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# 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 assess whether the Fed's asset purchases can be tailored to either restore market functioning or provide economic stimulus. When the communicated goal is restoring market functioning and purchases' implementation is flexible, flow effects are significant: relative price deviations narrow. However, stock effects remain near zero and hence not stimulative. When the communicated goal links purchases to the achievement of the dual mandate, improving their size's predictability, stock effects rise consistently above zero. When the communicated implementation improves the predictability of the purchases' maturity composition, stock effects become large. Jointly, the communicated goal and implementation can shape the purchases' effects.

JEL classification: E43, E44, E52, E58

Key words: quantitative easing, market-functioning asset purchases, communicated policy goals, asset purchases implementation

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# 1 Introduction

Central banks have employed large-scale asset purchases (LSAPs) for two distinct objectives: to provide monetary policy accommodation when the policy rate is near zero, and to support market functioning or financial stability.<sup>1</sup> A fundamental unresolved question in the literature is how LSAPs can be tailored to accomplish different objectives, or, put differently, how the same purchase operation can be used to achieve different goals in different economic and market conditions. This question has been highly debated in policy and academic circles.<sup>2</sup>

The answer depends on two crucial factors: (1) whether the LSAP's effects are affected by its communicated objective and (2) how the LSAP's implementation is adjusted to achieve that objective. Our focus is to analyze these two key factors using the ideal setting provided by the \$2.9 trillion of Treasury purchases conducted by the Federal Reserve (the Fed) in 2020-2022, which served multiple objectives over time. The initial goal was to support smooth market functioning, but later the goal was expanded to foster accommodative financial conditions as in previous QE.<sup>3</sup> As a result, the purchases' implementation was greatly changed. The purchase pace, which initially peaked around \$75 billion per day, was reduced to \$80 billion per month once the goal shifted.

To understand whether the program's communicated goal and implementation mattered for the achievement of each objective, we estimate how the purchases' stock and flow effects evolved with the communicated goal and communicated implementation.<sup>4</sup> To this end, we use an approach similar to D'Amico and King (2013), which we modify to account for the several novel features of the 2020-2022 purchase program. This program was open-ended rather than fixed in size. The purchase pace was characterized by unprecedented scale and speed. During March 2020, the New York Fed's Open Market Trading Desk (the

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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).

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.

Desk) bought in four days the same amount purchased during the seven-month-long 2009 Treasury LSAP. Finally, commitment and flexibility were key aspects of the program. The Fed committed to purchase securities “in the amount needed,” in effect putting no limit. The purchases’ size and maturity distribution were adjusted weekly and even daily as needed. This, at least initially, could have reduced the predictability of the total size and composition of purchases.

In open-ended programs, investors’ ability to predict the total reduction in privately-held securities and duration risk should be key to the stock effect—the permanent price impact of expected changes in the stock of debt and duration risk. How broadly these expected changes affect the yield curve is determined by 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 (D’Amico and King (2013)). In principle, substitution effects should be weak when markets are highly segmented. Hence, stock effects should grow larger as investors’ ability to predict the total size and composition of purchases improves and market segmentation decreases.

In contrast, the flow effect measures the average price impact of each purchase operation. Since the purchases’ intended size and composition is fully known before each operation, flow effects are mostly determined by changes in the willingness to hold certain Treasury securities, that is, changes in the relative demand for securities within the same auction sector. Those securities have very similar maturity, hence their relative demand is mostly driven by idiosyncratic characteristics such as liquidity and specialness in repo and future markets. It follows that flow effects mostly affect relative price deviations within a sector, smoothing bumps in the yield curve without necessarily shifting it down. Those effects should restore smooth market functioning, and should become insignificant once limits to arbitrage dissipate, as arbitrageurs can easily absorb relative demand shocks.

To assess the importance of the LSAPs’ communicated goal and implementation, using two-stage least squares over rolling windows, we analyze how stock effects evolve after

FOMC’s and Desk’s statements that provided crucial information about the purchase program. In particular, we have identified four key dates: (1) September 16, 2020, when the communicated objective shifts from sustaining market functioning to fostering accommodative financial conditions, effectively QE; (2) December 16, 2020, when the pace of purchases is conditioned to “substantial further progress” toward the FOMC’s dual mandate, which we view as rule-based QE; (3) February 21, 2021, when the auction calendars for the Treasury operations start being released at a monthly frequency; hence, dates/sectors/sizes of purchases become known earlier, reducing uncertainty about their maturity composition; (4) May 13, 2021, when the Desk releases the intended weights associated to each purchase sector, practically eliminating the uncertainty about the maturity distribution of purchases.

Three important findings emerge. First, the stock effect hovers around zero when the goal of purchases is supporting/sustaining market functioning, that is, from mid-March 2020 to mid-September 2020, what we label the MF period. This implies that MF purchases do not persistently shift down the yield curve and therefore are not stimulative. Second, the stock effect starts increasing consistently and significantly above zero soon after mid-December 2020, following the announcement of rule-based QE. This suggests that, in open-ended QE, providing guidance on the macroeconomic rule driving the size of purchases is beneficial. Third, the stock effect becomes significantly larger around February 21, 2021, and even larger after mid-May 2021. This indicates that earlier release of information about the intended maturity distribution of purchases greatly improves the efficacy of LSAPs.

Taken together, these findings reveal that the Fed’s communication about the goal of purchases and their implementation matters. Indeed, the stock effect moves significantly away from zero only in the QE period, when the goal is fostering accommodative financial conditions. Further, conditioning on being in the QE period, communication that increases the predictability of the purchase size by linking it explicitly to macroeconomic goals seems important. However, from our results, we cannot exclude that any rule facilitating the predictability of the purchase size would have been effective, as opposed to a macroeconomic

rule. Finally, conditioning on being in the QE period, communication about the maturity composition of purchases is at least as important as the communication about their goal and size. That is, the predictability of the total duration risk seems key to the magnitude of the stock effects. This is in line with the duration-risk channel being the main QE channel when arbitrageurs' risk-bearing capacity is not particularly limited (Vayanos and Vila (2021), Ray, Droste, and Gorodnichenko (2024)).

The importance of the predictability of the size and composition of purchases stands in contrast with the high flexibility in the scope and pace of purchases in the MF period. Hence, it is perhaps not surprising that the stock effect is very small during that period. Further, in the QE period, the stock effect is solely due to the price impact of each security's close substitute purchases, while in the MF period it is mostly due to the price impact of each security's own purchases, hence MF stock effects remain very localized and small in aggregate. This suggests that the purchase predictability matters for the magnitude of the substitution effects—the driver of the QE stock effect—while market segmentation matters for the relative importance of own and substitute purchases. That is, even if market segmentation improves and substitution effects activate, their magnitude does not grow if the size and composition of purchases are not predictable.

The stock effects are economically meaningful. In the QE period, when the price impact of purchases is at least 10 times bigger than in the MF period, a \$100-billion purchase is estimated to reduce the 10-year equivalent yield, on average, by about 6.5 basis points.<sup>5</sup> This implies that the \$1.2 trillion of Treasury purchases conducted in the QE period reduced the 10-year equivalent yield by about 78 basis points. In contrast, the \$1.7 trillion of purchases conducted in the MF period reduced the same yield by about 9 basis points. But, this does not imply that MF purchases were not effective in improving relative price deviations from the yield curve and therefore restoring normal market functioning.

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5. This effect is within the range of previous QE estimates. 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).

Indeed, 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. The price impacts are much larger in the 20- to 30-year sector of the yield curve, which initially experienced the largest price dislocations. A typical operation (\$7bn) would reduce sector yields by one basis point, but at longer maturities its impact would be three times larger. Flow effects are also quite large in the 2- to 7-year sector. Further, across all sectors, those effects are largest at the height of the crisis and start getting smaller in the second half of the MF period. All these findings are consistent with theories of market segmentation.

Since in the MF period the flow effects are much more important than in the QE period, to quantify the total effect of the Treasury purchases conducted for MF purposes, we add the average MF flow effect specific to each maturity sector to the MF stock effect, and compute a counterfactual yield curve. That is, we estimate what the yield curve would have looked like in mid-September 2020 (i.e., at the end of the MF period) in the absence of daily purchase operations in each maturity sector. This curve indicates that the MF purchases contributed to restore a smoother yield curve, as they corrected price deviations by different amounts in each maturity sector. In particular, they reduced yields by an average of 20 basis points in the 2-to-7 year sector, with the yields of some securities declining as much as 75 basis points, and by about 5 basis points in the 20-to-30 year sector.

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 purchases meant to ameliorate deflation risks and those meant to reduce financial market stress, and hence conclude that a well-communicated rationale matters. Our findings suggest that it is not only communication about the goal that matters, but also communication about the size and maturity composition of purchases. Moreover, communication about the goal might matter because it increases the predictability of the total size and persistence of the asset supply reduction.

Somewhat relatedly, Haddad, Moreira, and Muir (2025) study the impact of implicit central bank promises to intervene in severely adverse states, and find that expected large interventions in those states reduce tail risk. While we do not specifically investigate the value of the Fed’s commitment to unlimited Treasury purchases during the Covid episode, our findings seem to suggest that state-contingent LSAPs are beneficial. However, our results indicate that changing the goal/implementation of purchases based on economic and market conditions is effective as long as the flexibility does not come at the cost of purchase predictability. In other words, even if the rule guiding the purchases’ size and composition is state contingent, it seems helpful to provide earlier guidance about the rule.

The rest of the paper is organized as follows. Section 2 provides the building blocks of our approach to open-ended purchase programs. Section 3 focuses on the evolution of the stock effects, while Section 4 focuses on the flow effects. Section 5 summarizes key robustness checks. Section 6 offers concluding remarks.

## **2 Stock Effects in Open-Ended Programs**

In this section, we focus on the stock effects, that is, the impact that asset purchases have on prices by persistently reducing the stock of privately-held government debt. Expected changes in the stock of securities get impounded into their prices as soon as the market becomes aware of the Fed’s intentions, before any purchases take place. Presumably, this mechanism should account for the largest share of the price variation. However, since the goal of the purchases was shifting over time and their implementation was characterized by elevated flexibility, the expectation formation process related to the 2020-2022 open-ended purchases could have been more complicated than in previous LSAPs. Hence, we start with discussing the expectation formation process and how it has influenced our analysis.

D’Amico and King (2013) show that the bulk of the stock effect originates from the cross-price sensitivity of each security to the purchase of securities with similar maturity,

that is, the substitution effects. Therefore, to account for these effects, we also build buckets of substitute securities and detail their construction in this section.

Finally, we describe our estimation strategy and discuss its plausibility. This is important because, as pointed out in D’Amico and King (2013) and Vissing-Jorgensen (2021), during the purchase program, the quantities purchased by the Desk might have depended on price dislocations, hence we need to address the reverse causality between quantities and prices. The results for the stock effect are presented in Section 3.

## 2.1 Expectation Formation Process

In the case of open-ended purchase programs, the Fed does not reveal in advance the total size and composition of asset purchases. This implies that market participants’ expectation formation process about the size and composition of purchases consists of a sequence of revisions in expectations due to the information (signals) received from the FOMC and the Desk during the course of the purchase program. The sequence of revisions in expectations is what determines the evolution of the stock effect once impounded into security prices.

Under uncertain economic and financial conditions, to balance credibility and flexibility, the FOMC and the Desk often provide broad guidelines rather than precise signals. Therefore, the expectation formation process takes place under imperfect information (noisy signals). To illustrate this process, we borrow from D’Amico and King (2023), who develop a simple framework for revisions in expectations about the policy rate due to forward-guidance signals. The difference here is that agents receive signals about key parameters of the open-ended purchase program rather than the policy rate. Those key parameters are the monthly pace of purchases ( $Q_m$ ), the program’s length/persistence (i.e., number of months,  $m$ ), and the maturity distribution of purchases (i.e., the purchase weight,  $w_s$ , assigned to each maturity sector  $s$ ).

Table 1 reports the dates of each communication (first column) as well as the language used by the FOMC (second column) and the Desk (third column) to provide information

about the 2020-2022 program. Most of the dates coincide with FOMC meetings, but some implementation changes were announced during intermeeting periods. For each date, the new information is highlighted in bold and, in the case of the Desk statements and implementation notes, it is divided in three categories: pace of purchases, composition of purchases, and frequency of calendar releases. This facilitates mapping the new information to changes in the degree of uncertainty about the program’s key parameters, which is done in Table 2.

[Table 1 about here.]

The FOMC provided signals about the purchases’ size and goal, which helped investors to predict the total quantities and how long these quantities would stay in the Fed’s portfolio, that is, how persistent the supply shock would be. Those signals were characterized by different degree of noise, as they varied from broad guidelines (e.g., in the amounts needed as in March 23, 2020) to precise instructions (e.g., \$80 billion per month). Often, the program’s length/persistence could be guessed only from the goal (i.e., MF vs QE), but “rule-based” QE (e.g., conditioning to progress towards the Fed’s dual mandate as in December 16, 2020) potentially increased the length’s predictability.

The Desk statements and related implementation notes mostly provided information about the maturity distribution of purchases. But, in the early period, key information about the pace of purchases was released through the auction calendars. The Desk’s signals also varied from broad guidelines (e.g., “to roughly match the maturity composition of outstanding Treasury securities” as in March 12, 2020) to detailed information about  $w_s$  (e.g., the intended maturity distribution as in May 13, 2021). However, auction calendars released well in advance of auctions, by specifying the amount allocated to each maturity sector, helped investors to predict the purchases’ composition and therefore the reduction in duration risk.

To understand how the information described in Table 1 affects expectations, suppose that investors receive an unbiased signal  $s_t^h$  about a change in one of the three parameters

( $v_t = (Q_m, m, w_s)$ ) that will occur at time  $t + h$ . This signal is observed with noise  $\epsilon_t^h$  so that:

$$s_t^h = v_{t+h} + \epsilon_t^h, \quad (1)$$

where  $\epsilon_t^h$  is iid and uncorrelated with fundamentals. In general, the variance of  $\epsilon_t^h$  may vary across horizons, but for simplicity we assume this variance,  $\sigma_\epsilon^2$ , is horizon-independent (homoskedastic). If we assume that agents know the stochastic process governing  $v_t$  and  $\epsilon_t^h$  and update their beliefs in a Bayesian fashion, the revision in expectations is as follows:

$$E_t[v_{t+h}|s_t^h] - E_{t-1}[v_{t+h}] = K (s_t^h - E_{t-1}[v_{t+h}]), \quad (2)$$

where  $K$  is the Kalman gain:

$$K = \frac{\sigma_v^2}{\sigma_v^2 + \sigma_\epsilon^2} \quad (3)$$

(which is independent of the horizon because  $\sigma_\epsilon^2$  is homoskedastic, so learning is constant-gain). From equation 3, it is evident that the larger the variance of the noise, the smaller the gain, and therefore the smaller the revision in expectations induced by the signal.

In other words, the higher the uncertainty about key parameters of the purchase program, the smaller the update in expectations about the quantity purchased and the duration risk removed, therefore the smaller the asset price effect.<sup>6</sup> The information received through the FOMC and Desk statements, as well as through the auction calendars, helps to shrink the variance of the noise over time, pushing  $K$  closer to one. In this case, there would be a large revision in expectations to fully reflect the new signal, inducing larger changes in asset prices. This implies that as  $\sigma_\epsilon^2$  gets smaller, the stock effect should get larger in magnitude.

With this framework in mind, we investigate how changes in the communicated goal and implementation—the signals—have affected Treasury security prices. The extent to which

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6. It should be noted that, since in QE term structure models, the quantity purchased and the duration risk removed are factors that drive only the market price of risk (e.g., Li and Wei (2018); Vayanos and Vila (2021); Ray, Droste, and Gorodnichenko (2024)), time variation in expectations about these factors and the noise around those expectations will affect only term premia. If those factors were to enter the policy rate rule, then they would affect also the expectation component of yields.

those signals are reflected in investor beliefs, and hence prices, is useful to understand whether the goal communication and related implementation can shape investor beliefs, affecting the magnitude of the stock effect. This is crucial to determine whether asset purchases can be tailored to achieve different objectives.

In Table 2, we rely on the information provided in Table 1 to divide the 2020-2022 program in multiple periods (first column). In each period, the composite state for the goal and implementation (second column) has certain implications for the uncertainty about the key parameters of the purchases (third column). Because of the lack of data, it is hard to quantify  $\sigma_\epsilon^2$  for each parameter, nonetheless its qualitative characterization is instrumental to understand how changes in the goal/implementation state translate into changes in parameter uncertainty (i.e., the variance of the noise around each parameter’s signal). The latter, as shown in equation 3, determines the size of the revisions in investor expectations, affecting the magnitude of the stock effects in each period. This will be helpful in interpreting the evolution of the estimated stocks effect during the 2-year program, which are presented in the next section.

During the first period, which runs from 3/12/2020 to 6/10/2020, the primary goal is to support MF and the implementation is characterized by high flexibility, as the purchase parameters are determined on a daily basis as appropriate. As a result, the  $\sigma_\epsilon^2$  of each parameter should be very high. During the second period, which runs from 6/11/2020 to 9/15/2020, the goal shifts from supporting to sustaining MF, while the implementation is still characterized by flexibility. But, since market conditions were almost back to normal,<sup>7</sup> the monthly pace of purchases stabilizes at approximately \$80bn, reducing the uncertainty about  $Q_m$ . In our analysis, these two periods together constitute the “MF period.”

In the third period, which runs from 9/16/2020 to 2/20/2021, the primary goal is in line with QE, which greatly increases the likelihood that the securities purchased remain in the Fed’s portfolio until maturity, reducing the uncertainty about the program’s

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7. See Logan (2020).

length/persistence ( $m$ ). Further, there are no main changes in implementation, as the pace remains at \$80bn, effectively eliminating the uncertainty about  $Q_m$  (at least until tapering). Finally, in the fourth period (2/21/2021-9/21/2021), the goal is still QE, but changes in implementation greatly reduce the uncertainty about the purchases' composition. Starting in February 2021, the auction calendars are released monthly, specifying dates/sectors/sizes of purchases for the full month ahead; and, in May 2021, the sector weights ( $w_s$ ) become fully known. Those changes greatly improve the investors' ability to forecast reductions in duration risk.

These last two periods can both be considered as the “QE period,” which runs through the end of the program. But to understand the relative importance of the communicated goal and implementation, we start the QE analysis either from September 16, 2020, when the goal changes but implementation is unchanged, or from February 11, 2021, when the goal is unchanged but implementation changes. These two QE periods are denoted as “QE Goal” and “QE Implementation,” respectively.

[Table 2 about here.]

Based on Table 2, the *magnitude* of the stock effect should get larger during the QE periods, as parameter uncertainty declines and investors can better predict the size and persistence of the supply shock. Further, during the QE-Implementation period, when investors can better forecast the amount of duration risk removed from the market, the stock effect should get even larger, as the duration-risk channel of QE is very important for risk premia (e.g., it is the main channel in Vayanos and Vila 2021). Once the expectation formation process about QE is complete, the stock effect should reach its peak, and it should unwind once expectations about QT start forming, which is outside the scope of this study.

Finally, the degree of market segmentation across the MF and QE periods determines the *relative importance* of the security's own- and cross-price sensitivity to purchases (i.e., how sensitive a security's price is to its own purchases and those of similar securities).<sup>8</sup> When

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8. In Vayanos and Vila (2021) and Ray, Droste, and Gorodnichenko (2024), the degree of market segmen-

markets are segmented or partially segmented, the substitution effects tend to be weaker and occur more slowly; hence, we anticipate the cross-price sensitivity to be smaller during the MF period and larger in the QE period. In contrast, the own-price sensitivity should be more relevant during the MF period, as market segmentation will induce each security to be very sensitive to its own purchases, causing very localized stock effects.

Overall, we expect: (i) the magnitude of the stock effects to increase as  $\sigma_\epsilon^2$  decreases, (ii) the own-price sensitivity to be the main driver of these effects during the MF period, and (iii) the cross-price sensitivity to be the main driver during the QE period. Since the cross-price sensitivities determine the substitution effects and thus the global impact on the yield curve, its downward shift should mostly occur during the QE period. That is, MF purchases should not be very stimulative because they occur when markets are segmented and, therefore, the cross-price sensitivities are small.

## 2.2 Substitutes

To estimate the price sensitivity of each security to the purchases of similar securities, it is necessary to specify and build the “substitutes,” which are a key element of the propagation mechanism of purchases to the entire yield curve.

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  $n^{\text{th}}$  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 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.

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tation is approximated by the arbitrageurs’ risk-bearing capacity. According to the “localization hypothesis,” when risk-bearing capacity is low, the yield response is localized to the sector of the yield curve hit by the supply shocks. When risk-bearing capacity is high, the impact of the supply shocks propagates to the entire yield curve. Similarly, supply effects remain localized when markets are illiquid and capital moves slowly as in Greenwood, Hanson, and Liao (2018).

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 sets of substitutes are mutually exclusive. The “near” substitutes, shown in light gray, have the closest maturity distance from security  $i$ , the “far” substitutes, shown in black, have the farthest maturity distance from  $i$ , and the “mid” substitutes, shown in darker gray, are in between. Specifically, substitutes are defined as a function of the security’s maturity,  $\tau$ , to allow the bucket of substitutes to get wider as  $\tau$  increases.<sup>9</sup> For instance, in the case of a 2-year security, the near-substitute bucket is about 1 year wide, the mid-substitute bucket is about 3 years wide, and the far-substitute bucket about 7 years wide; while in the case of a 30-year security, the near-substitute bucket is 3 years wide, the mid-substitute bucket is nearly 7 years wide, and the far-substitute bucket is nearly 15 years wide. This is important because there are fewer securities outstanding at the long end of the yield curve, so expanding the bucket size avoids having empty buckets of substitutes for longer-term securities.

[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 impact of quantities purchased in a given sector is inversely related to the 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 Treasury issuance.

### 2.3 Estimation Strategy and Its Plausibility

To estimate the price effect of own and substitute purchases, we need to address the reverse causality between Treasury quantities ( $q$ ) and prices ( $P$ ). That is, for each security, we want to maximize the likelihood its  $P$  is responding to changes in  $q$  and not the reverse. Since

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9. The substitute bandwidth for a given bucket (near, mid, or far) is based on the time to maturity  $\tau$  and a logistic distribution with location = 15 and scale = 4. See Appendix A.

purchases can depend on ongoing price dislocations, we need exogeneity to the Desk's *actual* purchasing decisions. This is why we need the component of  $q$  that the Desk is *expected* to buy *before* the start of the purchase operations in each period. Moreover, as discussed in Section 2.1, expectations about  $q$  are what matters the most for the stock effect.

Hence, for each purchase period, we estimate the expected  $q$  as of the day before the purchases start. To form those expectations, investors will use all the available information, which includes the Desk's *perceived* purchase rules at that point in time. As those expectations are formed and measured before the actual purchases take place, by construction they cannot respond to the price changes that take place during the purchase period and, therefore, by construction are separate from the portion of  $q$  that is responding to those price changes. In other words, we want to avoid using the unexpected change in  $q$  that materializes in the purchase period, that is, the part of  $q$  due to the difference between the *perceived* and *actual* purchase decisions of the Desk. The unexpected change in  $q$  during the purchase period has the highest likelihood of responding to the price dislocations occurring *during* that period.

The security's characteristics that are *expected* to affect the Desk's purchase rules are likely good instruments for  $q$  (e.g., D'Amico and King (2013) and Vissing-Jorgensen (2021)). These characteristics, which are all exogenous to price changes, can be split in two categories: characteristics that affect prices only through  $q$ , that is, they matter only because they enter the Desk's purchase rules (e.g., Fed's self-imposed cap on individual amounts purchased and eligibility restrictions) and those that matter for prices not only through  $q$ . For instance, maturity and relative value to the curve are perceived to be very important for the purchase rules but are also important for prices variation in general. Hence, these variables do not meet the exclusion restriction and cannot be used as instrumental variables (IV).

To formalize this approach, let  $t$  denote the first day of each purchase period in which we segment the entire program (or March 11, 2020, in the case of the full period). And let  $T$  mark the end of the purchase period. Since we are interested in estimating the stock effect,

we need to estimate the total  $q$  that is expected to be purchased by time  $T$ . Then, we use the expected  $q$  as an instrument for the actual  $q$  at the second stage. That is, we estimate the following system of equations in two stages:

$$\begin{pmatrix} E_t(q_{i,own,T}|t-1) \\ E_t(q_{i,near,T}|t-1) \end{pmatrix} = \hat{\gamma}_0 + \hat{\gamma}_1 Z_{i,t-1} + \hat{\gamma}_2 X_{i,t-1} \quad (4)$$

$$\frac{\Delta P_{i,t,T}}{P_{i,t}} = \phi_0 + \beta_0 q_{i,own,T}^{IV} + \beta_1 q_{i,near,T}^{IV} + \phi_1 X_{i,t-1} + u_i, \quad (5)$$

where  $\frac{\Delta P_{i,t,T}}{P_{i,t}}$  is the percentage price change in each period,  $Z_i$  is the vector of IV, and  $X_i$  is the vector of additional security characteristics relevant for pricing.  $\beta_0$  and  $\beta_1$  are the coefficients of interest, as  $\beta_0$  measures the price sensitivity of each security to its own purchases, and  $\beta_1$  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.

Since  $\Delta P_{i,t,T}$  is not observable in  $t-1$ , by construction,  $E(q_{i,T}|t-1)$  cannot respond to  $\Delta P_{i,t,T}$ . Hence, in the second stage,  $E(q_{i,own,T}|t-1)$  is used to instrument the actual  $q_{i,T}$ , i.e.,  $E(q_{i,own,T}|t-1) = q_{i,own,T}^{IV}$  and  $E(q_{i,near,T}|t-1) = q_{i,near,T}^{IV}$  in equation 5. If some of our IV, which are measured at time  $t-1$ , had the power to predict future price changes,  $\Delta P_{i,t,T}$ , (causing  $u_i$  in eq. 5 to be correlated with  $q_{i,T}^{IV}$ ), it would imply that investors are not forward looking and markets are not efficient, as all the information available in  $t-1$  should have been already included in  $P_{t-1}$  and  $P_t$ , becoming irrelevant for changes in prices beyond  $t$ . Further, to address the persistence of some of our IV, we include the level of  $P_{t-1}$  and  $FE_{t-1}$  in the second stage.

More importantly, even if our IV were not strong enough to fully address the reverse causality between the individual  $P_i$  and  $q_i$ , biasing the estimate of the "own" coefficient  $\beta_0$ , this issue should hardly affect the coefficient of the near substitutes or any bucket of substitutes. That is, for every security  $j \neq i$ , during the purchase period,  $q_j$  would be responding

to  $P_j$  and not  $P_i$ . It follows that  $\sum_j q_j$  (i.e., the purchases of security  $i$ 's substitutes) most likely will not be responding to  $\Delta P_{i,t,T}$ . This implies that  $\beta_1$ , the most important coefficient for the aggregate stock effect, should be unbiased because there should not be reverse causality between  $\Delta P_{i,t,T}$  and  $\sum_j q_j$ .

The above reasoning is on a good footing as long as price dislocations are not systematically correlated within a maturity sector, which seems very plausible during normal market conditions, like in the QE-Goal and QE-Implementation periods. That is, if arbitrage activity is not limited, in each maturity sector of the yield curve, securities can not be miss-priced in the same directions and their price deviations from the curve usually average to zero. Nevertheless, in crisis periods like the MF period, because of limits to arbitrage, within certain maturity sectors, price dislocations can be highly correlated in the short run, making  $\Delta P_{i,t}$  and  $\Delta P_{j,t}$  correlated, and this is why we instrument also the near-substitute purchases.

### 3 Stock Effect Results

Before turning to the baseline results, we need to describe in detail the IV and controls used to estimate the two-stage least squares summarized by equations 4 and 5. In particular, we estimate two first stages, used to derive the expected own and near-substitute purchases, and a second stage in which we instrument the actual purchases with the expected purchases:

$$q_{i,own,t,T} = \gamma_0 + \gamma_1 CapDist_{i,t-1} + \gamma_2 FE_{i,t-1} + \gamma_3 \tau_{i,t-1} + \gamma_4 \tau_{i,t-1}^2 + \gamma_5 CtD_{i,t-1} + \gamma_6 X_{i,t-1} + \varepsilon_i \quad (6)$$

$$q_{i,near,t,T} = \zeta_0 + \zeta_1 \overline{CapDist}_{i,t-1} + \zeta_2 \overline{FE}_{i,t-1} + \zeta_3 \overline{\tau}_{i,t-1} + \zeta_4 \overline{\tau}_{i,t-1}^2 + \zeta_5 \overline{CtD}_{i,t-1} + \zeta_6 X_{i,t-1} + \eta_i \quad (7)$$

$$\frac{\Delta P_{i,t,T}}{P_{i,t}} = \beta_0 q_{i,own,t,T}^{IV} + \beta_1 q_{i,near,t,T}^{IV} + \phi_0 + \phi_1 \tau_{i,t-1} + \phi_2 \tau_{i,t-1}^2 + \phi_3 \log(P_{i,t-1}) + \phi_4 FE_{i,t-1} + u_i \quad (8)$$

As mentioned in Section 2.3, the IV are going to be the security characteristics that mattered only because of the Desk's purchase rules. The Desk's guidelines<sup>10</sup> indicated that

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10. Available at <https://www.newyorkfed.org/markets/treasury-reinvestments-purchases-faq-200312>

the Fed’s holdings of an individual security could not exceed 70% of its outstanding and could rise above the 35% threshold only in modest increments. These increments would get smaller as soon as the percentage reached 47.5% and even smaller once the percentage reached 59%. That is, the purchase pace decelerated faster as the percentage surpassed each threshold. To approximate this rule, we build a variable that approaches zero at an increasing rate as the security’s percentage held by the Fed gets closer to the 70% cap, which we label “cap distance:”

$$CapDist_{i,t-1} = \sqrt{\max(.70 - f_{i,t-1}, 0)} \quad (9)$$

where  $f_{i,t-1}$  is the security  $i$ ’s fraction owned by the Fed at the beginning of each purchase period considered in our estimation. Similarly to the dummy variable in Vissing-Jorgensen (2021), which tracks the securities that are at the cap and is a powerful IV, the variable cap distance equals zero at the 70% threshold, indicating that the Fed will no longer purchase the security. However, differently from a dummy variable, cap distance evolves in a continuous way, which is more helpful to our rolling estimation that covers purchasing periods as long as two years. Hence, our variable is closer to the instrument “percentage held by the Fed” in D’Amico and King (2013), but it accounts for the fact that purchases have to decelerate significantly once that percentage gets large.<sup>11</sup>

Further, unlike previous LSAPs, the Desk explicitly allowed purchases of securities that were cheapest-to-deliver (CtD) into futures contracts and notified the market of this on March 15, 2020. After about a month, the CtD were excluded from the purchases. Given these eligibility criteria, we include an indicator for the CtD securities as an instrument. We have also experimented with indicators for on- and off-the-run securities (D’Amico and King (2013); Vissing-Jorgensen (2021)) as the Desk excluded newly-issued coupon securities from purchases, but it did not make much difference, most likely because these indicators do not

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11. We have tried other functional forms that capture this pattern and the results are very similar.

meet the exclusion criteria.

It should be noted that while “own purchases” are instrumented using individual securities’ characteristics, the “near-substitute purchases” are instrumented using a weighted average of the characteristics of the securities included in the near substitutes, marked by the upper bar in equation 7 . The construction of each variable and their weighted averages are discussed in Appendix C. Importantly, 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).

In the first and second stage, we control also for the yield curve fitting errors ( $FE$ ), maturity, and maturity squared. These security’s characteristics are important for pricing in general and for the Fed’s purchase rules. The Desk stated that it evaluated security prices based on “their proximity to prevailing market prices at the close of the auction, as well as measures of relative value.” In addition, at the second stage, the maturity terms help control for possible secular changes in the slope and curvature of the yield curve resulting from varying macroeconomic conditions, including Treasury issuance. However, given the huge amount of issuance during the Covid period, in the robustness section, we account explicitly for its impact. Further, since we expect prices to be mean-reverting, we include the log of the initial price as control because its omission would bias the purchase coefficients  $\beta_0$  and  $\beta_1$ . Finally,  $X_i$  accounts for any additional control included in the second stage but not listed in the first-stage regressions for brevity.

In this cross-sectional specification, we can include only the 204 CUSIPs that existed from March 2020 to March 2022 and accounted for about \$1.7tr of total own purchases. Hence, because of the length of the purchase program, the stock effects do not include any securities with less than 2 years to maturity. However, it is important to note that the purchases of securities issued after March 2020 and before March 2022 still affect our estimates, because they are considered in the bucket of substitutes of each of the 204 securities (and account for an additional \$800bn). This implies that for substitute purchase the Fed’s cap of 70%

is not very relevant as, post March 2020, Treasury issuance was very large, and therefore there were plenty of newly-issued securities to buy. Finally, the number of securities in the cross-section implies that we have to drop the mid and far substitute purchases to reduce the number of coefficients that need to be estimated, but we can include those variables in the panel regressions used to estimate flow effects in Section 4, as the panel includes a much larger number of observations.

### 3.1 Baseline Results

We start with commenting briefly on the first-stage results, which are shown in Table A.2 in Appendix D.1, and then discuss in more detail the second-stage results, which are at the core of this study. To facilitate the economic interpretation of the coefficients, the amounts purchased in each sub-periods are shown in Table A.1 in Appendix B.

The most relevant aspect of the first-stage regressions is that all the F-statistics for own- and near-substitute purchases in the full sample as well as across the different sub-periods are well above 10, the critical value suggested by Staiger and Stock (1997).<sup>12</sup> In the case of the near-substitute purchases, the F-statistic is even above the higher refined values suggested by Stock and Yogo (2003) for strong instruments and the  $R^2$  are very large, indicating that sector-level characteristics explain a large portion of cross-sectional differences in sector-level purchases. However, the  $R^2$  are lower in the case of own purchases, indicating that it might be more difficult to predict the purchase distribution across individual securities.

Turning to the second-stage results, Table 3 summarizes the estimated stock effects over the full sample period (first column) and across the MF and the two QE periods, based on the criteria described in Section 2.1. A key finding is that the impact of the Fed purchases in the QE periods is at least 10 times bigger than in the MF period, as the coefficient on the purchases of near substitutes—the driver of the aggregate stock effects—is around 0.05 in the

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

MF period and between 0.6 and 0.8 in the QE periods. This suggests that the FOMC’s and Desk’s communication about the goal and key parameters of the purchase program matters. It is possible that in the QE periods, the reduced uncertainty about the size, composition, and persistence of the supply shock facilitated the forecast of the total change in supply and duration risk, allowing this change to get fully priced in.

[Table 3 about here.]

To better understand the main drivers of the stock effect’s magnitude, and thus the relative importance of market functioning, communicated goal of purchases, and their implementation, we re-estimate equation 8 over 6-month rolling windows, with the window rolling by one week at a time.<sup>13</sup> This allows us to better pin down the period in which the coefficients for the own and near-substitute purchases start changing. Figure 2 plots those coefficients along with 95% confidence bands. The vertical lines mark key dates reported in Table 1, which help us identify which FOMC’s and Desk’s communication triggered the most significant changes in the coefficients.

[Figure 2 about here.]

In the top panel, the estimated pattern of the near-substitute coefficient displays three important features. First, it starts being consistently positive and statistically significant after mid-December 2020; when, in the QE period, purchases are conditioned to “substantial further progress” toward the FOMC’s maximum employment and price stability goals. This rule-based QE, by explicitly linking the pace of purchases to macroeconomic goals, most likely facilitated the forecasting of the program’s length. A better predictability of the number of months spanning the program’s length, together with a stable monthly pace, implied a better predictability of the total size of purchases (i.e.,  $Q_m \times m$ ). This implies that, in open-ended

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13. It should be noted that also the first-stage needs to be re-estimated using IV observed as of the day before each window.

QE, communicating the goal of asset purchases by sketching the rule that guides decisions about the size of purchases seems important.

Second, the near-substitute coefficient becomes significantly larger after February 2021, the month in which the auction calendars for the Fed's purchase operations started being released one month in advance (marking the beginning of our QE-Implementation period). That is, starting on February 21, 2021, market participants learned 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. Further, once the sector weights  $w_s$  become fully known in May 2021, the coefficient's size gets even larger and stabilizes above 0.5. This indicates that implementation changes that remove uncertainty about the maturity distribution of purchases are another important driver of the stock effect.

It is also 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 frequently adjusting 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 when the purchase implementation aligned more closely with such goal.

Third, it is also telling that the change in the coefficient's magnitude does not occur soon after June 2020, when market functioning is effectively back to normal. As shown in the speech of Logan (2020), by June 2020, measures of market functioning in the Treasury and MBS markets had uniformly improved and were practically back to their pre-Covid levels. Hence, if the coefficient was improving because of better market functioning, it should have started increasing much earlier, around the summer of 2020, rather than hovering close to

zero until December 2020. This suggests that the improved market environment was not the main driver of the larger stock effects.

Taken together, these findings are very important because they indicate that the Fed’s communication about the goal of purchases and their implementation matters. The increased predictability of the size and, more importantly, of the maturity composition of purchases greatly amplified the stock effects, confirming the message of Table 3. 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 MF period we do not find economically significant stock effects.

Further, from Table 3 and Figure 2, it is possible to note that the relative importance of own and near-substitute coefficients changes from the MF to the QE periods. While in the MF period, the coefficient on own purchases is positive, statistically significant, and very similar in magnitude to the coefficient on near substitutes; in the QE periods, the coefficient on own purchases becomes insignificant, and that on near substitutes becomes much larger. This implies that supply effects are extremely localized—each security’s price is sensitive to its own purchases—when market functioning is poor, in line with theories of market segmentation.

However, the bottom panel of Figure 2 suggests another reason why, on net, the own purchases coefficient is close to zero and insignificant during the QE period: in the later part of the sample, the individual cap is increasingly binding. Specifically, although it is evident that the own coefficient approaches zero as market segmentation improves around June 2020, it increases again soon after the goal shifts from MF to QE in mid-September 2020. This suggests one more time that the communicated goal of purchases matters. But then, the own coefficient switches sign once a large share of securities considered in our regressions approaches the 70% cap or is at the cap, implying that the purchases of those securities had to slow down or stop altogether. (As we show in the robustness section, this result

is largely driven by securities with more than 15 years to maturity.) Hence, after January 2021, the positive change in price of each security is mostly driven by the purchases of their substitutes, as many of those substitutes are newly issued and far from the cap.

However, in the 6-month rolling-window regressions, the results for the own coefficient have to be taken with a grain of salt, because in some of windows, the F-statistics at the first stage are below 10. While for the results in Table 3, the F-stats are much larger and therefore the estimates are more robust.

### 3.2 Economic magnitude of the effects

The evidence reported in Table 3 and Figure 2 implies that the economic magnitude of the stock effect is substantial, especially considering that we estimate only the effect due to the supply channel of QE (i.e., scarcity and duration-risk channels). There could be other persistent effects from the signaling and liquidity channels that we do not capture.<sup>14</sup>

In particular, in the QE-Goal period (Table 3), the coefficient of 0.637 on near-substitute purchases implies that, on average, purchasing 1% of the total outstanding of a security's substitutes increased its return by about 0.637%; for a representative ten-year security with a duration of nine years, this translates into a yield decrease of about 6.5 basis points per \$100 billion of purchases.<sup>15</sup> This implies that the total amount purchased during the QE-Goal period (\$1.2tr) reduced the 10-year equivalent yield by about 78 basis points.

In the MF period, the coefficient of 0.044 on own purchases implies that, on average, purchasing 1% of the stock of a certain security increased its return by about 0.044%; for a representative 10-year security with a duration of nine years, this translates into a yield decrease of about 0.55 basis points per \$100bn purchased, that is, a yield impact 10 times

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14. See D'Amico et al (2012) for a detailed explanation of the QE channels.

15. This effect is obtained by multiplying the coefficient on near-substitute purchases, 0.637, by the average near-substitute percentage purchased in the QE-Goal period, 7.7%. We convert this average return of 4.9% into a 10-year equivalent yield by dividing by 9, the duration of the 10-year benchmark note. We then divide the implied yield effect by 8.2, given the purchase of \$820B, which includes only the securities used in our estimation (see amounts in columns 3 and 4 for the QE-Goal period in Table A.1 of Appendix B).

smaller than that found in the QE-Goal period.<sup>16</sup> This implies that the total amount purchased during the MF period (\$1.7 tr) reduced the yields on average by 9.4 basis points. Overall, the total amount of Treasury purchased (\$2.9tr) is estimated to have reduced yields by nearly 90 basis points only through the supply channel.

## 4 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. As mentioned in the introduction, these price impacts are mostly determined by changes in the relative demand for securities within the same auction sector, so they are distinct from stock effects that are mostly determined by changes in expectations about the total size and composition of purchases, which are fully known before each operation. To estimate flow effects, we have tracked, for each 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.<sup>17</sup> To ease the understanding of our empirical design and results, before turning to the estimation, we provide some details about the mechanics of the Desk’s purchase operations.

### 4.1 Mechanics of purchase operations

As in previous LSAP programs, the purchases were conducted by multiple-price auction. The sectors and size of each purchase operation were announced in advance. At the start of each auction, the Desk informed participants about specific CUSIPs that would be excluded from the operation. These exclusions were fairly predictable based on the Desk’s guidelines.

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16. This effect is obtained by multiplying the coefficient, 0.044, by the average own percentage purchased in the QE period, 12.8%. We convert this average return of 0.6% into a 10-year equivalent yield by dividing by 9. We then divide the implied yield effect by 11.35, given the own purchase of \$11.35B in the MF period.

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

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.<sup>18</sup> Hence, ahead of the auction, dealers did not know the actual purchase distribution across CUSIPs that would prevail after the auction because of the Desk’s proprietary model and other dealers’ bidding behavior. The difference between expected and actual purchase distribution could trigger price reactions following the release of each auction’s results. How pronounced these price reactions are and for how long they persist depend on the severity of limits to arbitrage (e.g., Lou, Yan, and Zhang (2013), D’Amico and King (2013), Bernardini and De Nicola (2020), Ray, Droste, and Gorodnichenko (2024)).

Auctions took place every day and settled on the following day. There were up to seven operations per day, spread across the maturity sectors in which the Desk conducted its auctions. Typically, each auction would take place within a 15-minute window separated by 30-minute intervals from adjacent auctions. Thus, to isolate the impact of each purchase operation, it is necessary to use intraday price quotes. 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. Hence, differently from previous studies, we can estimate the flow effects specific to each maturity sector.

The sector-specific flow effects are of interest because price dislocations were quite different across the yield curve. 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)), the long end of the yield curve experienced relatively larger price dislocations. Importantly, having estimates of the sector-specific price sensitivities can be helpful for future purchase programs, including Treasury buybacks. Specifically, 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

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

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. Hence, we estimate flow effects specific to each of these sectors.

## 4.2 Panel regression specification

We compute price changes in a 15-minute window ( $w$ ) around each operation taking place at time  $t$  in a specific maturity sector within a specific day. For each operation, the Desk provides data on the par value purchased across CUSIPs, as well as the time at 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 windows just before and after each operation.

Our flow-effect regressions take the following form:

$$\frac{\Delta P_{i,t-w,t+w}}{P_{i,t-w}} = \beta_0 q_{i,t}^0 + \beta_1 q_{i,t}^{near} + \beta_2 q_{i,t}^{mid} + \beta_3 q_{i,t}^{far} + cusip_i + \epsilon_{i,t-w,t+w}, \quad (10)$$

where, similarly to the stock effects' specification,  $\beta_0$  and  $\beta_n$  (with  $n=1, 2, 3$ ) are the coefficients of interest. Here, the large number of observations allow us to consider all three buckets of substitutes defined in Section 2 (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 achieve two goals: first, we eliminate other confounding factors influencing prices, therefore we just control for CUSIP fixed effects; second, we minimize the risk of reverse causality, hence we do not need to use the IV approach. That is, following the release of each operation's results, the quantities purchased cannot react to the price changes that occur after the release until the next operation, which however is outside the time-window  $t + w$ .

### 4.3 Results

Table 4 summarizes the flow-effect results for the full period, and across four different sub-periods, that is, the same three sub-periods used for the stock effect plus the “Height of Crisis” period, which goes from March 13, 2020 to April 17, 2020. This period should be particularly relevant for examining flow effects as price dislocations were very large.

We find that the coefficients on near- and mid-substitute purchases are positive and statistically significant only during the “Height of Crisis” and MF period (which includes the height of the crisis), and they get smaller in magnitude as the degree of substitutability decreases (i.e., the maturity distance from security  $i$  increases), in line with the hypothesis of market segmentation. In terms of economic magnitudes, flow effects are much stronger in the MF period than in the QE period. For instance, the return coefficient of 0.235 in response to a 1% reduction in the amount outstanding of near substitutes (which on average equals \$15bn) implies that, during the height of the crisis, a typical operation of about \$7bn reduced 10-year equivalent yield by about one basis point. This is about ten times bigger than the impact implied by the same coefficient in the QE period.<sup>19</sup> Moreover, most coefficients become insignificant in the QE period as limits to arbitrage dissipate.

In Table 5, we report the results specific to the five auction maturity sectors used by the Desk for its operations, during the height of the crisis. Since markets were extremely dysfunctional, purchase operations were very frequent and large in size. 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 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. Further, the flow effects are also quite large in the 2.5-to-7-year sector and,

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19. 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.

since this sector is characterized by an average duration much shorter than the 20-to-30-year sector, when converted into yields, those flow effects result in more economically meaningful impacts. Finally, in the 7- to-20-year sector, however, some of the coefficients are negative, which is most likely due to the fact that the sector was too wide and scarcely populated. In fact, this is the sector that in May 2021 was split into two smaller maturity sectors.

[Table 4 about here.]

[Table 5 about here.]

Table 6 reports the flow effects by maturity sectors for the entire MF period. By comparing these results to those in Table 5, it is possible to see that, as market conditions improve and the Fed transitions from supporting to sustaining smooth market functioning (June 10, 2020; Table 1), most coefficients become smaller and, the coefficient on own purchases is either very close to zero or statistically insignificant, 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. In particular, in this sector, the return coefficient of 2.5 (Table 5) in response to a 1% reduction in the amount outstanding of near substitutes of that sector (which on average equals \$9bn) implies that, at the height of the crisis, a typical operation of about \$3.5bn reduced the 10-year equivalent yield by about 4 basis points.<sup>20</sup> This is an impact nearly 3 times larger than that obtained for the same maturity sector in the MF period, where it amounts to about 1.5 basis points.

[Table 6 about here.]

Since in the MF period, the flow effects are much more important than in the QE period and economically meaningful, to quantify the total effect of the Treasury purchases conducted for MF purposes, we add the average MF flow effect specific to each maturity sector to the

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20. It should be pointed that when we compute sector-specific yield effects we use the average duration of each sector, which in our sample is 18.5 years in the case of the 20-30-year sector.

MF stock effect (computed in section 3). That is, to the initial impact due to the expected change in supply, we add the average impact due to the strength of relative demand at the Fed’s auctions. The counterfactual yield curve shown in Figure 3 helps visualize the sector-specific effects of the MF purchases.

In particular, we use the MF’s sector-level coefficients (if statistically significant) in Table 6 and the average amount purchased of each security to obtain the total flow effect pertaining to that security. We then convert these flow effects from returns into yields, using the duration of each security. Therefore, securities that have a large sensitivity in terms of return may display a small impact in terms of yields if they have a long duration. In addition, we also compute the security-level stock effect for the MF period by multiplying the significant MF own coefficient by the amount of each security’s own purchases in this sub-period. Then, on a security-by-security basis, we add those individual stock and flow effects back to the yield curve that prevailed in mid-September 2020 (i.e., the end of the MF period) and derive a counterfactual yield curve. This gives a picture of how the yield curve would have looked in the absence of purchases in each maturity sector and is marked by the gray triangles in Figure 3. In contrast, the black dots mark the actual yield curve as of September 15, 2020.

[Figure 3 about here.]

It is striking that by mid-September 2020, the yield curve was again perfectly smooth, as the MF’s purchase operations reduced yields by different amounts in each maturity sector, eliminating price deviations from fundamental values and therefore repristinating normal market functioning. This confirms the presence of local supply effects in periods characterized by limits to arbitrage. Over the MF period, it is evident that the purchases were the most effective in the 2-to-7-year sector, where yields declined on average by about 20 basis points, while at the long-end of the curve the improvement was limited to about 5 basis points. Indeed, this sector took much longer to recover as the actual yield curve fitting errors (not shown) stayed elevated for a long time.

## 5 Robustness

This section focuses on the most relevant robustness checks we have conducted for the stock and flow effects.

### 5.1 Robustness of stock effects across subperiods

To verify the robustness of our key findings in relation to the FOMC’s and Desk’s communication, we re-estimate equation 8 over a shrinking time window, 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.<sup>21</sup> Figure 4 shows the evolution of the coefficients for the own and near-substitute purchases over the shrinking sub-periods, along with 95% confidence bands.

It can be noted that as long as the the first three months of purchases are excluded from the sample, the magnitude of the estimated coefficient remains at least around 0.5. Importantly, it becomes increasingly larger as the sample starts from mid-December 2020 and onward, that is, after rule-based QE is announced, Finally, it stabilizes at a higher level once the QE-Implementation period begins (mid-February 2021).

These findings confirm that also under these alternative estimation windows, the predictability of the size and maturity composition of purchases are extremely important. This emerges not only because rule-based QE and the QE-implementation periods are relevant, but also because June 2020 is relevant. That is, when the pace of purchases stabilizes around \$80bn per month (Table 1), reducing uncertainty about the size of purchases.

This robustness exercise also confirms that the coefficient on own purchases is rarely statistically significant, except for the increase that followed the start of the QE period in September 2020.

[Figure 4 about here.]

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

## 5.2 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 8), we assume that the maturity-dependent yield-curve movements are sufficiently smooth to be well approximated by a second order polynomial in maturity,  $\tau$ . 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 5 about here.]

In particular, as shown in Figure 5, 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. 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 (see 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 for the issuance’s effect across 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 8 with the net issuance of near substitutes that took place over our sample period. We do not control for own issuance because all 204 securities considered in our sample had to exist before March 2020, and hence new issuance of those securities was limited to a few re-openings of small amounts.

As shown in table A.3 of Appendix D.2, in the QE periods, net issuance of near substitutes is statistically significant and is characterized by a negative sign, that is, it tends to offset the impact of the Fed’s purchases. Importantly, though, controlling for issuance does not

affect any of the estimated coefficients in our baseline, reported in Table 3. Hence, in the absence of Fed purchases, longer-term Treasury yields would have still been 90 basis points higher, on net, due to the increased supply Treasury securities. Further, the fact that the baseline coefficients are not affected by the addition of net issuance indicates that, in the baseline specification, maturity and maturity squared are doing a good job at controlling for other risk factors that could be affecting each security’s price.

### 5.3 Stock effects by maturity and liquidity

To examine how stock effects 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 in the middle of the yield curve, at 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.3.

In Table A.4, it is possible to note that the positively significant coefficient on own purchases in the MF period is due to far off-the-run securities with less than 15 years to maturity. The same is true for the coefficient on near-substitute purchases. Further, the results reported here also confirm that, during the MF period, the own and near-substitute coefficients are quite similar across the different cuts of the data, suggesting that they have similar importance.

In Table A.5, it can be noted that in the QE-Goal period, the effect of near-substitute purchases is much larger for securities with less than 15 years to maturity, where the co-

efficient is almost 25 times bigger than in the MF period. In contrast, there are no major differences between on- and off-the-runs. Interestingly, the coefficient on own purchases remains positive and significant only for securities with less than 15 years to maturity and it doubles in size.

Finally, the results shown in Table A.6 indicate that in the later QE-Implementation period, the negative coefficient for own purchases is mostly due to securities with more than 15 years to maturity, as a significant share of those securities are at or near the cap. And, in this period, the securities with more than 15 years to maturity and off-the-run are also the securities that benefit the most from the substitute purchases, as the size of the coefficients for those securities keep getting bigger.

## 5.4 Flow effects with near substitutes only

To make the flow effect specification directly comparable to the stock effect specification, we took out the mid- and far-substitute purchases. Those buckets were included because in the panel analysis for the flow effect we have many more observations than in the cross-sectional analysis for the stock effect and, therefore, we could afford a more granular estimation of the propagation of the flow effects along the entire yield curve.

By comparing Table 4 to Table 7, Table 5 to Table 8, and Table 6 to Table 9, it is possible to see that the omission of the mid- and far-substitute purchases does not affect at all the overall message for the own and near-substitute purchases. Hence, since the mid and far buckets add more information without altering the direct comparison to the stock effect results, we opted for keeping them in the baseline specification.

[Table 7 about here.]

[Table 8 about here.]

[Table 9 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 central banks' asset purchases can be tailored to achieve different objectives.

We find that in the QE period (September 2020-March 2022), the stock effect is at least 10 times larger than in the MF period (March-September 2020), implying average supply effects of about 6.5 basis points per \$100 billion, within the range of estimates obtained in previous studies of QE. Importantly, the stock effect becomes statistically and economically significant once QE gets conditioned to “substantial further progress” toward the Fed’s dual mandate, and it grows larger once the Desk provides earlier and more precise information about the maturity composition of purchases. This indicates that, in open-ended purchase programs, rule-based QE and communication that increases the predictability of the aggregate duration risk removed from the market are very relevant for the efficacy of this type of asset purchases. This is because the bulk of the evolution of the stock effect is due to changes in the magnitude of the substitution effects, and those are mostly driven by the *predictability of the maturity composition of total purchases*, which in the 2020-2022 program was jointly determined by the communicated goal and implementation.

In contrast, our results suggest that, in the MF period, purchases are not stimulative because stock effects are very localized, as the substitution effects are very small, most likely due to market segmentation. But, this is also the reason why, in the MF period, the estimated flow effects are quite large, especially in intermediate and long maturity sectors. The estimated counterfactual yield curve for the MF period shows that the purchase operations restored market functioning by improving relative price deviations from fundamental values. Hence, during the height of the crisis, conducting large and frequent purchases in each sector supported the improvement in Treasury market conditions.

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Date	FOMC Statement	Desk Statement and Implementation
Mar. 12, 2020	In consultation with the FOMC, Chair instructs the Desk to <b>redistribute \$60B</b> across Coupons, T-Bills, and FRN, to <b>support market functioning</b>	pace: <b>adjusted as appropriate</b> composition: <b>roughly match composition of Treasury debt</b> calendar: <b>daily</b>
Mar. 15, 2020	<b>At least \$500B;</b> to support smooth market functioning	pace: adjusted as appropriate composition: roughly in line with composition of Treasury debt calendar: daily
Mar. 23, 2020	<b>In the amounts needed;</b> to support smooth market functioning	pace: adjusted as appropriate composition: + Desk stands ready to <b>adjust composition as appropriate</b> calendar: from daily, to a few days, to weekly by mid-April
Jun. 10, 2020	<b>At least at the current pace;</b> to <b>sustain</b> smooth market functioning	pace: <b>approximately \$80B per month</b> , + Desk is prepared to increase the size as needed composition: Desk is prepared to adjust composition as needed calendar: <b>Bi-monthly</b>
Sep. 16, 2020	At least at the current pace; to help <b>foster accommodative</b> financial conditions	pace: approximately \$80B per month composition: – Desk is prepared to adjust composition as needed calendar: Bi-monthly
Dec. 16, 2020	At least \$80 billion per month; purchases <b>conditioned</b> to substantial further <b>progress toward FOMC’s dual mandates</b>	pace: \$80B per month composition: roughly in line with composition of Treasury debt calendar: Bi-monthly
Feb. 21, 2021	No FOMC statement No Desk statement	pace: \$80B per month composition: roughly in line with composition of Treasury debt calendar: <b>Monthly</b>
May 13, 2021	No FOMC statement But Desk statement	pace: \$80B per month composition: <b>release</b> of intended <b>weights</b> across 6 maturity sectors calendar: Monthly

**Table 1:** Changes to FOMC statements, Desk statements, and purchase implementation for the 2020-2022 Treasury purchase program

Period	Goal & Implementation	Implications
Mar. 12, 2020 - Jun. 10, 2020	Support smooth market functioning with highly flexible implementation	High flexibility $\Rightarrow$ high uncertainty <ul style="list-style-type: none"> <li>• <math>\sigma_{\epsilon(Q_m)}</math>: highest</li> <li>• <math>\sigma_{\epsilon(m)}</math>: highest</li> <li>• <math>\sigma_{\epsilon(w_s)}</math>: highest</li> </ul>
Jun. 11, 2020 - Sep. 15, 2020	From supporting to sustaining MF, with stable monthly pace of approximately \$80B	Desk retains flexibility to adjust size and composition as needed <ul style="list-style-type: none"> <li>• <math>\sigma_{\epsilon(Q_m)}</math> : <b>low</b></li> <li>• <math>\sigma_{\epsilon(m)}</math>: high</li> <li>• <math>\sigma_{\epsilon(w_s)}</math>: high</li> </ul>
Sep. 16, 2020 - Feb. 20, 2021	QE and conditional QE. Implementation stays unchanged.	Pace stays at \$80B but no more reference to flexibility; QE/conditional QE help predictability of $m$ <ul style="list-style-type: none"> <li>• <math>\sigma_{\epsilon(Q_m)} \approx \mathbf{0}</math></li> <li>• <math>\sigma_{\epsilon(m)}</math>: <b>lower</b></li> <li>• <math>\sigma_{\epsilon(w_s)}</math>: high</li> </ul>
Feb. 21, 2021 - Sep. 21, 2021	Goal stays unchanged. Implementation changes to monthly calendar releases, then to exact $w_s$ .	Implementation clarifies maturity distribution <ul style="list-style-type: none"> <li>• <math>\sigma_{\epsilon(Q_m)} \approx 0</math></li> <li>• <math>\sigma_{\epsilon(m)}</math>: lower</li> <li>• <math>\sigma_{\epsilon(w_s)}</math>: <b>low <math>\rightarrow \mathbf{0}</math></b></li> </ul>
Sep. 22, 2021 - Mar. 9, 2022	QT expectations start forming	Uncertainty about QT

**Table 2:** Division into periods by composite state for the Goal and Implementation

	Gross Return			
	Full Period	MF	QE Goal	QE Impl
Own (%)	0.042 (0.026)	0.044*** (0.010)	0.062 (0.040)	-0.021 (0.093)
Near Sub (%)	-0.011 (0.022)	0.048* (0.019)	0.637*** (0.076)	0.805*** (0.236)
Maturity	-0.006*** (0.001)	0.004*** (0.0004)	-0.004** (0.001)	-0.004*** (0.001)
Maturity Squared	0.0001 (0.00004)	-0.0001*** (0.00001)	-0.00004 (0.00005)	0.0001 (0.00004)
log(Initial Price)	-0.144*** (0.018)	-0.068*** (0.005)	-0.070*** (0.016)	-0.063** (0.022)
Fitting Error	-0.031 (0.033)	0.025** (0.009)	-0.836*** (0.116)	-0.237** (0.093)
Constant	0.646 (0.085)	0.299 (0.025)	0.235 (0.071)	0.222 (0.102)
Observations	204	204	204	204
Adjusted R <sup>2</sup>	0.944	0.852	0.962	0.786

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 3: Comparison of Second Stage Regression Results Across Periods** Coefficient estimates for equations 8 on data from subperiods as outlined in section 2. “Own Purchases (%)” indicates the coefficient on the own purchase amount, as a percentage of total outstanding of a given security. “Near Sub Purchases (%)” indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total outstanding of a given security’s near substitutes. Standard errors in parentheses are derived from Davidson and MacKinnon (2010), and p-values are based on the same paper. \* indicates p<0.1; \*\* indicates p<0.05; \*\*\* indicates p < 0.01.

All Maturity Sectors					
	Full	Height of Crisis	MF	QE Goal	QE Impl
Own Purchases %	0.006** (0.002)	0.007 (0.006)	0.005 (0.004)	0.002 (0.002)	0.003 (0.003)
Near Sub Purchases %	0.149*** (0.010)	0.235*** (0.026)	0.176*** (0.015)	0.022 (0.014)	0.025 (0.018)
Mid Sub Purchases %	0.050*** (0.006)	0.080*** (0.015)	0.064*** (0.010)	-0.006 (0.007)	-0.009 (0.008)
Far Sub Purchases %	0.100*** (0.011)	0.123*** (0.028)	0.110*** (0.016)	0.130*** (0.028)	0.091*** (0.033)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	17,016	5,823	9,098	7,918	5,710
R <sup>2</sup>	0.029	0.021	0.029	0.003	0.003
F Statistic	122.491***	29.616***	65.282***	6.681***	3.416***

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 4: Flow Effects by Period.** These estimates of flow effect coefficients are based on equation 10, estimated for purchase operations in the sub-periods described in section 2, with standard errors in parentheses. \* indicates p<0.1; \*\* indicates p<0.05; \*\*\* indicates p < 0.01.

	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001 (0.001)	0.003*** (0.001)	0.010*** (0.003)	-0.004 (0.022)	0.115*** (0.036)
Near Sub Purchases %	0.007** (0.003)	0.103*** (0.005)	0.220*** (0.017)	0.034 (0.064)	2.502*** (0.167)
Mid Sub Purchases %	0.004 (0.003)	0.013*** (0.003)	0.072*** (0.007)	-0.046 (0.036)	1.926*** (0.146)
Far Sub Purchases %				-0.006 (0.028)	0.555*** (0.109)
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 <sup>2</sup>	0.007	0.237	0.176	0.005	0.217

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 5: Flow Effects in the Height of Crisis Period (2020-03-13 to 2020-04-17), by Maturity Sector.** These estimates of flow effect coefficients are based on equation 10, 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.

	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001** (0.001)	0.002** (0.001)	0.006*** (0.002)	0.009 (0.015)	0.031 (0.024)
Near Sub Purchases %	0.013*** (0.002)	0.068*** (0.004)	0.136*** (0.008)	0.153*** (0.042)	0.744*** (0.074)
Mid Sub Purchases %	0.001 (0.002)	0.013*** (0.002)	0.046*** (0.004)	0.043* (0.022)	0.503*** (0.069)
Far Sub Purchases %				0.045*** (0.016)	0.274*** (0.080)
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 <sup>2</sup>	0.019	0.191	0.188	0.039	0.093

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 6: Flow Effects in MF (2020-03-13 to 2020-09-15), by Sector.** These estimates of flow effect coefficients (in terms of price returns) are based on equation 10, 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.

All Maturity Sectors					
	Full	Height of Crisis	MF	QE Goal	QE Impl
Own Purchases %	0.006*** (0.002)	0.007 (0.006)	0.005 (0.004)	0.002 (0.002)	0.003 (0.003)
Near Sub Purchases %	0.167*** (0.010)	0.219*** (0.026)	0.192*** (0.015)	0.023* (0.014)	0.030* (0.018)
CUSIP FE	Yes	Yes	Yes	Yes	Yes
Operation FE	No	No	No	No	No
Observations	17,016	5,823	9,098	7,918	5,710
R <sup>2</sup>	0.019	0.013	0.018	0.0005	0.001
F Statistic	159.216***	35.785***	81.750***	1.800	2.117

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table 7: Flow Effects by Period, Own and Near Subs Only.** These estimates of flow effect coefficients are based on equation 10, assuming  $\beta_2 = \beta_3 = 0$ , estimated for purchase operations in the sub-periods described in section 2, with standard errors in parentheses. \* indicates p<0.1; \*\* indicates p<0.05; \*\*\* indicates p < 0.01.

	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001 (0.001)	0.003*** (0.001)	0.008*** (0.003)	-0.002 (0.022)	0.098** (0.039)
Near Sub Purchases %	0.007** (0.003)	0.104*** (0.005)	0.152*** (0.017)	0.042 (0.064)	2.083*** (0.177)
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 <sup>2</sup>	0.005	0.223	0.082	0.001	0.098

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

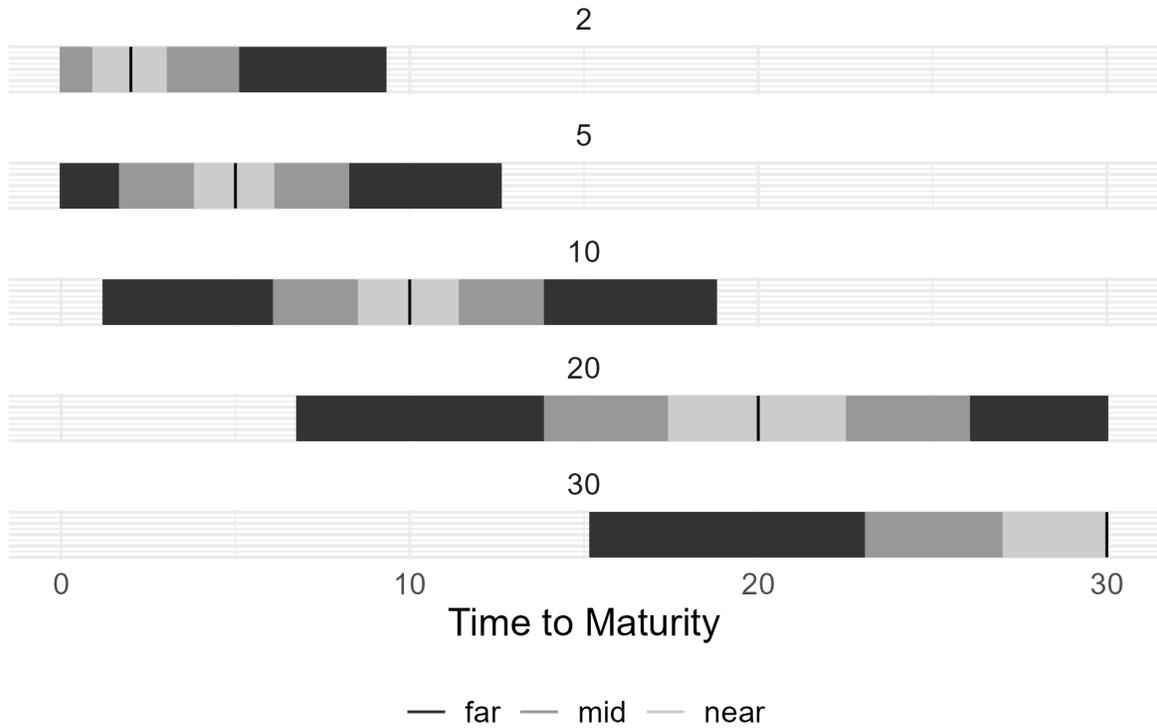
**Table 8: Flow Effects in the Height of Crisis Period (2020-03-13 to 2020-04-17), by Maturity Sector, Own and Near Subs Only.** These estimates of flow effect coefficients are based on equation 10, assuming  $\beta_2 = \beta_3 = 0$ , estimated for purchase operations in the highest stress period, from 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.

	0-2.25	2.25-4.5	4.5-7	7-20	20-30
	(1)	(2)	(3)	(4)	(5)
Own Purchases %	0.001** (0.001)	0.002*** (0.001)	0.005*** (0.002)	0.011 (0.015)	0.022 (0.025)
Near Sub Purchases %	0.013*** (0.002)	0.075*** (0.004)	0.134*** (0.009)	0.169*** (0.042)	0.860*** (0.074)
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 <sup>2</sup>	0.019	0.176	0.132	0.023	0.057

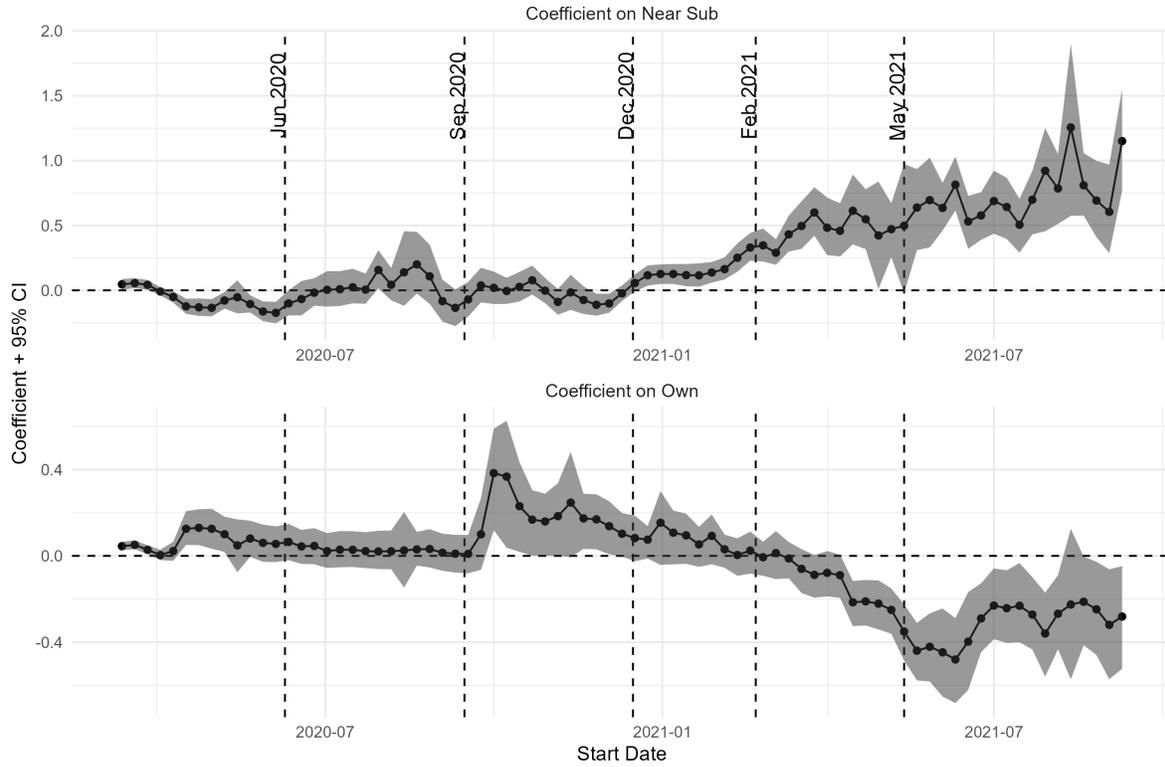
*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

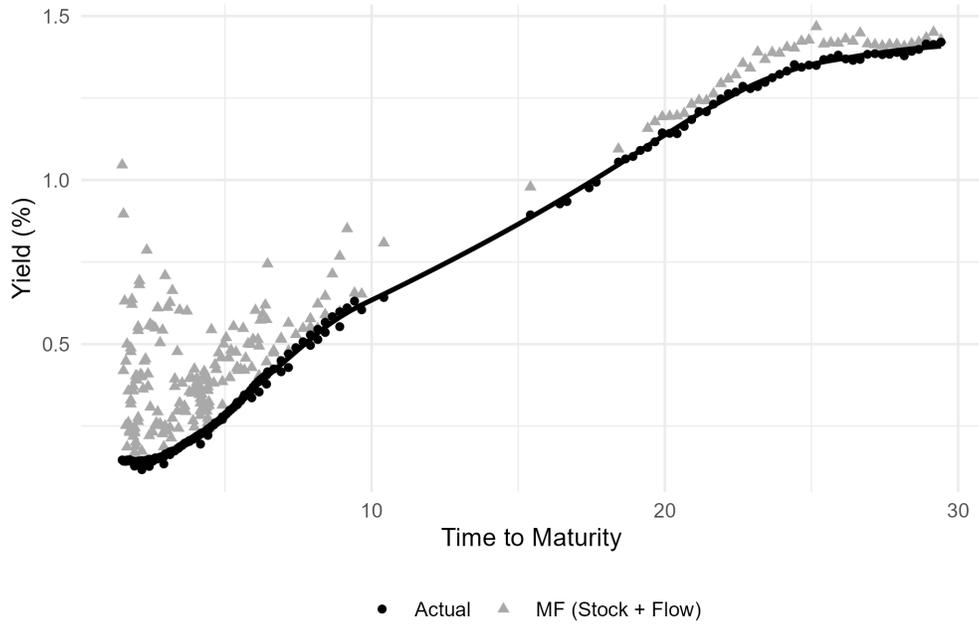
**Table 9: Flow Effects in MF (2020-03-13 to 2020-09-15), by Sector, Own and Near Subs Only.** These estimates of flow effect coefficients are based on equation 10, assuming  $\beta_2 = \beta_3 = 0$ , estimated for purchase operations in the MFI period, from 2020-03-13 to 2020-09-15, with each purchase sector estimated separately. Standard errors are in parentheses. \* indicates p<0.1; \*\* indicates p<0.05; \*\*\* indicates p < 0.01.



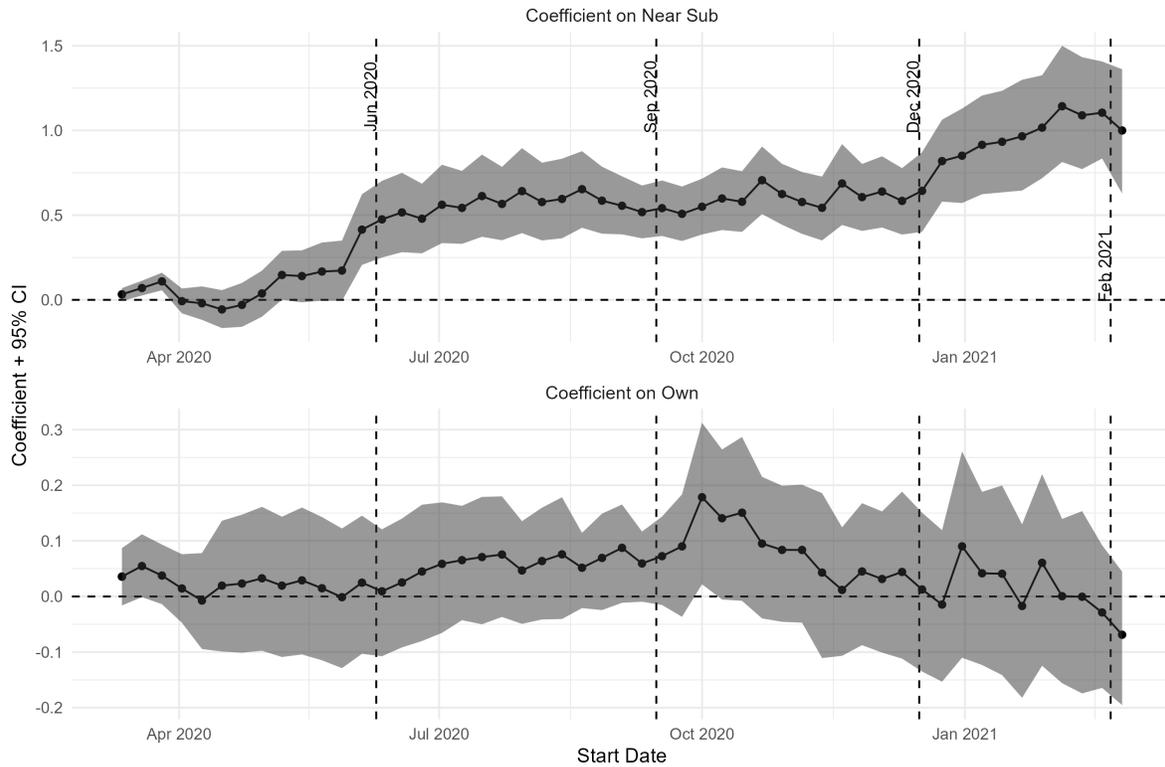
**Figure 1: Substitute bucket illustration.** Each row represents a security with a given time to maturity. The vertical black line represents that security itself. A security’s near substitutes fall within the light gray band around its tenor, its mid substitutes within the darker gray band, and its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



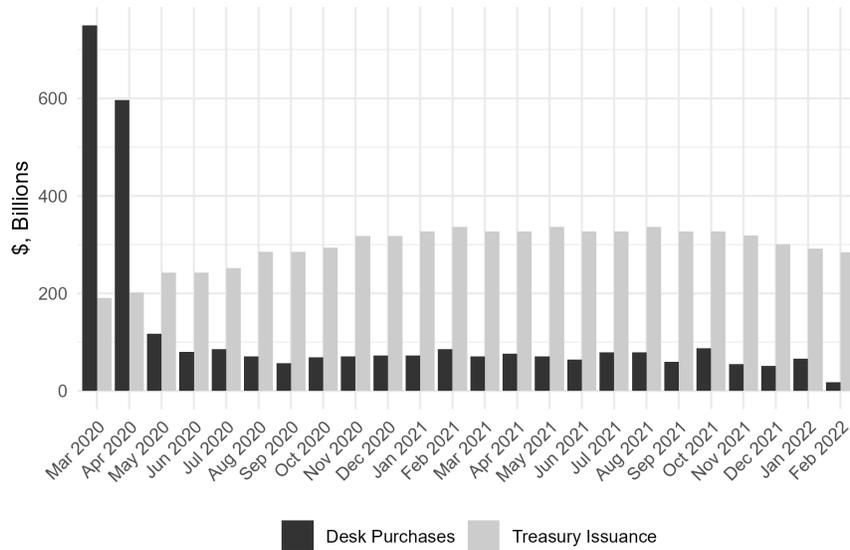
**Figure 2: Regression Results over Six Month Rolling Windows.** The top and bottom panels represent the coefficient on own purchases and near-substitute purchases from estimating equation 8. Each point represents the coefficient estimated with data from a given start date to 180 days from that start 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 rolling sample begins in March 13, 2020 and the last one on September 9, 2021, which marks exactly 6 months until the purchases' end. The vertical lines mark key dates reported in Table 1.



**Figure 3: Counterfactual and actual MF yield curves.** The black dots depict the yield curve as of September 15, 2020, the end of the MF period. The gray triangles depict the counterfactual yield curve, that is, how the yield of each CUSIP would have looked in the absence of the Fed purchase operations. Hence, the vertical distance between the gray triangles and the black dots measures the effect over the first six months of purchases.



**Figure 4: 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 8. Each point represents the coefficient estimated with data from a given start date to the end date of 2022-03-09, which is fixed. 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).



**Figure 5: 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.

# Appendices

## A Substitute Band Construction

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

$$p = \frac{1}{1 + e^{-(t-15)/4}} \quad (11)$$

$$b_{near} = 1 + 2 \times p \quad (12)$$

$$b_{mid} = 3 + 4 \times p \quad (13)$$

$$b_{far} = 7 + 8 \times p \quad (14)$$

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

## B Amounts purchased by subperiods for 204 CUSIPs

In order to quantify the stock effect size, we use the average percentages purchased and quantities displayed in Table A.1. The percentages displayed are the average own and near-substitute amounts purchased as a percentage of total outstanding, for the securities purchased in each period.

The total own purchase amount of the 204 securities that existed from March 2020 to March 2022 is reported for each period in the “Own (B)” column. However, since near substitutes only need to be issued before the sub-period starts, some of their purchase amounts are not reflected in “own” purchases. To understand the total impact of purchases, though,

it is important to also consider the purchases of securities that fall into “near subs” above and beyond “own” purchases. That is the value reported in the “Near ex. Own (B)” column.

Finally, the total purchase amount of all coupon securities in a given sub-period – including those coupons that were issued after the sub-period started or matured before the sub-period ended – is given in the “Total (B)” column. Those are the actual quantities that the Fed bought and not just the quantities used in our estimation.

Period	Own %	Near %	Own (B)	Near ex. Own (B)	Total (B)
Full	19.2	21.8	1,707.6	612.5	2,913.2
MF	12.8	13.3	1,135.4	540.8	1,714.2
QE Goal	6.5	7.7	572.2	250.9	1,199.0
QE Implementation	4.1	5.1	370.9	228.5	834.9

**Table A.1: Purchase Amounts** within all coupon operations, in all subperiods as defined in section 1. “Own %” represents the average own purchase amount as a percent of its total outstanding for a given security in the subperiod. “Near %” represents the average purchase amount of all near substitutes as a percent of the total outstanding of all near substitutes for a given security in the subperiod. “Own (B)” represents the total purchase amount for the securities in the panel, in billions. “Near ex. Own (B)” represents the total purchase amount, in billions, for the CUSIPs considered near substitutes for the securities in the panel, if the CUSIP is not already part of the own substitutes in the panel. “Total (B)” represents the total purchase amount in that subperiod.

## C Variable Construction Details

The 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 Treasury issuance and buyback data. Quantity outstanding at time  $t$  of

security  $i$ . This data is available by reducing the Treasury auction amount outstanding data by the amount bought in any Treasury buybacks.

- $AO_{i,1,t}$ : via Treasury issuance and buyback data. Quantity outstanding 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  $t$ .
- $CtD_{i,t}$  or “Cheapest to Deliver”: via Bloomberg. 1 if  $i^{th}$  security is cheapest to deliver at  $t$ , 0 otherwise.
- $S_n(i)$ : 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. For the purposes of our substitute calculations, these securities must have been issued before the time  $t$  of interest.
- $Q_{i,1,t} = \sum_{i \in S_{n,1}} Q_{i,0}$ : Near substitutes of  $i$  purchased by time  $t$ .
- $\bar{X}_{i,t} = \sum_{j \in S_1(i)} \alpha_{i,j} * X_j$  or “Wtd. X”: Weighted variable X for security  $i$  at time  $t$ .

So those normalized quantity variables are:

$$q_{i,0,t} = \frac{Q_{i,0,t}}{AO_{i,0,t=0}} \quad (15)$$

$$q_{i,1,t}^T = \frac{Q_{i,1,t}}{AO_{i,1,t=0}} \quad (16)$$

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  $q_{i,t,t+w}^b$ . 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 (%) Mar 2020 - Mar 2022	Near Sub (%) Mar 2022	Own (%) MF: Mar 2020 - Sep 2020	Near Sub (%) Mar 2020 - Sep 2020	Own (%) QE Goal: Sep 2020 - Mar 2022	Near Sub (%) Mar 2022	Own (%) QE Impl: Feb 2021 - Mar 2022	Near Sub (%) Mar 2022
Cap Distance	0.346*** (0.049)		0.238*** (0.039)		0.091*** (0.024)		0.072*** (0.016)	
Wtd. Cap Distance		0.020 (0.045)		0.148*** (0.012)		-0.011 (0.008)		-0.012 (0.009)
Wtd. Fitting Error		0.922*** (0.194)		0.243*** (0.053)		1.014*** (0.096)		0.580*** (0.089)
Wtd. Cheapest-to-Deliver		0.408*** (0.083)		0.219*** (0.023)		0.002 (0.017)		-0.123*** (0.015)
Wtd. Maturity		-0.246*** (0.042)		-0.064*** (0.012)		-0.003 (0.009)		-0.007 (0.008)
Wtd. Maturity Squared		0.007*** (0.001)		0.002*** (0.0003)		0.001*** (0.0002)		0.0004** (0.0002)
Fitting Error	0.383** (0.150)	-0.208** (0.091)	0.214* (0.120)	0.002 (0.025)	1.088*** (0.232)	0.217*** (0.070)	0.401*** (0.136)	-0.097 (0.059)
Cheapest-to-Deliver	0.121*** (0.043)		0.085** (0.034)		0.088*** (0.021)		0.046*** (0.018)	
Maturity	0.004 (0.007)	0.200*** (0.043)	0.011** (0.005)	0.064*** (0.012)	-0.003 (0.003)	-0.010 (0.009)	0.001 (0.002)	0.003 (0.008)
Maturity Squared	-0.0001 (0.0002)	-0.006*** (0.001)	-0.0004** (0.0002)	-0.002*** (0.0003)	0.0001 (0.0001)	-0.0005** (0.0002)	-0.00001 (0.0001)	-0.0003 (0.0002)
log(Initial Price)	0.108 (0.125)	-0.019 (0.042)	0.062 (0.100)	-0.013 (0.011)	-0.021 (0.068)	-0.016** (0.008)	-0.021 (0.048)	-0.015 (0.010)
Constant	-0.599 (0.593)	0.396* (0.204)	-0.384 (0.476)	0.053 (0.056)	0.109 (0.324)	0.202*** (0.039)	0.091 (0.228)	0.139*** (0.046)
Instrument F	30.727	39.903	22.639	170.282	16.705	97.309	13.511	33.429
Observations	204	204	204	204	204	204	204	204
Adjusted R <sup>2</sup>	0.353	0.693	0.271	0.864	0.285	0.919	0.185	0.665

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table A.2: First Stage Regression Results.** Coefficient estimates for equations 6 and 7. Each column represents a sub-period (based on sub-periods outlined in section 2) as well as a given dependent variable: either own or near substitute 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, and “Wtd” in front of a independent variable refers to the weighted average of the individual characteristics within the bucket of substitutes. \* indicates p<0.1; \*\* indicates p<0.05; \*\*\* indicates p < 0.01.

## D.2 Results with Treasury issuance

	Gross Return			
	Full Period	MF	QE Goal	QE Impl
Own (%)	0.062** (0.026)	0.044*** (0.010)	0.056 (0.036)	0.090 (0.077)
Near Sub (%)	-0.177*** (0.040)	0.048* (0.020)	0.452*** (0.094)	0.767*** (0.158)
Maturity	-0.012*** (0.001)	0.005*** (0.0004)	-0.005*** (0.001)	-0.005*** (0.001)
Maturity Squared	0.0002*** (0.00003)	-0.0001*** (0.00001)	0.00000 (0.00005)	0.0001 (0.00004)
Near Sub Net Issuance	-0.028*** (0.006)	0.003 (0.004)	-0.010*** (0.003)	-0.029*** (0.004)
log(Initial Price)	-0.155*** (0.017)	-0.068*** (0.006)	-0.081*** (0.015)	-0.057*** (0.018)
Fitting Error	0.043 (0.026)	0.024** (0.009)	-0.723*** (0.122)	-0.473*** (0.088)
Constant	0.792 (0.078)	0.297 (0.026)	0.314 (0.072)	0.217 (0.083)
Observations	204	204	204	204
Adjusted R <sup>2</sup>	0.957	0.851	0.965	0.844

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table A.3: Second Stage Regression Controlling for Treasury Net Issuance.** Coefficient estimates for equation 8 on data from sub-periods 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 outstanding in a given security. “Near Sub Purchases (%)” indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total 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.

### D.3 Results by security’s liquidity

$$\frac{P_{i,T}}{P_{i,0}} - 1 = \gamma_{offrun} \hat{q}_{i,own}^T \mathbb{1}_{offrun} + \gamma_{onrun} \hat{q}_{i,own}^T \mathbb{1}_{onrun} + \beta_{offrun} \hat{q}_{i,near}^T \mathbb{1}_{offrun} + \beta_{onrun} \hat{q}_{i,near}^T \mathbb{1}_{onrun} + \phi_0 + \phi_1 \tau_i + \phi_2 (\tau_i)^2 + \log(P_i) + FE_i + \epsilon_i \quad (17)$$

	Gross Return				
	full	>15y	<15y	off-run	on-run
Own Purchase %	0.044*** (0.009)	0.023* (0.011)	0.054*** (0.014)	0.043*** (0.009)	0.041 (0.030)
Near Sub Purchase %	0.048* (0.019)	0.056* (0.026)	0.044** (0.020)	0.049** (0.019)	0.046 (0.031)
Controls	X	X		X	
Observations	204	204		204	
Adjusted R <sup>2</sup>	0.852	0.856		0.851	

Note:

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table A.4: MF Period Regression Results.** Coefficient estimates for equation 8, with dummy variables to split the sample based on security characteristics, in the MF period as outlined in section 2. “Own Purchases (%)” indicates the coefficient on the own purchase amount, as a percentage of total outstanding in a given security. “Near Sub Purchases (%)” indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total outstanding in a given security’s near substitutes. The “full” column has no splitting variables and is only 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 %	0.062 (0.049)	-0.040 (0.068)	0.130** (0.056)	0.072 (0.052)	-0.000 (0.046)
Near Sub Purchase %	0.637*** (0.103)	0.592*** (0.104)	1.060*** (0.179)	0.660*** (0.095)	0.871*** (0.299)
Controls	X	X		X	
Observations	204	204		204	
Adjusted R <sup>2</sup>	0.962	0.970		0.961	

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table A.5: QE-Goal Period Regression Results.** Coefficient estimates for equation 8, with dummy variables to split the sample based on security characteristics, in the QE-Goal period as outlined in section 2. “Own Purchases (%)” indicates the coefficient on the own purchase amount, as a percentage of total outstanding in a given security. “Near Sub Purchases (%)” indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total outstanding in a given security’s near substitutes. The “full” column has no splitting variables and is only 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 %	-0.021 (0.097)	-0.596*** (0.150)	0.327** (0.124)	-0.013 (0.099)	0.289 (0.295)
Near Sub Purchase %	0.805*** (0.187)	0.888*** (0.204)	0.437 (0.308)	0.844*** (0.195)	0.666 (0.547)
Controls	X	X		X	
Observations	204	204		204	
Adjusted R <sup>2</sup>	0.786	0.829		0.784	

*Note:*

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01

**Table A.6: QE-Implementation Period Regression Results.** Coefficient estimates for equation 8, with dummy variables to split the sample based on security characteristics, in the QE-Implementation period as outlined in section 2. “Own Purchases (%)” indicates the coefficient on the own purchase amount, as a percentage of total outstanding in a given security. “Near Sub Purchases (%)” indicates the coefficient on the total purchase amount of near substitutes, as a percentage of total outstanding in a given security’s near substitutes. The “full” column has no splitting variables and is only 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.