}_{i,t,t+1} +$$

$$\phi_0 \sum_{j=2}^{N} q^0_{i,t+1,t+j} + \phi_1 \sum_{j=2}^{N} q^{near}_{i,t+1,t+j} + \phi_2 \sum_{j=2}^{N} q^{mid}_{i,t+1,t+j} + \phi_3 \sum_{j=2}^{N} q^{far}_{i,t+1,t+j} + cusip_i + \epsilon_{i,t} \quad (5)$$

The graphs below show the IRFs of returns to own, near-substitute, and mid-substitute purchases in the 10-day period following a purchase, estimated using data from March 13, 2020 to April 17, 2020, that is, during the height of the Covid crisis. In particular, Figure 6 shows the evolution of β_0 for all five maturity sectors, while Figure 7 and Figure 8 focus on β_1 and β_2, respectively. (The results for β_3 are in Appendix E).

It can be seen that all the positive flow effects are short-lived, as they revert to zero in at most three or four days, even at the long-end of the yield curve where they are estimated to be quite sizeable. Thus, it seems likely that frequent and large operations were needed in this episode to support market functioning in a consistent manner. This, in turn, suggests that, when using LSAP for market functioning purposes, the flexibility to adjust the size and frequency of purchases is helpful for ensuring that price improvements are sustained.

Further, it seems that in the first month of the MF period, the statistical significance of own purchases is mostly due to the large and statistically significant coefficient in the 20- to 30-year maturity sector. Interestingly, in the 0- to 2.25-year maturity sector, purchases of near and mid substitutes have negligible effects, most likely because of the massive issuance of Treasury Bills and Cash Management Bills used to initially finance the fiscal stimulus.

[Figure 6 about here.]

[Figure 7 about here.]

[Figure 8 about here.]

The fact that the estimated flow effects die out quickly does not imply that their overall impact was small in the MF period. This is because, during the MF period, the Fed purchased securities daily at an aggressive pace and, therefore, did not allow the flow effects to revert. In other words, by entering the market every day, the Fed was able to remain at the peak of the IRF, because as the effect of a specific operation would start dying out, a new operation would immediately follow within the same sector. As a result, we can quantify the total average flow effect for the MFI period, as in this period it is reasonable to assume that the coefficients estimated in Table 5 apply to the entire period.

In particular we use the MFI's sector-level coefficients (if statistically significant) and amount purchased of each security to obtain the total flow effect pertaining to that security. Then, we add those individual flow effects back to the yield curve (YC) that prevailed in mid-September 2020 (i.e., the end of the MFI period) and derive a counterfactual YC. This gives a picture of how the YC would have looked in the absence of daily purchase operations in each maturity sector. This counterfactual curve is marked by blue crosses in Figure 9, which also shows the YC of September 15, 2020 (black dots) and March 12, 2020 (red dots).

The counterfactual YC, which mechanically displays discontinuities where the coefficients of each maturity sector change, indicates that yields in the 20- to 30-year sector would have been about 75 basis points higher than they were in mid-March 2020. In the intermediate sectors, yields would have largely remained as high as they were in mid-March, rather than declining between 25 and 50 basis points by mid-September 2020. At maturities shorter than 2.5 years, the flow effects did not contribute much to the yield reduction that occurred by mid-September. At these maturities, the fast decline in the expected policy rate most likely drove the yields down.

It is striking that by mid-September 2020, the YC was again perfectly smooth, as the MFI's purchase operations reduced yields by different amounts in each maturity sector, eliminating price deviations from fundamental values and therefore repristinating normal market functioning.

[Figure 9 about here.]

5.4 Persistence of the flow effects over entire period

In the remaining part of this section, we focus on the persistence of the flow effects over the entire sample period (March 2020 to March 2022).

One complicating factor in tracking the IRFs over the full period is that the Desk increased the number of the auction maturity sectors. On May 13, 2021, the Desk split the 7- to 20-year and 20- to 30-year sectors into three sectors: 7- to 10-year, 10- to 22.5-year, and 22.5- to 30-year. Thus, we focus first on the three auction sectors that were left unchanged throughout the two years of the program, and then consider the relatively newer sectors.

[Figure 10 about here.]

In Figure 10, it can be seen that at shorter maturities, over the full sample period, the flow effects of own, near-, and mid-substitute purchases get much smaller than those estimated during the height of the crisis. In contrast, as shown by the shaded panels in Figures 11, 12, and 13, after May 2021, at the long-end of the yield curve, not only the flow effects become more persistent, but their magnitude gets larger. This suggests that, even in the 22.5-30-year sector that tends to be the least liquid, daily operations are not necessary once market stress fades. Since each purchase operation's effect persists for at least 10 business days, it would be sufficient to enter that sector bi-weekly to sustain the improved market functioning.

Importantly, the IRFs in those last three figures also indicate that the estimated coefficients are typically positive, significant, and sizable in the 7- to 10-year segment, while they are indistinguishable from zero in the 10- to 20-year segment. This is not surprising as the 10- to 20-year maturity sector of the yield curve is scarcely populated (see Figure 5), hence our estimates there may not be reliable. Finally, based on these more granular results, it is possible to conclude that in the QE period, the flow effects shown in Table 3 were not significant because, when we combine all maturities together, the negative flow effects at the front-end of the yield curve offset the positive ones at the longer end.

[Figure 11 about here.]

[Figure 12 about here.]

[Figure 13 about here.]

6 Conclusions

From March 2020 to March 2022, the Federal Reserve used Treasury purchases to achieve multiple objectives over time: support smooth market functioning and provide monetary policy accommodation. Hence, we exploit those asset purchases to understand whether LSAPs can be tailored to achieve different objectives.

This should depend crucially on two factors: (1) whether the effects and transmission mechanism of LSAPs are affected by its communicated objective and (2) how this tool's design and implementation are adjusted to achieve different objectives.

We find that in the QE period (September 2020-March 2022), the stock effect is about 10 times larger than in the MF period (March 2020-September 2020), implying effects very similar to those obtained in studies of previous QE interventions (about 4.5bp per $100bn). This suggests that the LSAP's communicated objective matters as, while in the QE period the purchases are stimulative, in the MF period they are not. This is because, in the MF period, the stock effects are very localized as the substitution effects are insignificant.

Further, in the QE period, the stock effect gets larger once the auction calendars for the Treasury purchase operations are released at monthly frequency. It is possible that the increased transparency around auction dates/sectors/sizes reduced uncertainty about the expected amount and duration of total purchases, facilitating the impounding of these expectations into prices. Hence, these findings seem to suggest that it is not only the communicated goal of the purchases that matters, but also the design and implementation of the purchase operations.

In contrast, we find that in the MF period, the estimated flow effects are quite large, especially at the long end of the yield curve. Using those estimates, we derive a counterfactual yield curve, that is, how the yield curve would have looked at the end of the MF period in the absence of daily purchase operations. This curve indicates that in the 20- to 30-year sector, yields would have been about 75 basis points higher than they were in mid-March 2020. In the intermediate sectors, yields would have largely remained as high as they were in mid-March, rather than declining between 25 and 50 basis points by mid-September 2020. At maturities shorter than 2.5 years, the flow effects did not contribute much to the yield reduction that occurred by mid-September. These findings imply that the purchase operations restored market functioning in part by improving relative price deviations from fundamental values.

However, in the MF period, flow effects do not appear to persist for more than 2-3 days, hence it seems likely that frequent and large operations were needed in this episode to support market functioning in a consistent manner. Indeed, during the height of the crisis, conducting daily purchases in each sector prevented the reversion of the flow effects and sustained the ongoing improvement in market conditions. In the QE period, flow effects in 7-to-10-year and 22.5-to-30-year sectors are found to be persistent, suggesting that less frequent operations may be needed when market functioning is back to normal.

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	Gross Return				
	Full Period	MFI	MFII	QEI	QEII
Own Purchases (%)	0.018	0.019^{***}	0.020^{**}	0.017	−0.048
	(0.011)	(0.006)	(0.009)	(0.079)	(0.050)
Near Sub Purchases (%)	0.008	−0.015	−0.030	0.197^{***}	0.224^{***}
	(0.016)	(0.012)	(0.017)	(0.029)	(0.046)
Maturity Squared	-0.512^{***}	0.156^{***}	-0.288^{***}	-0.587^{***}	-0.230^{***}
	(0.00003)	(0.00002)	(0.00003)	(0.0001)	(0.00003)
Maturity	0.089^{***}	-0.063^{***}	-0.074^{***}	0.069^{***}	0.132^{***}
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
log(Initial Price)	−0.144	−0.071	−0.080	−0.091	−0.063
	(0.021)	(0.006)	(0.013)	(0.037)	(0.019)
Fitting Error	−0.005	0.050	0.023	−0.485	0.035
	(0.030)	(0.012)	(0.019)	(0.294)	(0.101)
Constant	0.594^{***}	0.347^{***}	0.364^{***}	0.324^{*}	0.223^{***}
	(0.095)	(0.027)	(0.061)	(0.173)	(0.088)
Observations	195	195	195	195	195
Adjusted R^2	0.948	0.834	0.930	0.964	0.839
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1: Comparison of Second Stage Regression Results Across Periods Coefficient estimates for equations 3 on data from subperiods as outlined in section 2. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates p < 0.01.

Period	Calendar Frequency	Purchase Pace
3/16/20 to 3/23/20	Daily	Irregular
3/23/20 to 4/3/20	Every 2-3 days	Irregular
4/6/20 to 6/11/20	Weekly	Decreases weekly
6/12/20 to 2/11/21	Bi-weekly	**$80bn per month**
2/12/21 to 11/12/21	**Monthly**	$80bn per month

Table 2: Dates of Changes in the Frequency of the Auction Calendar Releases and Related Pace of Purchases. The calendar release frequency and the pace of purchases fluctuated over time.

	All Maturity Sectors				
	Full	MFI	MFII	QEI	QEII
Own Purchases %	0.004**	0.003	0.004	0.002	0.002
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Near Sub Purchases %	0.109***	0.134***	0.132***	0.015	0.016
	(0.008)	(0.012)	(0.010)	(0.010)	(0.012)
Mid Sub Purchases %	0.039***	0.046***	0.048***	−0.005	−0.009
	(0.004)	(0.007)	(0.006)	(0.005)	(0.006)
Far Sub Purchases %	0.041***	0.044***	0.045***	0.072***	0.047**
	(0.005)	(0.007)	(0.006)	(0.016)	(0.019)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	17,016	9,098	11,306	7,918	5,710
R^2	0.024	0.024	0.029	0.003	0.003
F Statistic	104.167***	54.940***	81.703***	6.450***	3.461***
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 3: Flow Effects by Period. These estimates of flow effect coefficients (in terms of price returns) are based on equation 4, estimated for purchase operations in the subperiods described in section 2, with standard errors in parentheses. * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

	By Maturity Sector				
	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001	0.002**	0.009***	−0.015	0.083***
	(0.001)	(0.001)	(0.002)	(0.013)	(0.025)
Near Sub Purchases %	0.003	0.072***	0.186***	0.010	1.697***
	(0.003)	(0.004)	(0.015)	(0.044)	(0.123)
Mid Sub Purchases %	0.0001	0.008***	0.052***	−0.051**	1.518***
	(0.002)	(0.002)	(0.005)	(0.022)	(0.114)
Far Sub Purchases %				−0.011	0.169***
				(0.013)	(0.044)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	1,505	1,401	1,069	473	1,375
R^2	0.003	0.189	0.157	0.015	0.183
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 4: Flow Effects in the Highest Stress Period (2020-03-13 to 2020-04-17), by Sector. These estimates of flow effect coefficients (in terms of price returns) are based on equation 4, estimated for purchase operations in the highest stress period, from 2020-03-13 to 2020-04-17, with each purchase sector estimated separately. Standard errors are in parentheses. * indicates $p<0.1$; ** indicates $p<0.05$; *** indicates $p < 0.01$.

	By Maturity Sector				
	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001^{**}	0.002^{**}	0.005^{***}	-0.003	0.018
	(0.001)	(0.001)	(0.001)	(0.009)	(0.017)
Near Sub Purchases %	0.008^{***}	0.051^{***}	0.120^{***}	0.090^{***}	0.456^{***}
	(0.002)	(0.003)	(0.008)	(0.030)	(0.051)
Mid Sub Purchases %	-0.001	0.011^{***}	0.036^{***}	0.011	0.386^{***}
	(0.002)	(0.002)	(0.003)	(0.014)	(0.049)
Far Sub Purchases %				0.024^{***}	0.051
				(0.007)	(0.031)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	1,984	2,137	1,803	753	2,421
R^2	0.013	0.161	0.171	0.030	0.072
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 5: Flow Effects in MFI (2020-03-13 to 2020-09-15), by Sector. These estimates of flow effect coefficients (in terms of price returns) are based on equation 4, estimated for purchase operations in the MFI period, from 2020-03-13 to 2020-09-15, with each purchase sector estimated separately. Standard errors are in parentheses. * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

	By Maturity Sector				
	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001**	0.002***	0.005***	0.003	0.016
	(0.0005)	(0.001)	(0.001)	(0.007)	(0.011)
Near Sub Purchases %	0.008***	0.047***	0.123***	0.076***	0.416***
	(0.002)	(0.003)	(0.006)	(0.022)	(0.039)
Mid Sub Purchases %	−0.0002	0.014***	0.034***	0.020*	0.348***
	(0.002)	(0.002)	(0.003)	(0.011)	(0.038)
Far Sub Purchases %				0.026***	0.047*
				(0.006)	(0.025)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	2,105	2,554	2,279	942	3,426
R^2	0.012	0.174	0.183	0.042	0.074
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 6: Flow Effects in MFII (2020-03-13 to 2021-02-11), by Sector. These estimates of flow effect coefficients (in terms of price returns) are based on equation 4, estimated for purchase operations in the MFII period, from 2020-03-13 to 2021-02-11, with each purchase sector estimated separately. Standard errors are in parentheses. * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

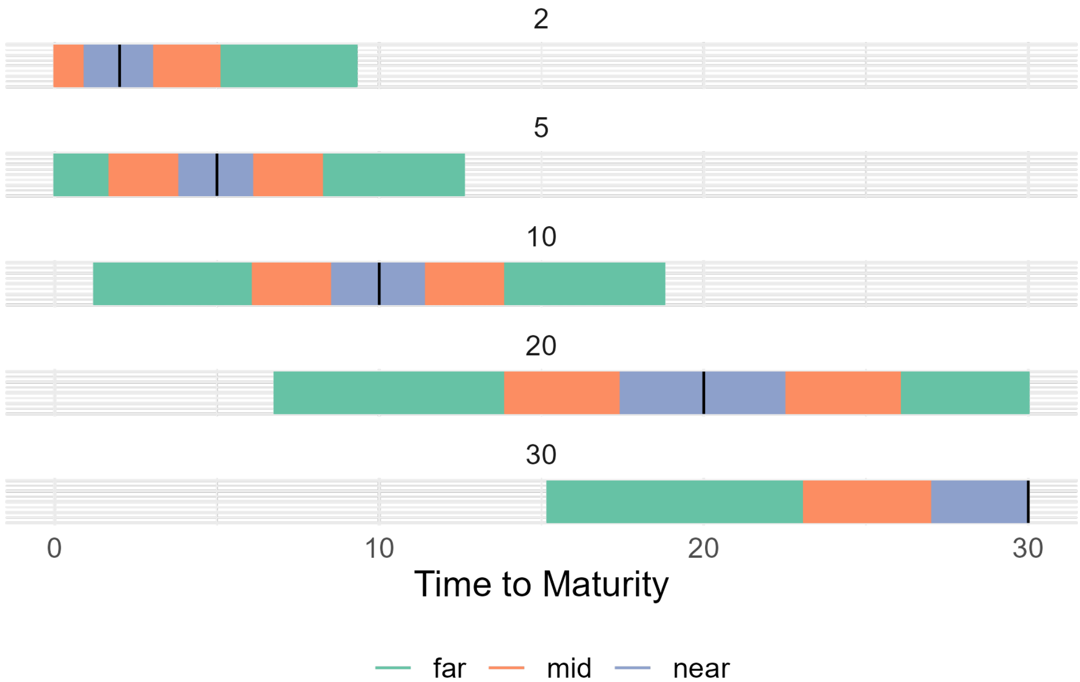

Figure 1: Substitute bucket illustration. Each row represents a security with a given time to maturity. The vertical black line represents that security itself. A security's near substitutes fall within the blue band around its tenor, its mid substitutes within the orange band, and its far substitutes within the green band. Note that the bands grow wider as the security's tenor increases.

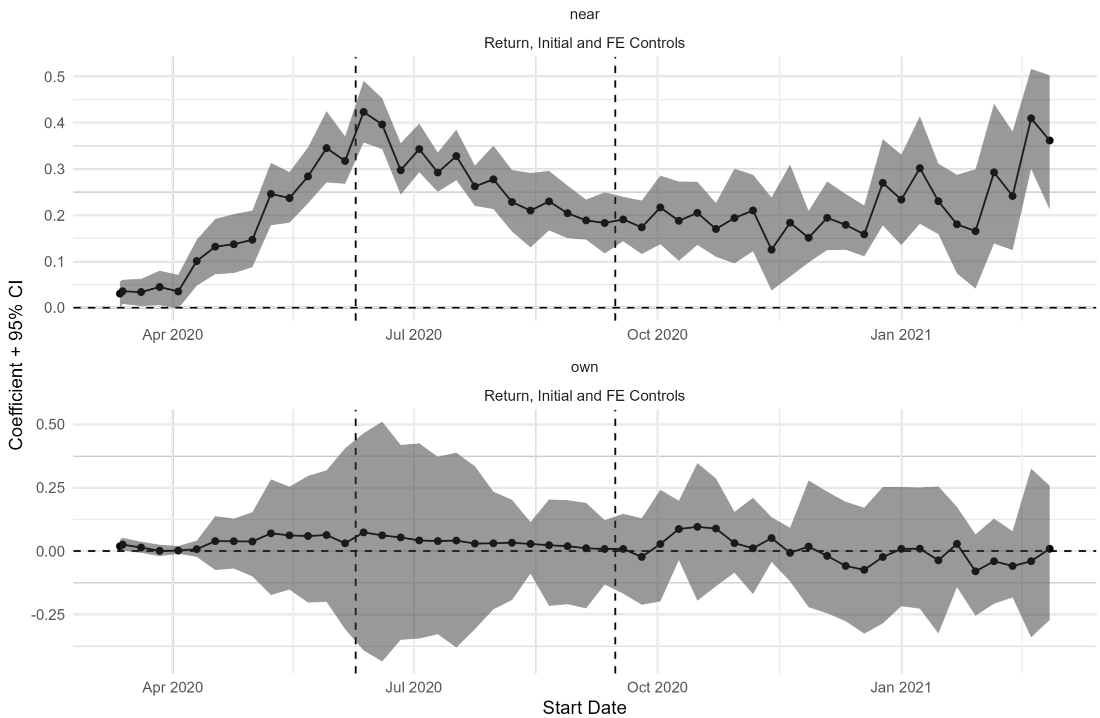

Figure 2: Robustness of QE Period Results to Changing the Start Date. The top and bottom panels represent the coefficient on own purchases and near-substitute purchases from estimating equation 3. Each point represents the coefficient estimated with data from a given start date to the end of the period, 2022-03-09. These points are approximately one week apart. The shaded area represents a 95% confidence interval around the point estimate, based on the bootstrapped interval from Davidson and MacKinnon (2010). The first vertical line is the 2020-06-09, the day before the FOMC statement with modified language. The second vertical line is 2020-09-15, the start of our QEI subperiod.

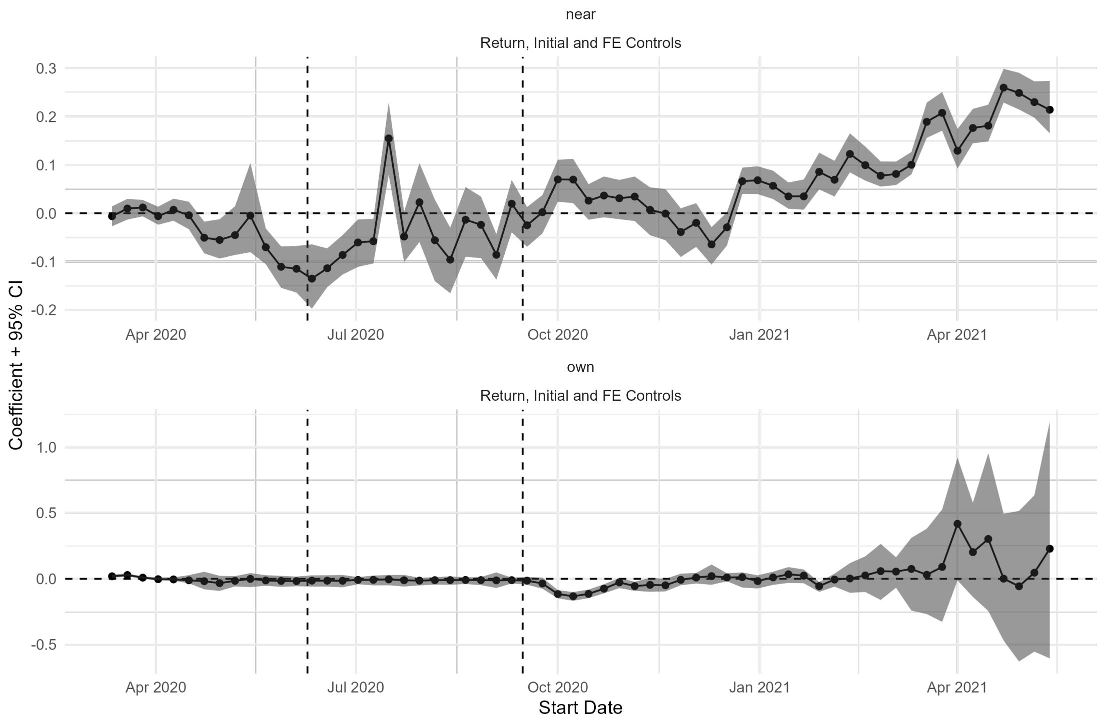

Figure 3: Regression Results over Six Month Rolling Windows. The top and bottom panels represent the coefficient on own purchases and near-substitute purchases from estimating equation 3. Each point represents the coefficient estimated with data from a given start date to 180 days from that start date. These points are approximately one week apart. The shaded area represents a 95% confidence interval around the point estimate, based on the bootstrapped interval from Davidson and MacKinnon (2010). The first vertical line is the 2020-06-09, the day before the FOMC statement with modified language. The second vertical line is 2020-09-15, the start of our QEI subperiod.

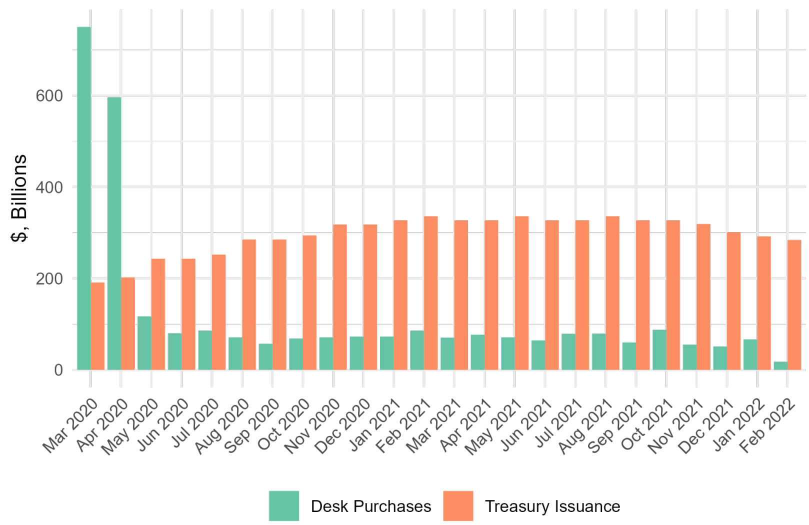

Figure 4: Treasury Issuance and Desk Purchases. For the first two months, the pace of Desk purchases exceeded Treasury coupon issuance. The pace of purchases stabilizes around June 2020; the pace of issuance stabilizes around November 2020. Source: US Treasury, Federal Reserve Bank of New York.

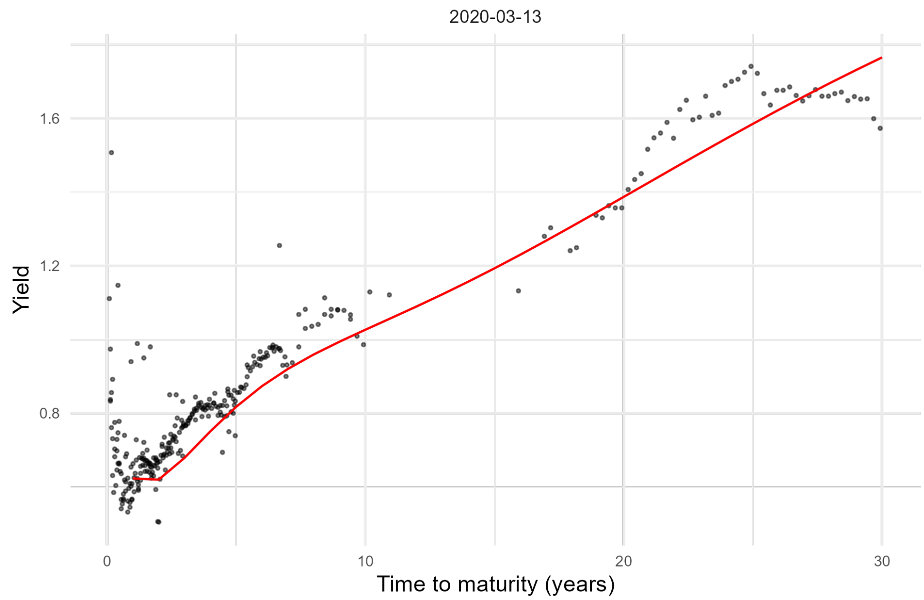

Figure 5: Yield curve in market dysfunction on March 13, 2020. The black dots represent the bid-side yields for each Treasury security. The red line represents the Federal Reserve Board's fitted curve on that date (Gürkaynak, Sack, and Wright (2007)). Note the poor fit. Source: Federal Reserve Board, Refinitiv

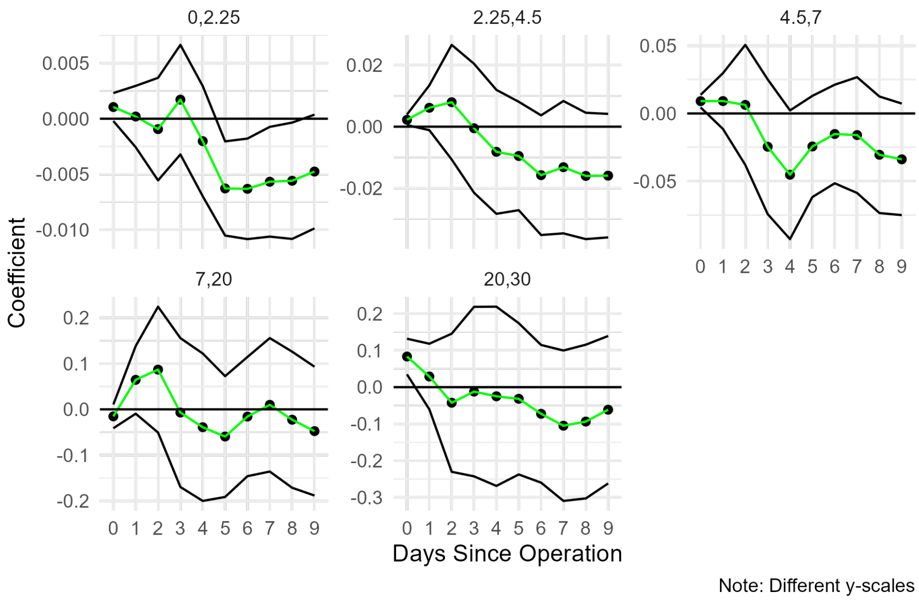

Figure 6: IRF, Own Purchases, March 2020 - April 2020. Own purchase coefficient estimates based on equation 5-style models are shown in the green line, with 95% error bands. These estimates are based on the period from March 13, 2020 to April 17, 2020.

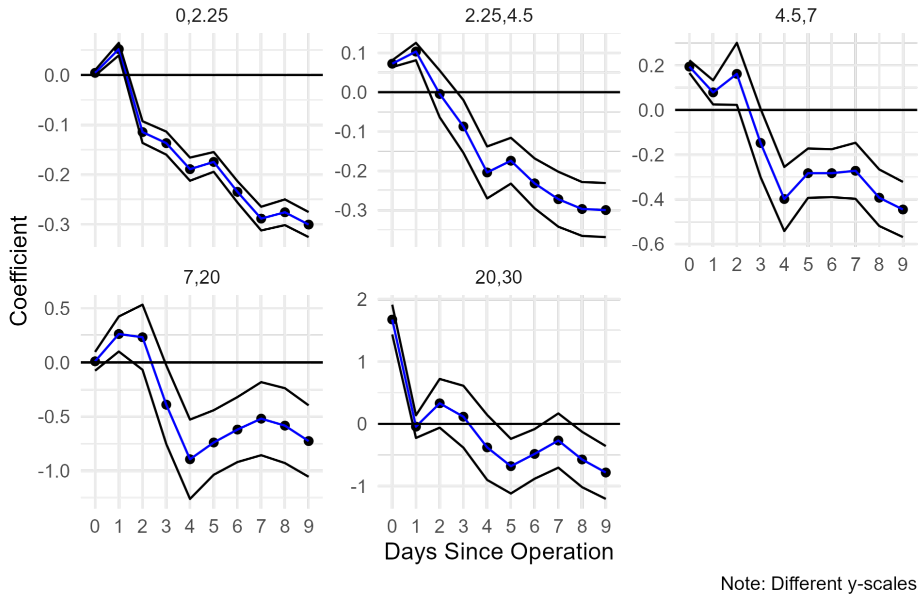

Figure 7: IRF, Near Substitutes, March 2020 - April 2020. Near substitute purchase coefficient estimates based on equation 5-style models are shown in the blue line, with 95% error bands. These estimates are based on the period from March 13, 2020 to April 17, 2020.

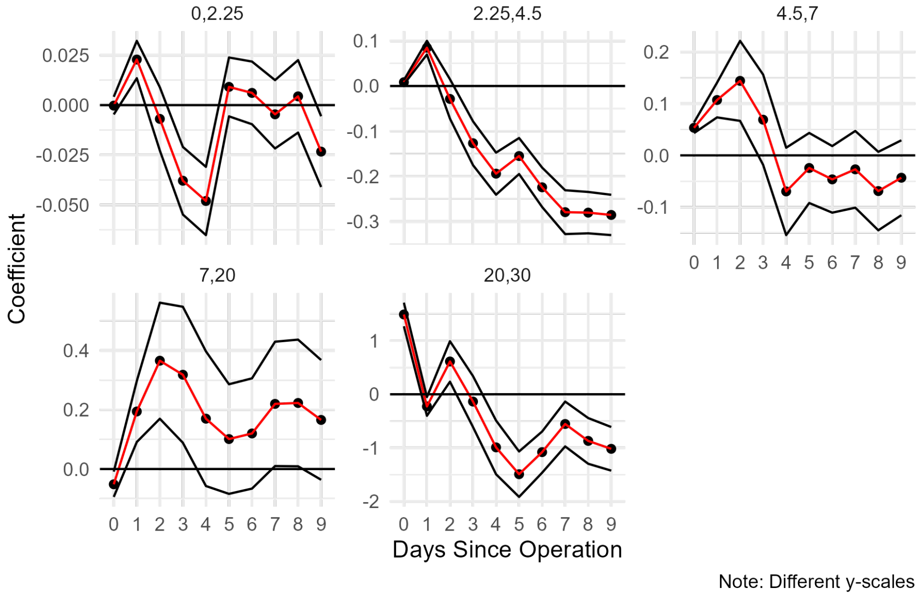

Figure 8: IRF, Mid Substitutes, March 2020 - April 2020. Mid substitute purchase coefficient estimates based on equation 5-style models are shown in the red line, with 95% error bands. These estimates are based on the period from March 13, 2020 to April 17, 2020.

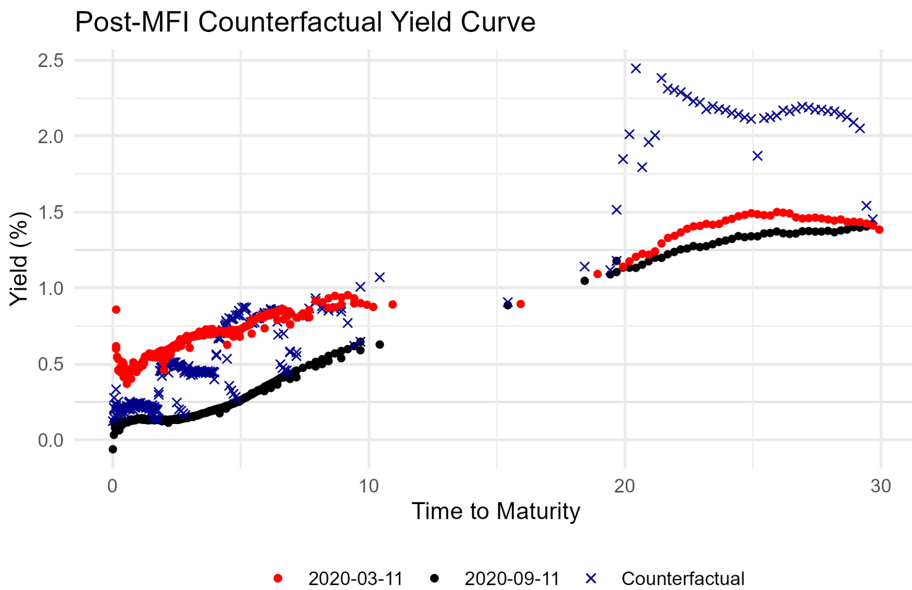

Figure 9: Counterfactual and actual MFI yield curves

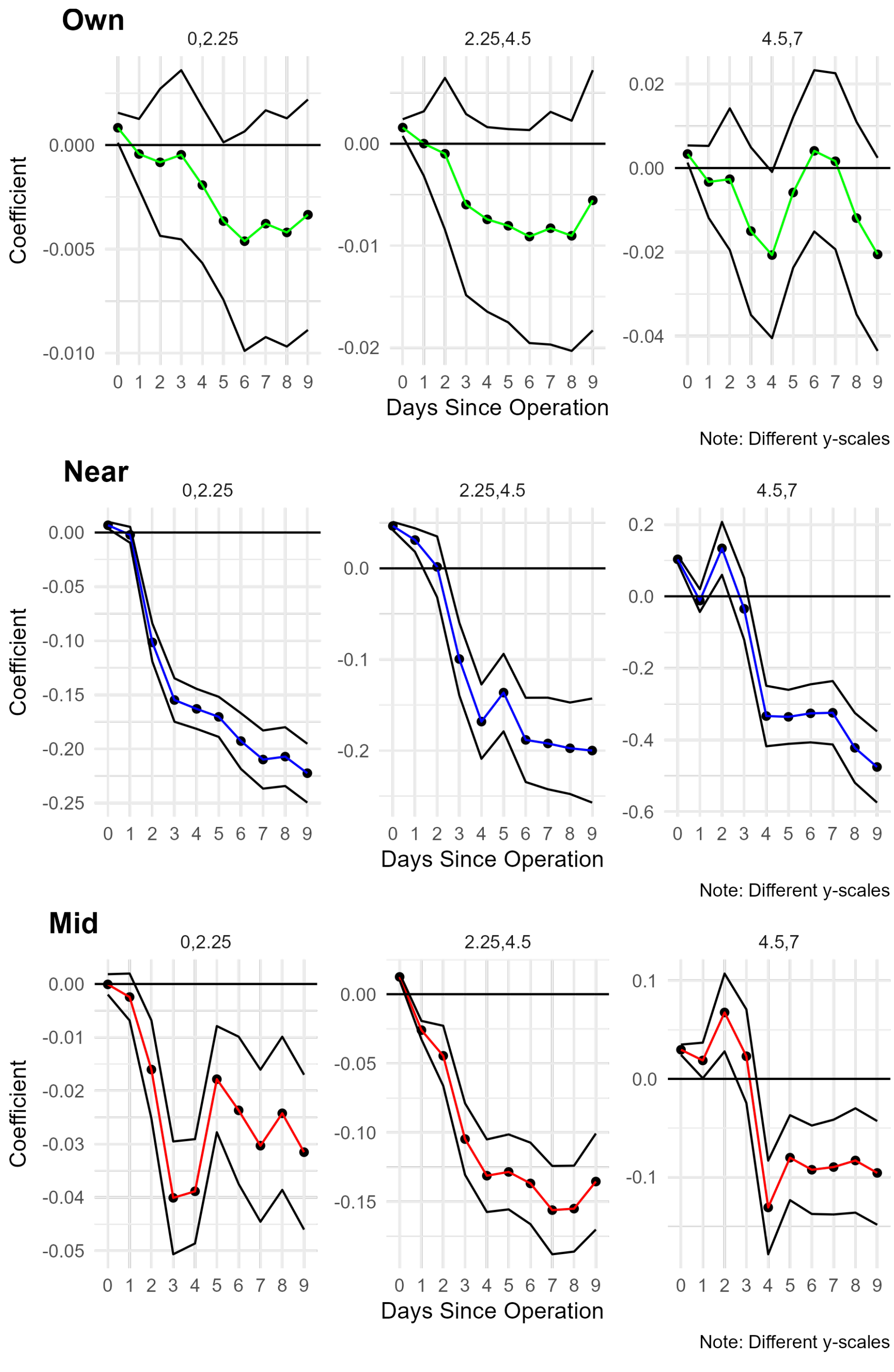

Figure 10: IRF, Own, Near, Mid Purchases, March 2020 - March 2022.Purchase coefficient estimates based on equation 5-style models are shown in the green line, with 95% error bands. These estimates are based on the period from March 13, 2020 to March 9, 2022.

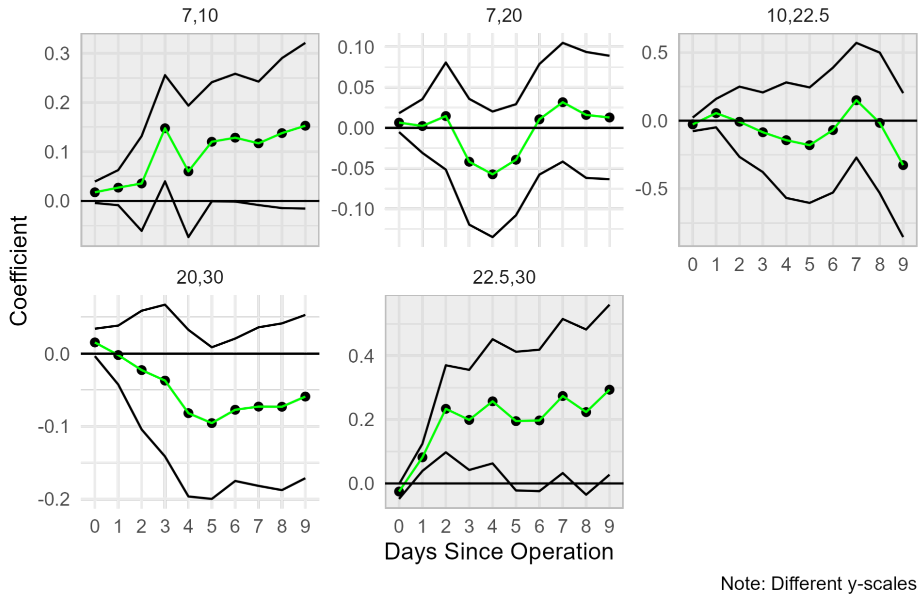

Figure 11: Long Maturity IRF, Own Purchases, March 2020 - March 2022. Own purchase coefficient estimates for the long-end sectors based on equation 5-style models are shown in the green line, with 95% error bands. These estimates are based on the period from March 13, 2020 to March 9, 2022.

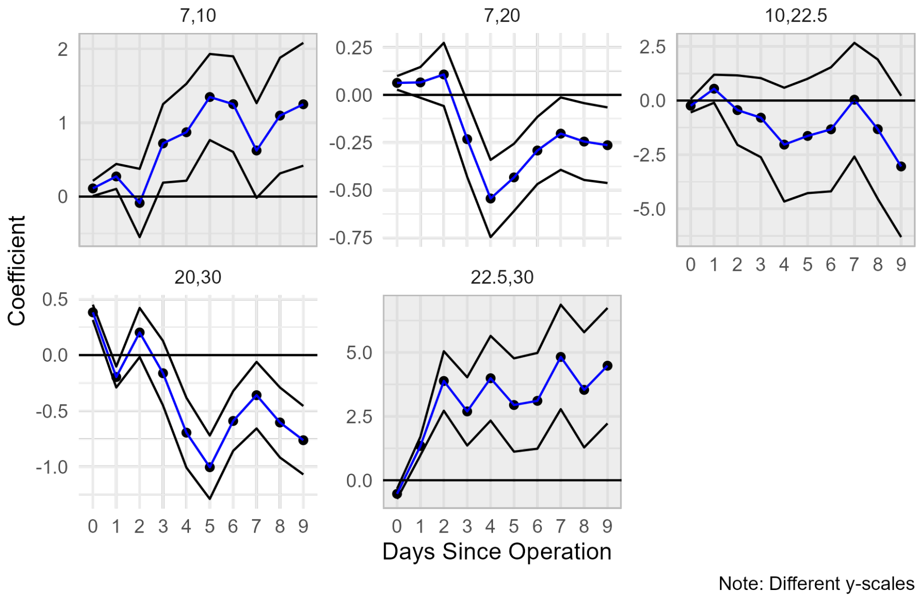

Figure 12: Long Maturity IRF, Near Purchases, March 2020 - March 2022. Near substitute purchase coefficient estimates for the long-end sectors based on equation 5-style models are shown in the blue line, with 95% error bands. These estimates are based on the period from March 13, 2020 to March 9, 2022.

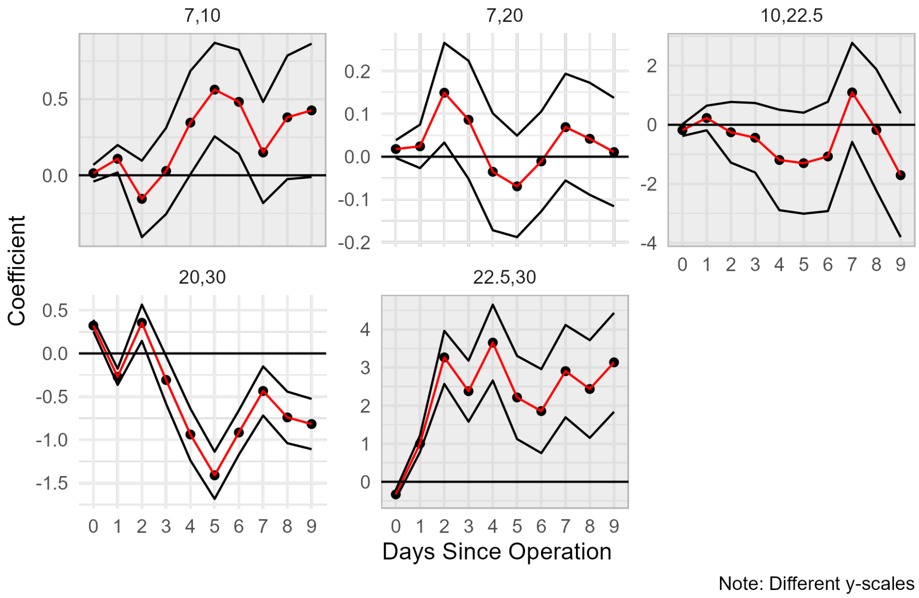

Figure 13: Long Maturity IRF, Mid Purchases, March 2020 - March 2022. Mid substitute purchase coefficient estimates for the long-end sectors based on equation 5-style models are shown in the red line, with 95% error bands. These estimates are based on the period from March 13, 2020 to March 9, 2022.

Appendices

A Substitute Band Construction

The bandwidths for the substitute buckets are defined as a logistic function, with location = 15 and scale = 4, of the security's maturity, τ.

$$p = \frac{e^{-(t-15)/4}}{4 \times (1 + e^{-(t-15)/4})^2} \tag{6}$$

$$b_{near} = 1 + 2 \times p \tag{7}$$

$$b_{mid} = 3 + 4 \times p \tag{8}$$

$$b_{far} = 7 + 8 \times p \tag{9}$$

The near substitutes of security i are securities in $[t - b_{near}, t + b_{near}]$, excluding i itself. The mid substitutes are those securities lying within the bandwidth b_{mid}, but outside the bandwidth b_{near}, and similar for the far substitutes. This is illustrated for various t in Figure 1.

B Amounts purchased by subperiods for 195 CUSIPs

Period	Own %	Near %	Total (B)
Full	35.2	31.9	1,707.6
MFI	21.1	19.4	1,135.4
MFII	26.0	23.2	1,327.3
QEI	11.5	11.7	572.2
QEII	7.3	7.9	380.3

Table A.1: Purchase Amounts within all coupon operations, in all subperiods as defined in section 2. "Own %" represents the average own purchase amount (as a percent of its total privately-held outstanding) for a given security in the subperiod. "Near %" represents the average purchase amount of all near substitutes (as a percent of the total privately-held outstanding of all near substitutes) for a given security in the subperiod. "Total (B)" represents the total purchase amount in that subperiod. Note that these are summaries only over securities in our panels; thus only coupon securities that were issued after 2020-03-12 or that matured before 2022-03-09 are not included.

Period	Own % (>15y)	Near % (>15y)	Total (B) (>15y)	Own % (<15y)	Near % (<15y)	Total (B) (<15y)
Full	44.4	37.6	397.8	32.6	30.3	1,309.8
MF2	31.8	26.9	309.4	24.3	22.1	1,017.9
MFI	24.3	21.8	261.2	20.2	18.7	874.2
QEI	15.0	14.8	136.6	10.5	10.8	435.6
QEII	9.2	10.6	88.4	6.8	7.1	291.9

Table A.2: Purchase Amounts in Sample Splits: Maturity. This table is similar to table A.1, but with summaries based on the tenor of each security as of the first date of each subperiod.

Period	Own % (Off Run)	Near % (Off Run)	Total (B) (Off Run)	Own % (On Run)	Near % (On Run)	Total (B) (On Run)
Full	34.4	32.3	1,383.3	40.6	29.3	324.3
MF2	24.8	23.4	1,057.5	34.0	21.8	269.9
MFI	19.8	19.5	895.0	30.0	18.3	240.5
QEI	11.6	11.8	548.8	7.7	7.3	23.5
QEII	7.5	7.9	376.9	1.7	4.1	3.4

Table A.3: Purchase Amounts in Sample Splits: Off-the-run. This table is similar to table A.1, but with summaries based on the on-the-run status of each security as of the first date of each subperiod.

C Variable Construction Details

These variables are defined as follows:

- $P_{i,t}$: These end of day prices can be constructed on day t of security i. In the default specifications, we use the midpoint price, which is available via Bloomberg as the field PX_MID. This is a dirty price, since it includes accrued interest, which is computed from Bloomberg fields $PX\_DIRTY\_MID - PX\_MID$.

- $Q_{i,0,t}$: via NY Fed SOMA data. Quantity purchased of security i from the start of the program to time t. This "own" purchase amount is band 0, explaining the second index.

- $AO_{i,0,t}$: via NY Fed SOMA data and Treasury issuance data. Quantity outstanding, outside of SOMA, at time t of security i. This data is available by reducing the Treasury auction amount outstanding data by the amount in the SOMA portfolio.

- $AO_{i,1,t}$: via NY Fed SOMA data and Treasury issuance data. Quantity outstanding, outside of SOMA, at time t of all securities within the 1st band of security i (excluding i itself).

- $\alpha_{i,j} = \frac{AO_{i,0}}{AO_{j,1}}$: Weighting of security i information for instrument variable of security j.

- $FE_{i,t}$ or "Fitting Error": Actual bid yield (TradeWeb) minus fitted bid yield from Svensson model, for the i^{th} security, at time t. Svensson yields are continuously compounded par yields, with the yield curve parameters from the Federal Reserve Board's public model Gürkaynak, Sack, and Wright 2007.

- $\tau_{i,t}$ or "Maturity": via Time to maturity of i^{th} security as of time t.

- Off_i or "Far Off-the-Run": via Treasury issuance data. Far off the run indicator of i^{th} security at time t. For non-TIPS, "far off the run" is 1 if the security is the sixth or older security of a given term. For TIPS, "far off the run" is 1 if the security is the third or older security of a given term.

- $PO_{i,t}$ or "Private Owned %": Percent of security i held in private hands as of time t. Derived from Treasury issuance and SOMA purchase data.

- $CTD_{i,t}$ or "Cheapest to Deliver": via Bloomberg. 1 if i^{th} security is cheapest to deliver at t, 0 otherwise.

- $PD_{i,t}$ or "Primary Dealer %": Percent of the primary dealer coupon holdings held in the same maturity bucket as security i, at t. These are coarse buckets and we uniformly assign the same value to each CUSIP in the bucket. E.g., if 7% of primary dealer holdings are in the 1Y - 2Y bucket, and there are 10 securities in that bucket, we assign each .7%.

- $S_n(i)$: Set of securities within the n^{th} band of security i. These bands are defined based on the time to maturity of the security i, as "donut-shaped" rings. The bands get progressively wider as the time to maturity of n gets larger.

- $Q_{i,1,t} = \sum_{i \in N_{n,1}} Q_{i,0}$: Near substitutes of i purchased by time t.

- $\overline{X}_{i,t} = \sum_{j \in S_1(i)} \alpha_{i,j} * X_i$ or "Wtd. X": Weighted variable X for security i at time t.

So those normalized quantity variables are:

$$q_{i,0,t} = \frac{Q_{i,0,t}}{AO_{i,0,t}} \tag{10}$$

$$q^T_{i,1,t} = \frac{Q_{i,1,t}}{AO_{i,1,t}} \tag{11}$$

In the flow effect regressions, price and quantity variables have a slightly different form. They include a second time subscript to indicate the small operation window in which the purchases and price changes take place, as in $P_{i,t,t+w}$ and $q^b_{i,t,t+w}$. Here w is the length of the operation. The q^b for each band are normalized with amounts outstanding as of t, before the operation. As we depend on small time intervals in the flow effect estimation, the prices are acquired via TradeWeb, and the price is the average price for security i for time t and time $t+w$. By default, we take the average of the midpoint dirty price in a small window, to ameliorate microstructure noise. These windows are the 15 minutes before and 15 minutes after an operation.

D Additional Stock Effect Results

D.1 First Stage Results

	Own (%)	Near Sub (%)	Own (%)	Near Sub (%)	Own (%)	Near Sub (%)	Own (%)	Near Sub (%)	Own (%)	Near Sub (%)
	Mar 2020 - Mar 2022		MFI: Mar 2020 - Sep 2020		QEI: Sep 2020 - Mar 2022		MFII: Mar 2020 - Feb 2021		QEII: Feb 2021 - Mar 2022	
Fitting Error	0.805*	2.280***	0.109	1.056***	2.839***	2.627***	0.310	1.393***	0.948***	0.911***
	(0.434)	(0.115)	(0.267)	(0.055)	(0.656)	(0.089)	(0.366)	(0.066)	(0.357)	(0.075)
Private Owned %	0.426***	0.149***	0.170**	0.055***	0.060	-0.160^{***}	0.287***	0.114***	0.063	0.095***
	(0.117)	(0.027)	(0.072)	(0.019)	(0.057)	(0.020)	(0.099)	(0.023)	(0.045)	(0.029)
Maturity	0.034**	0.002	0.029***	0.014***	-0.019^{***}	-0.026^{***}	0.031**	0.013***	-0.002	0.002**
	(0.017)	(0.004)	(0.011)	(0.001)	(0.007)	(0.001)	(0.014)	(0.002)	(0.005)	(0.001)
Maturity Squared	-0.001^{**}	0.00003	-0.001^{***}	-0.0005^{***}	0.001***	0.001***	-0.001^{***}	-0.0004^{***}	0.0001	-0.0002^{***}
	(0.0005)	(0.0001)	(0.0003)	(0.00005)	(0.0002)	(0.00003)	(0.0004)	(0.0001)	(0.0002)	(0.00004)
Far Off-the-Run	-0.079	0.009	-0.111^{***}	-0.089^{***}	0.048	0.053***	-0.102^{*}	-0.061^{***}	0.051	-0.001
	(0.065)	(0.044)	(0.040)	(0.019)	(0.055)	(0.009)	(0.055)	(0.022)	(0.049)	(0.009)
Primary Dealer %	29.166	12.946	46.790**	14.484***	1.714	26.473***	46.098	20.497***	1.880	33.638***
	(37.178)	(11.976)	(22.922)	(5.227)	(9.674)	(3.115)	(31.392)	(5.688)	(6.926)	(2.931)
Cheapest-to-Deliver	0.317**	1.393***	0.114	0.663***	0.233***	0.168***	0.193*	1.098***	0.073*	0.327***
	(0.126)	(0.129)	(0.078)	(0.074)	(0.051)	(0.057)	(0.106)	(0.092)	(0.044)	(0.055)
Constant	-0.145	0.161***	-0.053	0.141***	0.049	0.213***	-0.124	0.082***	-0.031	-0.098^{***}
	(0.152)	(0.042)	(0.094)	(0.023)	(0.078)	(0.020)	(0.128)	(0.029)	(0.060)	(0.030)
Observations	195	195	195	195	195	195	195	195	195	195
Adjusted R^2	0.134	0.871	0.144	**0.846**	0.201	0.922	0.107	**0.868**	0.059	**0.806**
F Statistic (df = 7; 187)	5.287***	188.250***	5.646***	153.708***	7.974***	330.705***	4.308***	182.457***	2.745***	115.915***

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.4: First Stage Regression Results. Coefficient estimates for equations 1 and 2. Each column represents a subperiod (based on data from subperiods as outlined in section 3.3) as well as a given dependent variable: either own or near subtitute purchases. "Own (%)" indicates the coefficient for the the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub (%)" indicates the coefficient for the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. * indicates p<0.1; ** indicates p<0.05; *** indicates p < 0.01.

D.2 Results by security's liquidity

	Gross Return				
	full	>15y	<15y	off-run	on-run
Own Purchase %	0.019***	−0.042***	0.026**	0.030**	0.040***
	(0.006)	(0.014)	(0.012)	(0.014)	(0.008)
Near Sub Purchase %	−0.015	0.017	−0.036*	−0.001	−0.036
	(0.012)	(0.031)	(0.021)	(0.017)	(0.048)
Controls	X	X		X	
Observations	195	195		195	
Adjusted R^2	0.834	0.872		0.844	
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table A.5: MF I Period Regression Results. Coefficient estimates for equation 3, with dummy variables to split the sample based on security characteristics, on data from the first market functioning subperiod as outlined in section 3.3. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. The "full" column has no splitting variables and is for comparison purposes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

	Gross Return				
	full	>15y	<15y	off-run	on-run
Own Purchase %	0.017	0.050	0.020	0.010	0.051
	(0.079)	(0.204)	(0.245)	(0.098)	(0.276)
Near Sub Purchase %	0.197***	0.180	0.557***	0.194***	0.123
	(0.029)	(0.237)	(0.045)	(0.030)	(0.097)
Controls	X	X		X	
Observations	195	195		195	
Adjusted R^2	0.964	0.969		0.964	
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table A.6: QE I Period Regression Results. Coefficient estimates for equation 3, with dummy variables to split the sample based on security characteristics, on data from the first QE subperiod as outlined in section 3.3. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. The "full" column has no splitting variables and is for comparison purposes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

	Gross Return				
	full	>15y	<15y	off-run	on-run
Own Purchase %	0.020**	−0.024	0.028**	0.025**	0.032**
	(0.009)	(0.022)	(0.011)	(0.014)	(0.013)
Near Sub Purchase %	−0.030	−0.010	−0.037*	−0.020	−0.049
	(0.017)	(0.031)	(0.021)	(0.019)	(0.041)
Controls	X	X		X	
Observations	195	195		195	
Adjusted R^2	0.930	0.932		0.931	
Note:				*p<0.1; **p<0.05; ***p<0.01	

Table A.7: MF II Period Regression Results. Coefficient estimates for equation 3, with dummy variables to split the sample based on security characteristics, on data from the second market functioning subperiod as outlined in section 3.3. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. The "full" column has no splitting variables and is for comparison purposes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

	Gross Return				
	full	>15y	<15y	off-run	on-run
Own Purchase %	−0.048	−0.212*	0.057	0.013	−0.745
	(0.050)	(0.118)	(0.112)	(0.097)	(1.042)
Near Sub Purchase %	0.224***	0.293***	0.232**	0.248***	0.868**
	(0.046)	(0.083)	(0.135)	(0.050)	(0.355)
Controls	X	X		X	
Observations	195	195		195	
Adjusted R^2	0.839	0.849		0.843	
Note:				*p<0.1; **p<0.05; ***p<0.01	

Table A.8: QE II Period Regression Results.Coefficient estimates for equation 3, with dummy variables to split the sample based on security characteristics, on data from the second QE subperiod as outlined in section 3.3. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. The "full" column has no splitting variables and is for comparison purposes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

D.3 Results with Treasury issuance

	Gross Return				
	Full Period	MFI	MFII	QEI	QEII
Own Purchases (%)	0.011	0.016***	0.023**	0.015	−0.050
	(0.011)	(0.005)	(0.009)	(0.078)	(0.049)
Near Sub Purchases (%)	0.006	−0.015	−0.029	0.196***	0.224***
	(0.016)	(0.013)	(0.017)	(0.029)	(0.046)
Maturity Squared	−0.503***	0.157***	−0.291***	−0.587***	−0.230***
	(0.00003)	(0.00002)	(0.00003)	(0.0001)	(0.00003)
Maturity	0.085***	−0.064***	−0.072***	0.069***	0.132***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)
log(Initial Price)	−0.146	−0.071	−0.080	−0.091	−0.063
	(0.020)	(0.005)	(0.013)	(0.037)	(0.019)
Fitting Error	−0.004	0.048	0.024	−0.481	0.037
	(0.028)	(0.011)	(0.019)	(0.285)	(0.100)
Change in Private Outstanding (T)	−0.186	−0.050	0.069	−0.073	−0.071
	(0.113)	(0.079)	(0.145)	(0.634)	(0.071)
Constant	0.604***	0.348***	0.361***	0.323*	0.223**
	(0.091)	(0.025)	(0.061)	(0.173)	(0.088)
Observations	195	195	195	195	195
Adjusted R^2	0.949	0.834	0.930	0.964	0.838
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table A.9: Comparison of Second Stage Regression Results Across Periods with Additional Net Issuance control. Coefficient estimates for equation 3 on data from subperiods as outlined in section 2, with an additional control for net issuance of each security. "Own Purchases (%)" indicates the coefficient on the own purchase amount, as a percentage of total privately-held outstanding in a given security. "Near Sub Purchases (%)" indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total privately-held outstanding in a given security's near substitutes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010). * indicates p<0.1; ** indicates p<0.05; *** indicates $p < 0.01$.

E Additional Impulse Response Functions

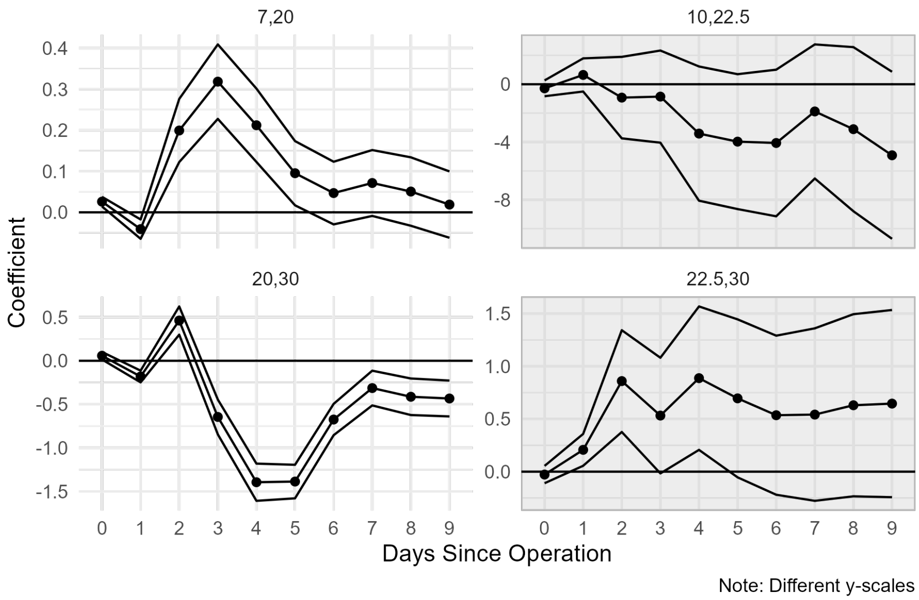

Figure A.1: Long Maturity IRF, Far Purchases, March 2020 - March 2022. Far substitute purchase coefficient estimates for the long-end sectors based on equation 5-style models are shown in the black line, with 95% error bands. These estimates are based on the period from March 13, 2020 to March 9, 2022.