

Unbundling Quantitative Easing: Taking a Cue from Treasury Auctions*

Walker Ray
London School of Economics

Michael Droste
Harvard University

Yuriy Gorodnichenko
UC Berkeley and NBER

November 5, 2022

Abstract

We study empirically and theoretically the role of preferred habitat in understanding the economic effects of the Federal Reserve’s quantitative easing (QE) programs. Using high-frequency identification and exploiting the structure of the primary market for U.S. Treasuries, we isolate demand shocks that are transmitted solely through preferred habitat channels, but otherwise mimic QE shocks. We document large “localized” yield curve effects when financial markets are disrupted. Our calibrated model, which embeds a preferred habitat model in a New Keynesian framework, can largely account for the observed financial effects of QE. We find that QE is modestly stimulative for output and inflation, but alternative policy designs can generate stronger effects.

Keywords: quantitative easing, monetary policy, market segmentation, treasury auctions

JEL Classification: E52, E43, E44

*We thank Harald Uhlig, anonymous referees, Michael Bauer, Rhys Bidder, Michael Fleming, Ed Knotek, Matteo Maggiori, Eric Swanson, Michael Weber, Milena Wittwer, and seminar participants at Berkeley, New York Fed, Cleveland Fed, San Francisco Fed, Chicago Fed, ASU, DEC, CMC, Bilkent, GWU, Texas A&M, and Northwestern for comments on an earlier version of the paper. We are grateful to Maxime Sauzet for excellent research assistance.

1 Introduction

While evaluating the first rounds of quantitative easing (QE), then-Fed chair Ben Bernanke observed, “The problem with QE is it works in practice but it doesn’t work in theory.” Indeed, QE was successful in reducing short- and long-term interest rates, but the mechanisms behind these effects are still not well-understood. Nevertheless, this theoretical ambiguity has not stopped the Fed from continuing to utilize QE programs, both during the onset of COVID-19, and then reversing course by implementing quantitative tightening (QT) in response to recent inflationary pressures.

Although workhorse macroeconomic models imply that Treasury demand is determined solely by economic agents’ intertemporal consumption decisions, several explanations have been put forth to rationalize the workings of QE. For instance, QE could have signaled to financial markets a commitment to keep short-term interest rates low for a long time (forward guidance). Or, perhaps the Fed exploited financial market frictions (limited arbitrage and market segmentation) by purchasing securities in a particular segment. Alternatively, large-scale asset purchases by the Fed could signal a poor state of the economy, pushing interest rates down (“Delphic effect”).¹ Given the paucity of QE events, it has been difficult to provide clear empirical evidence for (and assess the relative contributions of) the proposed channels. Moreover, QE policies have been implemented as responses to severe macro-financial conditions, which further confounds identification and interpretation and raises questions about the effectiveness of QT going forward.

The objective of this paper is to unbundle the effects of QE by focusing on a specific channel: market segmentation in the form of *preferred habitat*, which posits that certain investors have preferences for specific maturities. To this end, we take the following approach. First, we identify shifts in *private* demand for Treasuries that mimic QE, but are independent of all other plausible channels of QE. Next, we analyze the propagation of these demand shocks across financial markets. In particular, we assess the ability of preferred habitat theory to rationalize the observed responses, and we confirm key predictions regarding pass-through of demand shocks in and out of financial crises. Informed by our empirical analysis, we then develop a general equilibrium macroeconomic model designed to study QE policies. We find that the preferred habitat channel accounts for the bulk of the observed response to QE in financial markets. Our model suggests that the first rounds of QE had modest stimulative effects on output and inflation, but given the relative health of financial markets in the present period, QT alone is unlikely to be successful in reducing inflation to target. Finally, we explore alternative QE implementations that can help improve the design of future asset purchases.

Our analysis starts with the key insight that the mechanism through which market segmentation and preferred habitat forces operate is not the source of Treasury quantity

¹See, [Campbell et al. \(2012\)](#), [Martin and Milas \(2012\)](#) and [Bhattarai and Neely \(2020\)](#) for surveys.

shocks *per se*, but rather how marginal investors absorb these shocks. We utilize the primary market for Treasuries to identify demand shifts that are independent of all QE propagation mechanisms besides preferred habitat. Although the primary market is the venue through which the Treasury issues debt (a supply-side action), the institutional structure of Treasury auctions has a number of desirable features for identifying demand-side shocks. Because all of the supply information is announced by the Treasury in advance of each auction, the release of the auction results reveal unexpected shifts in demand alone, allowing us to rule out a host of confounding factors. By utilizing high-frequency (intraday) changes in Treasury yields around the close of Treasury auctions, we are able to construct a novel measure of Treasury demand shocks.

We document that demand shocks are reasonably large and persistent, with effects on yields typically lasting for many weeks following the auction. Furthermore, the surprise movements in demand are driven by institutional investors such as foreign monetary authorities, investment funds, insurance companies and the like. We show that these shocks are not driven by market-wide changes in expectations about inflation, output, or other general macro-financial conditions. Therefore, variation in Treasury yields around the release of Treasury auction results can help us to isolate the effect of *idiosyncratic* purchases in specific asset segments on the level and shape of the yield curve, which is difficult to achieve by examining only QE events. Because Treasury auctions are frequent and information spans many decades, we can study state dependence in the effect of targeted purchases of assets (e.g., crisis vs. non-crisis states), which is instrumental for understanding how QE programs can work in normal times. Importantly, because Treasury auctions for specific maturities are spread over time, we can identify changes in demand for government debt of specific maturities and trace the effect of these changes on other parts of the yield curve. In this sense, we have natural experiments which can mimic targeted purchases of the Fed during QE programs.

We use our auction demand shocks to empirically evaluate the “localization hypothesis,” a characteristic prediction of preferred habitat theory and a key input into our subsequent quantitative analyses. After deriving a simple regression specification informed by theory, we document strong evidence in favor of localized yield curve effects during financial crisis periods (i.e., the location of the demand shock in maturity space matters and the effects on the yield curve are larger for bonds of similar maturities). These results imply potentially powerful effects of QE on targeted yields in crises. However, we cannot reject the null of no localization effects during normal times, which suggests a limited use of QE as a conventional policy tool.

Building on seminal work by [Vayanos and Vila \(2021\)](#), we develop a general equilibrium model with risk-free and risky debt to rationalize the empirical responses of the yield curve to shocks in demand for Treasury securities and to better understand the effects of QE on financial markets and the broader macroeconomy. We calibrate the model to match

a variety of moments for yields and macroeconomic variables as well as the responses of yields to surprise movements in *private* demand during Treasury auctions in “crisis” and “non-crisis” times. When fed a shock mimicking QE1 in size and duration, our model generates movements in the yield curve remarkably close to those observed in the data. This is consistent with the view that QE works mainly via market segmentation and preferred habitat, and that the *net* effect of other channels is small. Our model also allows us to study the macroeconomic effects of QE1. Given the disruption in financial markets, our calibration implies that QE1 stimulated output and inflation by as much as a 50-75 basis point rate cut.

Policy experiments in our model indicate that these relatively modest macroeconomic effects are sensitive to implementation details. In particular, holding securities on the balance sheet longer (and making this clear to markets on announcement) boosts the stimulative power of QE significantly. The expansionary effects of QE fall precipitously when undertaken during periods when bond markets are relatively healthy. We also show that QE may have unintended consequences: uncertainty surrounding the Fed’s asset purchases may lead to excess macroeconomic volatility, thus calling for policy guidance. Finally, QE programs tilted towards risky assets (e.g., mortgage-backed securities) are more effective in stimulating the economy, particularly when these assets are more volatile. Our results indicate that QE should remain in policymakers’ toolkit, but must be utilized with caution and realistic expectations. For example, while our model predicts that the Fed’s ongoing QT program is disinflationary, the effects are similar to a 25-50 basis point rate hike, and thus dwarfed by the current rise in inflation.

Our paper makes three primary contributions. Theoretically, we embed a financial model of the entire term structure of interest rates for risky and safe assets within a dynamic model of the macroeconomy and thus can provide an integrated analysis of QE.² This is important because previous studies of QE largely focus separately on either financial variables or macroeconomic variables. For example, [Krishnamurthy and Vissing-Jorgensen \(2012\)](#) and [Chodorow-Reich \(2014\)](#) study the effects of QE announcements on financial markets, but do not quantify the macroeconomic effects of QE. [Vayanos and Vila \(2021\)](#), [Greenwood and Vayanos \(2014\)](#), [Greenwood et al. \(2016\)](#), [King \(2019a\)](#) and related work explore the financial market implications of preferred habitat theory, but are silent on any potential effects on output or inflation. On the other hand, recent developments in macroeconomic theory (e.g., [Sims and Wu \(2020\)](#), [Gertler and Karadi \(2011\)](#), [Karadi and Nakov \(2020\)](#), [Cúrdia and Woodford \(2011\)](#), [Carlstrom et al. \(2017\)](#), and [Chen et al. \(2012\)](#)) concentrate on aggregate variables, but are unable to capture the rich dynamics in bond markets which we document. Moreover, many of these theories rely on reserve requirements or moral hazard/enforcement constraints on banks as the key channel through which QE works. In contrast, we focus on the interaction of preferred

²[Ray \(2019\)](#) develops additional analytical and normative results in a version of this model.

habitat with limited risk-bearing capacity in bond markets, which we argue is a core mechanism behind QE effects. Our quantitative model merges these literatures: we utilize financial data and high-frequency identification to discipline our model, which we then use to quantify the macroeconomic effects of QE.

Empirically, we develop a novel, high-frequency measure of demand shocks for Treasuries by exploiting the institutional structure of Treasury auctions. A well-identified shock series is crucial for improving our understanding of many quantity-driven macro-finance theories, and we hope our measure will be analyzed and extended in future work in a fashion similar to the high-frequency monetary shocks pioneered by [Kuttner \(2001\)](#), [Bernanke and Kuttner \(2005\)](#), [Gürkaynak et al. \(2007\)](#), and others. Our approach is a natural complement to existing empirical approaches estimating affine term structure models ([Hamilton and Wu \(2012\)](#), [Kaminska and Zinna \(2020\)](#)) or demand systems ([Kojen et al. \(2021\)](#)) using lower-frequency data.

Combining the insights of our model with our high-frequency demand shocks (and building on extensive research studying how QE purchases impacted the yield curve, such as [D’Amico and King \(2013\)](#), [Li and Wei \(2013\)](#), [Cahill et al. \(2013\)](#), [King \(2019b\)](#)), we provide strong empirical evidence for *state-dependent* (i.e., “crisis” vs. “non-crisis”) localization effects in the spillovers across maturities and asset classes of surprise movements in Treasury demand. Put differently, we use QE-like events (rather than QE directly, in the spirit of [Fieldhouse et al. \(2018\)](#) and [Di Maggio et al. \(2020\)](#)) in order to exploit rich cross-sectional and time-series variation to obtain sharp identification and precise estimates of demand shock spillovers. This new finding confirms one of the characteristic predictions of our model (and preferred habitat theory more generally), and thus our paper shows that these mechanisms are crucial in understanding the Treasury market and channels through which QE affects yields.

Our paper is related to a broad literature studying Treasury auctions, investigating how yields move around Treasury auctions (e.g., [Lou et al. \(2013\)](#), [Fleming and Liu \(2016\)](#)) and respond to variation in demand (e.g., [Cammack \(1991\)](#), [Beetsma et al. \(2016, 2018\)](#), [Forest \(2018\)](#)). However, our focus is not Treasury auctions in and of themselves; rather, we exploit the institutional structure of the primary market for Treasuries to better understand the mechanisms behind QE. Relative to this early important work, we *structurally* link demand shocks identified from Treasury auctions to a general equilibrium preferred habitat model.

2 Data and Institutional Details

In this section we describe the primary sources of our data and present basic statistics. First, we describe the U.S. Treasury auctions for U.S. government notes and bonds (coupon-bearing nominal securities). Second, we describe the details of the data regarding

intraday secondary-market Treasury prices.

2.1 Primary Market for Treasury Securities

The Treasury sells newly issued securities to the public on a regular basis through auctions. In recent years, 2-, 3-, 5- and 7-year notes are auctioned monthly. 10-year notes and 30-year bonds are auctioned in February, May, August and November with reopenings in the other 8 months. The frequency of auctions has changed over time. For example, 30-year bonds were not issued between 1999 and 2006 and were issued only twice a year between 1993 and 1999; and 20-year bonds were auctioned in May 2020, the first time since 1986.

There are two types of bids: noncompetitive and competitive. Noncompetitive bidders agree to accept the terms settled at the auction, and are typically limited to \$5 million per bidder. Competitive bidders submit the amount they would like to purchase, not exceeding 35% of the amount offered at auction, and the price (the interest rate) at which they would like to make the purchase.

Auction participants include primary dealers, other non-primary brokers and dealers, investment funds (for example, pension, hedge, mutual), insurance companies, depository institutions, foreign and international entities (governmental and private), the Federal Reserve System Open Market Account (SOMA), and individuals. These participants are classified into three groups: primary dealers, direct bidders, and indirect bidders. Primary dealers (brokers and banks) trade on their account with the Federal Reserve Bank of New York; they are required to participate in every Treasury auction, and typically buy the largest share of auctioned debt. Direct bidders are non-primary dealers who submit bids for their own proprietary accounts. Indirect bidders submit competitive bids via a direct submitter, including foreign and international monetary authorities placing bids through the Federal Reserve Bank of New York. Additionally, the Treasury divides investors into the following classes: Investment Funds; Pension and Retirement Funds and Insurance Companies; Depository Institutions; Individuals; Dealers and Brokers; Foreign and International; Federal Reserve System; Other. [Fleming \(2007\)](#) describes the breakdown by types and class of bidders in greater detail.

Figure 1 depicts the stages of a Treasury auction.³ First, the Treasury releases all pertinent information regarding an upcoming auction a few days prior to the auction date. An announcement includes the amount offered, additional security information (e.g., maturity, CUSIP, coupon schedule), and other information describing the rules of the auction. After the announcement, investors may submit bids up until the auction closing time. For typical note and bond auctions, non-competitive bids may be submitted by 12:00 p.m., while the deadline for competitive bids is 1:00 p.m.

After the auction closes, competitive bids are accepted in ascending order (in terms of

³Appendix Figure B2 presents a typical announcement of an auction and its results.

yields) until the quantity meets the amount offered minus the amount of non-competitive bids. Winning bidders receive the same yield as the highest accepted bid. Once the winning bids are determined, auction results are released immediately; beginning in the early 2000s, results are released within minutes of the close of the auction (see [Garbade and Ingber \(2005\)](#)). Besides the winning yield, the Treasury announces various aggregate statistics regarding the bidding, such as the total demand (bids tendered) for the security and the composition of bids and winners by investor and bid type. One particularly salient piece of information is the “bid-to-cover,” the ratio of all bids received to all bids accepted. A few days after the close of an auction, the Treasury delivers the securities and charges the winning bidders for payment of the security.

Data from the announcements and results of every auction since late 1979 are available from TreasuryDirect.gov. Data regarding amounts accepted and tendered by bidder type (primary dealer, direct, and indirect) are available starting in 2003. The Treasury provides information regarding allotment by investor class starting in 2000.

2.2 Intraday Treasury Yields

Once a Treasury security auction is complete, the security is issued to the winning bidders and the security is free to trade in the over-the-counter (OTC) secondary market. Following the announcement of an auction but before issuance, there is a forward market for newly auctioned Treasuries. The forward contracts mature on the same day as the securities are issued, and hence this market is referred to as the “when-issued” market. Our data on secondary market yields (including when-issued yields) comes from GovPX, which provides comprehensive intraday coverage of all outstanding U.S. Treasuries for the period 1995-2017.⁴ We use changes in intraday Treasury yields in order to construct market-based measures of demand surprises occurring during Treasury auctions.⁵

2.3 Summary Statistics

Our analysis focuses on Treasury note and bond auctions. We exclude inflation-protected securities (TIPS) and floating rate notes because these securities have different structural arrangements than simple coupon-bearing nominal securities. We also exclude Treasury bills (zero-coupon securities with maturity one year or less) because the QE programs mainly bought long-maturity nominal U.S. government debt.

⁴Our online data appendix provides more information on data sources including GovPX.

⁵An earlier draft of this paper used Treasury futures to construct auction demand shocks. Treasury futures provide a natural market-based measure of such shifts, but in practice movements in the secondary market around auctions are not predictable. In addition, Treasury futures markets are less liquid and cannot be tied to a specific CUSIP-level bond. Thus, we construct demand shocks using secondary market Treasury yields; but our results are robust to using futures (see [Gorodnichenko and Ray \(2017\)](#)).

Panel A of Table 1 presents summary statistics for note and bond auctions from 1995-2017, the period for which we have intraday Treasury yields (Appendix Figure B1 plots the number and size of note and bond auctions split by maturity). Since 1995, a typical offering of \$20 billion generates more than \$50 billion in demand. Primary dealers account for the largest source of demand (bid-to-cover ratio ≈ 2), but other types of bidders also account for a large fraction of auction offerings. Primary dealers purchase ≈ 60 percent of auctioned Treasuries, with the rest split between investment funds and foreign buyers. There is considerable variation in the offered amounts (standard deviation $\approx \$9$ billion) as well as the level and composition of demand (standard deviation for the bid-to-cover ratio ≈ 0.5 , and the standard deviation of bid-to-cover ratio for primary dealers is ≈ 0.35).

3 Quantifying Demand Shocks

This section describes our procedure to measure surprise movements in Treasury yields around Treasury auctions and documents properties of these surprises. Our key assumption is that in a small window around the release of Treasury auction results, shifts in Treasury yields reflect unexpected changes in market beliefs about the demand for Treasuries with a specific maturity. Indeed, the Treasury announces an offered amount well before an auction happens, thus fixing supply in advance of investor bidding. Hence, between the announcement and close of the auction, Treasury yields should move only in response to unexpected changes in demand conditions. Our high-frequency approach isolates variation only due to unexpected shifts in demand arising from a specific auction.

3.1 Shock Construction

Let $y_{t,pre}^{(m)}, y_{t,post}^{(m)}$ be the Treasury yields before and after the close of the auction on date t with maturity m . We measure the surprise movements in Treasury yields as:

$$D_t^{(m)} = y_{t,post}^{(m)} - y_{t,pre}^{(m)}. \quad (1)$$

For all auctions, $y_{t,pre}^{(m)}$ is the last yield observed 10 minutes before the close of the auction, while $y_{t,post}^{(m)}$ is the first yield observed 10 minutes following the release of the auction results. If the date t auction is a re-opening of a previously issued security, we use secondary market yields to construct our shocks. If the date t auction is instead a newly issued security, we use yields from the “when-issued” market. In our sample, auctions typically close at 1:00PM, or less frequently at 11:30AM. However, the time between the close of the auction and the release of the results is a function of how long it takes the Treasury to compile the results. The Treasury began releasing results within minutes in the early 2000s, but in the 1990s frequently took longer. We collect wire reports from

Bloomberg, which gives a tight upper bound on the release time.⁶

Summary statistics of our constructed shock measures $D_t^{(m)}$ are presented in Panel B of Table 1.⁷ The shock means are close to zero (and statistical tests do not reject the null of zero means). Moreover, there is essentially no serial correlation in $D_t^{(m)}$ ($\rho = -0.03$). Hence, these summary statistics indicate that surprises are not systematic and do not contain predictable movements. In our sample period, the standard deviation of $D_t^{(m)}$ increases in maturity m and ranges from 1.4 basis points for 2-year maturity to 3.3 basis points for 30-year maturity. For comparison, Chodorow-Reich (2014) reports that the largest intraday movements in yields following a QE announcement occurred on March 18, 2009, when Treasury (5-year) yields fell by 23 basis points. Panel C presents statistics separately for periods of a binding/non-binding ZLB and for expansion/recessions. Regardless of regime, on average our demand shocks are close to zero.

To verify that these shocks are not spurious, we also report movements in Treasury yields on non-auction days (Panel D of Table 1; for days without auctions, the same “pre” and “post” windows are used as auctions in the same period). In all cases, the variance of the shocks on auction dates is larger than on non-auction dates. This pattern further suggests that surprise auction results influence secondary-market Treasury yields.

3.2 Narrative Evidence

To provide a better understanding of what forces are behind these surprise movements, Figure 2 plots 30-year Treasury yields during two 30-year Treasury bond auctions. The dashed vertical lines denote the close of the auction and the release of results, respectively. The first auction occurred on December 9, 2010. This auction was a reopening of previously issued 30-year bonds from the month prior. Yields are relatively stable in the lead up to the close of the auction, but drop sharply and immediately following the release of the the results. The Financial Times wrote:

“Large domestic financial institutions and foreign central banks were big buyers at an auction of 30-year US Treasury bonds on Thursday. ‘Investors weren’t messing around...You don’t get the opportunity to buy large amounts of paper outside the auctions and ‘real money’ were aggressive buyers.’ ”

The second is from an auction of newly issued bonds on August 11, 2011. When-issued yields were relatively stable prior to auction close, but after the close and release of the auction results, yields immediately rose. The Financial Times wrote:

⁶Lou et al. (2013) and Fleming and Liu (2016) show there are predictable price movements in the days and hours before and after the auction, but near the close of the auction and release of the results price movements unpredictable. Hence, the use of small (10-minute) intraday windows is key to identifying unanticipated demand shocks.

⁷Time series plots of these shocks are presented in Appendix Figure B3.

“An auction of 30-year US Treasury bonds saw weak demand...bidders such as pension funds, insurers and foreign governments shied away. ‘There’s not too many ways you can slice this one, it was a very poorly bid auction.’”

We interpret these two examples as follows. Before the auctions closed, the market information set consists of all the supply information, both for outstanding securities and the amount on offer for the current 30-year auction. The 30-year Treasury yields reflect beliefs about the expected path of short-term interest rates, inflation expectations, and demand for long-maturity Treasury securities. After the auctions closed and the results were released, the only update to the information set is the news regarding the bidding that took place in the auction, which solely reflects demand for Treasury debt. The change in the 30-year yields is a reaction to the unexpected shift in Treasury demand revealed at the auction (of course, this shift reflects many factors, including individual investors’ beliefs about interest rates and economic fundamentals).

These articles also highlight why auctions can have important elements of price discovery: when investors wish to purchase large amounts of Treasuries to meet their needs, they may prefer to use auctions rather than make large transactions on the secondary market. As a result, auctions reveal new information about demand for government debt that is not already reflected in OTC secondary market trades.

3.3 Demand Determinants

The institutional structure of the primary market and narrative evidence from the financial press suggest that $D_t^{(m)}$ captures unexpected shifts in the demand for Treasuries. But because $D_t^{(m)}$ is an equilibrium response, it is important to establish that these shifts are in fact related to observable measures of demand. The bid-to-cover ratio is a natural measure, since a higher bid-to-cover indicates higher demand relative to the amount of Treasuries offered.

The binned scatter plot in Figure 3 shows that the bid-to-cover ratio (after controlling for its four own lags) is a strong predictor of our demand shocks. Table 2 presents formal evidence by regressing our shocks on measures of demand reported at the auction:

$$D_t^{(m)} = \alpha^{(m)} + \beta^{(m)} X_t^{(m)} + \varepsilon_t^{(m)}. \quad (2)$$

We present estimates separately for auctions of different maturities in columns (1)-(6). Column (7) reports results when we pool across maturities and impose that $\beta^{(m)}$ is the same across maturities m . Consistent with our interpretation of our intraday yield changes as a measure of unexpected demand shocks, the results show that a higher bid-to-cover ratio predicts a larger intraday fall in Treasury yields following the close of the auction.

Our results show that the effect of typical surprise increases in demand is economically large. For example, a one standard deviation (0.45) increase in the bid-to-cover ratio in

a Treasury auction for 10-year notes leads to a $3.05 \times 0.45 \approx 1.4$ basis point decline in 10-year Treasury yields. We can back out a simple estimate for the sensitivity of yields as a function of the change in quantity demanded (in terms of dollars). A typical offering amount in a 10-year Treasury note auction is between \$20 and \$30 billion. Hence, our estimates imply that an increase in demand for 10-year Treasuries by \$10 billion decreases 10-year yields by $3.05 \times \left(\frac{10}{30}, \frac{10}{20}\right) \approx (1.02, 1.53)$ basis points.

Panel B explicitly decomposes the bid-to-cover ratio responses from Panel A into “expected” and “surprise” components. For these regressions, we first estimate a univariate AR(4) model of the bid-to-cover ratio separately for each maturity group. This filters out predictable, low-frequency variation in demand for Treasuries in the primary market. We then construct the fitted (expected) and residual (surprise) values of the bid-to-cover ratio, and regress $D_t^{(m)}$ on these expected and surprise components. We find that the variation in our demand shocks is determined by the surprise component, and is unaffected by expected movements.

In order to assess sensitivity of our demand shocks to changes in demand by bidder type, Panel C reports estimates of equation (2) using the bid-to-cover ratio of indirect bidders, direct bidders, and primary dealers. The sensitivity of surprises $D_t^{(m)}$ to unexpected demand of indirect bidders increases with maturity. For example, a unit increase in the bid-to-cover ratio for indirect bidders decreases the yields of 2-year Treasuries by 4.7 basis points, and the yields of 30-year Treasuries by 15.8 basis points. Direct bidders exhibit the same pattern, although the coefficients are smaller. The sensitivity to changes in the bid-to-cover ratio coming from primary dealers is smaller still. When we pool across maturities, demand of direct and especially indirect bidders generates *ceteris paribus* more variation in Treasury yields than demand of primary dealers, although for all bidder types an increase in bidder demand implies a decline in intraday yields $D_t^{(m)}$.

Panel D uses additional investor allotment data from the Treasury to break down the amount accepted by types of bidders: Investment Funds, Foreign, Dealers, and remaining smaller investors classes (aggregated into a “Miscellaneous” category). Since the fractions by group add up to one, we set Dealers as the leave-out category. Our estimates suggest that as the fraction accepted for investment funds and foreign buyers increases, $D_t^{(m)}$ declines. Estimates for the Miscellaneous category are generally smaller and less robust.

Our results indicate that movements in demand, proxied by the bid-to-cover ratio, are a key determinant of $D_t^{(m)}$. Furthermore, we observe that the demand from institutional investors is important in accounting for variation in $D_t^{(m)}$. We stress that our identifying assumption only relies on observing the changes in *yields* immediately following the close and release of auction results. Our empirical approach does not require a measure of the unanticipated movement in quantity demanded. Hence, our empirical analysis in the remainder of the paper only relies on our constructed measure $D_t^{(m)}$.

3.4 Co-movement Across Markets

We now turn to analyzing how our demand shocks for Treasuries propagate across other financial markets. We measure the impact of demand shocks on other assets by estimating univariate regressions of the form

$$y_t = \gamma + \phi D_t + u_t, \quad (3)$$

where y_t is the change in the price or yield of some asset on auction date t and D_t is our auction demand shock. We pool across all auction maturities to simplify presentation, but our results are robust to estimating equation (3) separately by maturity groups.

Where available, we use intraday changes measured in the same window as our shocks. We also examine daily changes, both due to data limitations for some series and because daily changes may pick up responses that do not occur immediately. A strong relationship between D_t and y_t indicates either that D_t and y_t have a common determinant (e.g., changes in inflation expectations alter the behavior of bids in Treasury auctions and change prices of inflation swaps) or that there is a propagation channel from D_t to y_t (e.g., higher revealed demand for Treasuries results in repricing of other debt securities).

Panel A of Table 3 reports results for debt markets. The dependent variable in the first row is the intraday change in the *price* (co-moves negatively with the yield) of the Exchange Traded Fund (ETF) “LQD,” the iShares iBoxx \$ Investment Grade Corporate Bond tracking investment grade corporate bonds. The estimated coefficient $\hat{\phi}$ is interpreted as the impact in log points of a one basis point increase in D_t . We observe a strong reaction to the Treasury demand shock, accounting for more than 50 percent of variation observed in corporate bond ETF prices during the short windows around the close and release of the Treasury auction results. The second row reports the results using “HYG,” the iShares iBoxx \$ High Yield Corporate Bond ETF tracking high yield corporate bonds. Although the sign of the estimated coefficient is as expected, the pass-through from our demand shocks to high yield corporate bonds is weaker than that of investment grade bonds. The estimated coefficient is not statistically significant, and the magnitude is smaller than for investment grade debt by a factor of ten. Moreover, the R^2 is much lower, suggesting that our demand shocks account for only 1 percent of the observed variation in high yield corporate bond ETF prices during these intraday periods. The next two rows examine pass-through to mortgage rates, as measured by the ETFs “MBB” and “VMBS” (from iShares and Vanguard respectively; both ETFs track investment-grade mortgage-backed pass-through securities guaranteed by U.S. government agencies). Similar to our findings for investment-grade corporate debt, we find economically large and statistically significant pass-through of demand shocks to mortgage borrowing rates. We also find relatively high R^2 s of 34% and 13%, respectively.

The next rows repeat the above analysis using daily measures of corporate bond *yields*,

as measured by Moody’s Aaa, Moody’s Baa, and Bank of America’s C corporate yield indices. Consistent with the intraday results, our demand shocks have a strong effect on safe (Aaa) corporate bonds. Moreover, the pass-through of our demand shocks to corporate bond yields is nearly one-to-one. However, using daily rather than intraday changes as the dependent variable leads to a decline in R^2 , which underscores the benefits of using intraday data. While our demand shocks still have large effects on moderately safe debt (Baa), there appears to be much smaller transmission to highly risky corporate debt (C), consistent with our intraday findings.

Secondary market yields react not only strongly, but also persistently. Figure 4 plots the contemporaneous reaction of 10-year Treasury spot rates (top panel) and the Aaa corporate bond yields (bottom panel) to our shocks D_t , as well as the reactions up to 60 days in the future. The reaction remains strongly statistically significant over three weeks later, while the point estimate is quite stable even 2 months later. To provide a perspective on the magnitude of this persistence, Figure 4 also plots the change in yields following the QE1 announcement on March 18, 2009 (normalized such that the change on impact is equal to 1). Consistent with Wright (2012) and Greenlaw et al. (2018), yields had returned to roughly their starting point within a few months.

One may be concerned that these reactions in the bond market are driven by some omitted factor, rather than idiosyncratic changes in institutional investors’ demand for Treasuries. Our high-frequency identification goes a long way towards assuaging this concern, but it is still possible that our demand shocks reflect systematic changes in bidders’ expectations of macroeconomic or financial fundamentals. This is an issue for our interpretation if two conditions hold: (i) this information was not already reflected in market prices, and instead is only revealed at the auction; (ii) the market as whole updates their beliefs about fundamentals by observing the results of the auction. If this “information factor” drives the bond market reactions we observe, we should find strong co-movement between D_t and indicators capturing beliefs about current or future states of the economy and financial markets. The “information factor” can take any number of forms, so it is difficult to conclusively rule out this channel; we focus on a battery of key indicators to assess the quantitative significance of this alternative explanation.

Panel B of Table 3 reports estimates for the response of equities to our demand shocks. Rows 1 and 2 report the results for the intraday change in ETFs tracking the S&P 500 and the Russell 2000 indices. Rows 3 and 4 are for the daily changes in these indices. Although the estimated slope is generally positive, the estimate is typically insignificant. Moreover, the quantitative importance is small, as the auction demand shocks account for a trivial share of variation in equities. Thus, there is little evidence on average for a common factor driving Treasury and equity prices during small windows around the release of auction results, or for strong propagation of our demand shocks to equity prices.

Panel C of Table 3 presents results for a wider array of assets. The dependent variable

in row 1 is the intraday change in the ETF “GLD,” which tracks the price of Gold Bullion. Row 2 reports results for the daily change in the S&P Total Commodity Index. For the Commodity Index we do not find a significant correlation with D_t . For Gold, while the relationship is statistically significant, the R^2 is very low. Rows 3 and 4 use the daily change in inflation expectations implied by inflation swaps at the 10- and 2-year horizons. Our demand shocks are not associated with a significant comovement in inflation expectations. Row 5 uses the daily change in the 3-month USD LIBOR-Overnight Index Swap spread (a common measure of credit risk in the banking sector). Rows 6 and 7 use daily changes in two CDS indices from Credit Market Analysis that track the automotive industry (a highly cyclical industry) and banks (a proxy for the financial sector). These three measures proxy for expectations about future output and market conditions. Our demand shocks have no tangible relationship with these measures, consistent with our interpretation that the shocks do not capture superior information of Treasury auction bidders about future recessions and the like. Finally, row 8 documents that D_t shocks are not associated with the VIX (a measure of market perceptions of future volatility). In short, these null results suggest that our demand shocks are not driven by changes in expectations regarding inflation, output, liquidity, default risk, or volatility.

As a final test, Panel D of Table 3 reports results with expected federal funds rates, which are derived from federal funds futures contracts. We view this as a “catch-all” test of the “information factor” story: if our demand shocks reflect changes in market expectations of fundamentals, then the market should also expect a Fed response (to the extent these fundamentals matter for the macroeconomy). We find that our demand shocks are not associated with changes in expected federal funds rates: the estimated coefficients on our demand shocks are very close to zero in these specifications, and demand shocks explain virtually none of the variation in federal funds futures in our sample.⁸

The results of Tables 2 and 3 allow for some broad observations. First, given our high-frequency approach and the institutional structure of Treasury auctions, our constructed shocks are likely only driven by new information regarding the demand side of the market. Second, these shifts are largely driven by shifts in the demand arising from institutional investors. Third, these demand shocks from the primary market for Treasuries propagate to private borrowing rates. We do not observe the underlying sources of demand shocks, and indeed it is likely driven by a host of factors, including shifts in a given investor’s idiosyncratic beliefs about the macroeconomy. However, these demand shifts are not driven by *systematic* or market-wide shifts in macroeconomic expectations (e.g., flight to quality or inflation expectations) that may move demand for Treasuries at all maturities.

⁸We plot rolling regressions for select asset prices in Appendix Figure B4. Appendix Figure B5 plots rolling regressions for h -month ahead federal funds futures h up to 12 months.

4 Channels of Treasury Demand Shocks

The results of Section 3 show that our shock series offer useful variation to study the transmission of Treasury demand shocks. However, as discussed above we cannot interpret D_t as “structural” shocks, since these intraday yield changes are equilibrium outcomes of the underlying (imperfectly observed) shifts in demand. Moreover, our end goal is to make sense of the transmission of QE, both to asset prices and to the broader macroeconomy. Thus, in order to make more progress understanding shock transmission along these dimensions, we need to develop a theoretical framework with meaningful interactions between financial markets and the macroeconomy. This will allow us to be precise about the transmission mechanisms of demand shocks, as well as help us extrapolate from private shocks observed at auctions to large scale asset purchases (or sales). This section develops such a model, derives key predictions regarding the transmission of shocks, and develops empirical tests which can be applied using our shock measures D_t .

4.1 Overview: Agents and Financial Assets

The financial block of our model builds on [Vayanos and Vila \(2021\)](#), extended to allow for both riskless and risky assets. Formally, we assume two sets of assets: riskless and risky zero coupon bonds with maturity $\tau \in (0, T)$. A τ -maturity riskless bond has price $P_t^{(\tau)}$ and pays \$1 at maturity with certainty in period $t + \tau$. A risky τ -maturity bond has price $\tilde{P}_t^{(\tau)}$ and instead pays $D_{t+\tau} \equiv e^{d_{t+\tau}}$ at maturity in period $t + \tau$, where D_t is a stochastic process. We will assume that both sets of assets are in zero net supply, but for completeness we denote the supply of assets by $S_t^{(\tau)}$ and $\tilde{S}_t^{(\tau)}$, respectively.

As in [Vayanos and Vila \(2021\)](#), financial assets are traded between two sets of investors: arbitrageurs and preferred habitat funds. The key idea is the existence of “clientèle” investors who have idiosyncratic demand (“preferred habitat”) for specific assets and maturities. For example, pension funds can have a preference for long-maturity assets to better match the maturity structure of pension liabilities. The other side of the market are risk-averse arbitrageurs such as hedge funds and dealers, who smooth out these preferred-habitat demand shocks.

The real side of our model is largely built on a standard New Keynesian framework. A representative household consumes and supplies labor to firms producing differentiated goods while facing pricing frictions. As we show, the equilibrium aggregate dynamics will depend on two familiar equations: an IS curve which determines the dynamics of the output gap x_t , and a Phillips curve which determines the dynamics of inflation π_t . The links between the financial and the macroeconomic blocks of our model are two-fold. First, the central bank sets the policy rate i_t in reaction to aggregate fluctuations. In equilibrium, i_t will be the return on a riskless bond as maturity $\tau \rightarrow 0$; therefore, aggregate fluctuations will result in changes in asset prices. Second, we depart from the

usual New Keynesian setup and assume that households cannot access financial markets directly, but instead must borrow through the preferred habitat funds. Through the household Euler equation, output in equilibrium will depend on a weighted average of the returns on both short- and long-term assets, rather than only on the policy rate. Therefore, asset price movements will lead to changes in macroeconomic conditions. Our model formalizes this intuition, and characterizes the general equilibrium solution. For ease of exposition, we summarize the model without aggregate demand and supply shocks, but these are included in our quantitative exercises in Section 5. We stress that our aim is to develop a tractable model, and discuss the simplifying assumptions necessary for our model.

Households: The representative household in our model chooses consumption bundle C_t and labor N_t given nominal wealth A_t in order to maximize lifetime discounted utility. The household faces nominal wage \mathcal{W}_t and aggregate price index P_t . Our point of departure from a textbook New Keynesian model is that households can only invest with the preferred habitat funds, and allocate a fixed fraction of their wealth across these funds. The household problem is given by

$$\max E_0 \int_0^\infty e^{-\rho t} \left(\frac{C_t^{1-\varsigma}}{1-\varsigma} - \frac{N_t^{1+\psi}}{1+\psi} \right) dt \quad (4)$$

$$\text{s.t. } dA_t = [\mathcal{W}_t N_t - P_t C_t] dt + A_t \int_0^T \left(\eta(\tau) \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \tilde{\eta}(\tau) \frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} \right) d\tau + dF_t, \quad (5)$$

and A_0 given. The parameter ψ is the Frisch elasticity of labor supply, and the parameter ρ is the household discount factor. The term dF_t captures all (flow) nominal transfers to the household. Households therefore borrow or lend their wealth A_t at an “effective” borrowing rate (rather than the short-term policy rate), given by the the integral term in the household budget constraint. The weight functions satisfy $\int_0^T (\eta(\tau) + \tilde{\eta}(\tau)) d\tau = 1$. Thus, household borrowing depends on a weighted average of the returns across the term structure and asset types. Denote the drift of the effective borrowing rate by

$$\hat{r}_t \equiv E_t \int_0^T \left(\eta(\tau) \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \tilde{\eta}(\tau) \frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} \right) d\tau, \quad (6)$$

which is endogenous but taken as given by households.

We think of the weighting functions $\eta(\tau), \tilde{\eta}(\tau)$ as capturing a type of preferred habitat on the part of households (for instance, due to demographics such as age) without explicitly introducing heterogeneous households. This also captures imperfect access to financial markets, as households typically do not directly buy and sell financial assets such as corporate bonds; instead, investments are done through pension funds and mutual funds, that tend to allocate their portfolio using fixed weights and rebalance sluggishly

(e.g., [Kojen and Yogo \(2019\)](#), [Kojen and Yogo \(2022\)](#), [Bretscher et al. \(2022\)](#), [Peng and Wang \(2022\)](#)). Our key assumption is that the weighting functions can be taken as a primitive of the model, and do not respond endogenously to aggregate fluctuations. This strong assumption permits a tractable solution of the model and keeps the macroeconomic dynamics as close as possible to a standard New Keynesian model, while still allowing fluctuations in long-term borrowing rates to affect household decisions.

Firms: The production block of the model is standard. Intermediate goods are produced by monopolistically competitive firms indexed by $j \in [0, 1]$. Each firm hires workers and produces using linear technology $Y_{j,t} = N_{j,t}$. Firms face Rotemberg pricing frictions when choosing prices, and must pay a cost $\Theta(\pi_{j,t}) \equiv \frac{\theta}{2} \pi_{j,t}^2 P_t Y_t$, where $\frac{dP_{j,t}}{P_{j,t}} = \pi_{j,t} dt$ is the inflation rate of firm j . Firms are owned by households and hence maximize expected real profits discounted using the household real stochastic discount factor $e^{-\rho t} Q_t$. The firm problem is therefore given by

$$\max E_0 \int_0^\infty e^{-\rho t} Q_t \frac{\Pi_{j,t}}{P_t} dt, \quad \text{where } \Pi_{j,t} = P_{j,t} Y_{j,t} - \mathcal{W}_t N_{j,t} - \Theta(\pi_{j,t}).$$

Intermediate goods are sold to competitive final goods producers with demand elasticity ϵ , which imply the usual demand and price index for differentiated goods (see e.g., [Gali \(2015\)](#)): $Y_{j,t} = \left(\frac{P_{j,t}}{P_t}\right)^{-\epsilon} Y_t$ where the price index $P_t = \left(\int_0^1 P_{j,t}^{1-\epsilon}\right)^{\frac{1}{1-\epsilon}}$.

Arbitrageurs: Arbitrageurs have mean-variance preferences and allocate their wealth W_t to holdings $X_t^{(\tau)}, \tilde{X}_t^{(\tau)}$ across τ riskless and risky bonds, respectively. They solve

$$\max E_t dW_t - \frac{a}{2} \text{Var}_t dW_t \tag{7}$$

$$\text{s.t. } dW_t = W_t i_t dt + \int_0^T X_t^{(\tau)} \left(\frac{dP_t^{(\tau)}}{P_t^{(\tau)}} - i_t dt \right) + \tilde{X}_t^{(\tau)} \left(\frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} - i_t dt \right) d\tau, \tag{8}$$

where the parameter a governs the risk-return trade-off that arbitrageurs face. This parameter can be taken literally as a risk aversion parameter, or more generally can be thought of as a proxy for factors that lead to the imperfect risk-bearing capacity of arbitrageurs. Arbitrageurs transfer all profits or losses to the household each period. Taking a as time-invariant is important for tractability; however, we might expect a to increase in periods of financial distress. We analyze how the predictions of the model depend on the risk-bearing capacity of arbitrageurs.⁹

Preferred Habitat Funds: On the other side of the market is a continuum of habitat investors, who specialize in (riskless and risky) bonds of specific maturities. We follow [Vayanos and Vila \(2021\)](#) and assume that these investors respond to prices through the

⁹[He and Krishnamurthy \(2013\)](#), [Kyle and Xiong \(2001\)](#) and others show how risk aversion can be endogenously higher in times of crises.

following demand curves:

$$Z_t^{(\tau)} = -\alpha(\tau) \log P_t^{(\tau)} - \beta_t(\tau), \quad \tilde{Z}_t^{(\tau)} = -\tilde{\alpha}(\tau) \log \tilde{P}_t^{(\tau)} - \tilde{\beta}_t(\tau). \quad (9)$$

The functions $\alpha(\tau), \tilde{\alpha}(\tau)$ are the semi-elasticities of a τ -habitat investor's demand for riskless and risky assets, respectively. The time-varying demand intercept is given by $\beta_t(\tau), \tilde{\beta}_t(\tau)$, where we assume a factor structure such that

$$\beta_t(\tau) = \sum_{k=1}^K \theta^k(\tau) \beta_t^k - \zeta(\tau), \quad \tilde{\beta}_t(\tau) = \sum_{k=1}^{\tilde{K}} \tilde{\theta}^k(\tau) \tilde{\beta}_t^k - \tilde{\zeta}(\tau). \quad (10)$$

The functions $\theta^k(\tau), \tilde{\theta}^k(\tau)$ govern how demand factors $\beta_t^k, \tilde{\beta}_t^k$ lead to changes in demand from τ -habitat investors. In general, there are no restrictions on the dynamics of the demand factors (up to linearizing). For the quantitative analysis in Section 5, we assume that the habitat demand factors are independent from one another, but may respond to the short rate (as in King (2019a)). Hence, for each demand factor we have

$$d\beta_t^k = -(\kappa_\beta^k \beta_t^k + \phi_{i,\beta}^k i_t) dt + \sigma_\beta^k dB_{\beta^k,t}, \quad (11)$$

where the parameters $\kappa_\beta^k, \phi_{i,\beta}^k$, and σ_β^k govern the mean-reversion, response to short rates, and volatility of each demand factor, respectively (and with analogous parameterization and dynamics for demand factors $\tilde{\beta}_t^k$).

The τ -maturity riskless and risky funds have wealth $W_t^{(\tau)}$ and $\tilde{W}_t^{(\tau)}$. In order to fund their positions in their respective asset classes, the fund receives investment from the household sector based on the weights $\eta(\tau), \tilde{\eta}(\tau)$. Any remaining wealth is invested at the short rate. The budget constraint of a τ -maturity riskless fund is therefore

$$dW_t^{(\tau)} = Z_t^{(\tau)} \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \left[W_t^{(\tau)} - Z_t^{(\tau)} + \eta(\tau) A_t \right] i_t dt - \eta(\tau) A_t \frac{dP_t^{(\tau)}}{P_t^{(\tau)}},$$

and the risky fund faces an analogous budget constraint. Each preferred habitat fund also transfers profits or losses to the household each period.

Interest Rate and Payoff Processes: To close the model, we need to specify how the instantaneous interest rate i_t and the payoff process d_t is determined. We assume the central bank sets the nominal interest rate i_t according to the following policy rule:

$$di_t = -\kappa_i (i_t - \phi_\pi \pi_t - \phi_x x_t - i^*) dt + \sigma_i dB_{i,t}, \quad (12)$$

where the response of the policy rate to inflation and the output gap are governed by ϕ_π, ϕ_x , κ_i is a mean-reversion parameter, and i^* is the central bank's target policy rate. Note that if $\kappa_i \rightarrow \infty$, we recover a standard Taylor rule.

Finally, because risky assets are in zero net supply ($\tilde{S}_t^{(\tau)} = 0$), they can be interpreted as synthetic securities which are created by the financial sector (since arbitrageurs and preferred-habitat funds take non-zero positions in risky assets across all maturities). We assume that the payoff processes for these synthetic securities evolves according to

$$dd_t = -\kappa_d (d_t - \psi_x x_t - \psi_\pi \pi_t - d^*) dt + \sigma_d dB_{d,t}. \quad (13)$$

This reduced-form approach to modelling payoffs of risky assets allows us to capture salient features of how private borrowing rates fluctuate over the business cycle. The process is mean-reverting (with inertia κ_d) and may depend on movements in output and inflation through parameters ψ_x, ψ_π (which are primitives of the model). Stepping outside of the model, assets besides financial institution securities influence the borrowing decisions of the household sector. In reality, this also includes risky private bonds, mortgage debt, equities, and a host of other assets. Rather than complicate the model by specifying a corporate structure for firms, we collapse all of these sources of payoff risk into a single process $D_t \equiv e^{d_t}$, which we allow to respond in a flexible manner to aggregate dynamics.¹⁰

4.2 Equilibrium

The household and firm problems are highly similar to a textbook New Keynesian model; detailed derivations can be found in Appendix C. The optimizing behavior of these agents and market clearing give rise to a Phillips curve and IS curve for inflation and the output gap π_t, x_t , where the output gap is the deviation of output from the “natural” level that would prevail in the absence of nominal rigidities ($\theta = 0$). The only modification to the standard (linearized) New Keynesian dynamics is that the effective borrowing rate \hat{r}_t replaces the policy rate i_t . We have

$$E_t d\pi_t = (\rho\pi_t - \delta x_t) dt, \quad (14)$$

$$E_t dx_t = (\hat{r}_t - \pi_t - \bar{r}) dt, \quad (15)$$

where the model is linearized around a zero inflation, zero output gap steady state. The composite parameter $\delta = \frac{(\epsilon-1)(1+\psi)}{\theta}$ measures the degree of price rigidity in aggregate and \bar{r} is the “natural” borrowing rate.

We collect the state variables, jump variables, and Brownian terms into vectors $\mathbf{y}_t = [i_t \quad d_t \quad \dots \quad \beta_t^k \quad \dots]^\top$, $\mathbf{x}_t = [\pi_t \quad x_t]^\top$, and $\mathbf{B}_t = [B_{i,t} \quad B_{d,t} \quad \dots \quad B_{\beta^k,t} \quad \dots]^\top$, respec-

¹⁰Our results are not sensitive to this precise microfoundation of the payoff process. We could have chosen a formulation whereby the payoff process D_t captures claims on a portion of firm profits not paid directly and immediately to households. Under the zero net supply assumption and with the payoff process given by equation (13), the macroeconomic dynamics of the model are identical. Although this formulation brings the interpretation of D_t closer to corporate bonds, it does not explicitly model the financing frictions leading to this distribution of profits (and our model does not feature firm investment).

tively. The following Lemma describes the aggregate dynamics of the model, taking as given the effective borrowing rate. All proofs are in Appendix A.

Lemma 1 (Aggregate Dynamics). *Suppose the effective borrowing rate drift is given by*

$$\hat{r}_t = \hat{\mathbf{A}}^\top \mathbf{y}_t + \hat{C}. \quad (16)$$

Then the rational expectations equilibrium is given by

$$d\mathbf{y}_t = -\mathbf{\Gamma}(\mathbf{y}_t - \bar{\mathbf{y}}) dt + \boldsymbol{\sigma} d\mathbf{B}_t, \quad (17)$$

$$\mathbf{x}_t - \bar{\mathbf{x}} = \mathbf{\Omega}(\mathbf{y}_t - \bar{\mathbf{y}}), \quad (18)$$

where the matrices $\mathbf{\Gamma}, \mathbf{\Omega}$ are a function of the eigendecomposition of the linearized dynamics of the model (and therefore functions of $\hat{\mathbf{A}}$).

If $\hat{\mathbf{A}} = \mathbf{e}_i$, the vector which “selects” the policy rate $\mathbf{e}_i^\top \mathbf{y}_t = i_t$, then the effective borrowing rate responds one-for-one with the policy rate i_t and the aggregate dynamics of the model reduce to a standard New Keynesian model.¹¹

Next, we turn to characterizing the behavior of asset prices. We focus on a solution to the model in which (log) asset prices are affine functions of the state variables, given by (endogenous) coefficient functions:

$$-\log P_t^{(\tau)} = \mathbf{A}(\tau)^\top \mathbf{y}_t + C(\tau), \quad -\log \tilde{P}_t^{(\tau)} = \tilde{\mathbf{A}}(\tau)^\top \mathbf{y}_t + \tilde{C}(\tau). \quad (19)$$

Lemma 2 (Asset Prices). *Suppose that the state variables \mathbf{y}_t evolve according to equation (17). Then the affine coefficients in equation (19) are given by*

$$\mathbf{A}(\tau) = [\mathbf{I} - e^{-\mathbf{M}\tau}] \mathbf{M}^{-1} \mathbf{e}_i, \quad \tilde{\mathbf{A}}(\tau) = [\mathbf{I} - e^{-\mathbf{M}\tau}] \mathbf{M}^{-1} \mathbf{e}_i - e^{-\mathbf{M}\tau} \mathbf{e}_d. \quad (20)$$

where $\mathbf{e}_i, \mathbf{e}_d$ are vectors such that $\mathbf{e}_i^\top \mathbf{y}_t = i_t$ and $\mathbf{e}_d^\top \mathbf{y}_t = d_t$. The matrix \mathbf{M} solves the fixed point problem:

$$\begin{aligned} \mathbf{M} = \mathbf{\Gamma}^\top - a \int_0^T & [-\alpha(\tau) \mathbf{A}(\tau) + \boldsymbol{\Theta}(\tau)] \mathbf{A}(\tau)^\top \\ & + [-\tilde{\alpha}(\tau) \tilde{\mathbf{A}}(\tau) + \tilde{\boldsymbol{\Theta}}(\tau)] \tilde{\mathbf{A}}(\tau)^\top d\tau \boldsymbol{\sigma} \boldsymbol{\sigma}^\top, \end{aligned} \quad (21)$$

where $\boldsymbol{\Theta}(\tau), \tilde{\boldsymbol{\Theta}}(\tau)$ stack the habitat demand functions $\theta^k(\tau), \tilde{\theta}^k(\tau)$ into vectors.

The matrix \mathbf{M} can be thought of as the risk-adjusted dynamics of the state. Note

¹¹In this case, the determinacy conditions are the standard ones; in particular, the central bank can ensure determinacy when the response to inflation $\phi_\pi > 1$. However, in general $\hat{\mathbf{A}} \neq \mathbf{e}_i$ and the determinacy conditions are more complicated. In our quantitative exercises, we verify that these determinacy conditions are satisfied numerically.

that when arbitrageurs are risk-neutral ($a = 0$), we have $\mathbf{M} = \mathbf{\Gamma}^\top$. However, when $a \neq 0$, \mathbf{M} appears on both sides of equation (21) (through the affine coefficients $\mathbf{A}(\tau)$, $\tilde{\mathbf{A}}(\tau)$).

With the results in Lemmas 1 and 2, we can characterize the equilibrium of the model.

Proposition 1 (Existence and Uniqueness). *An affine equilibrium is one in which the state and jump variables evolve according to equations (17) and (18), and asset prices are determined by the solution to the expressions (20) and (21). In this case, the effective borrowing rate is given by equation (16), where $\hat{\mathbf{A}}$ solves the fixed point problem*

$$\hat{\mathbf{A}} = \mathbf{e}_i + (\mathbf{\Gamma}^\top - \mathbf{M}) \int_0^T \left[\eta(\tau) \mathbf{A}(\tau) + \tilde{\eta}(\tau) \tilde{\mathbf{A}}(\tau) \right] d\tau. \quad (22)$$

In a neighborhood of risk-neutrality ($a \approx 0$), the equilibrium exists and is (locally) unique.

Note that the dynamics matrix of the state $\mathbf{\Gamma}$ depends on the effective borrowing rate coefficients $\hat{\mathbf{A}}$, which itself is a function of the risk-adjusted dynamics matrix \mathbf{M} . Thus, equilibrium is determined as a fixed point that produces asset price dynamics consistent with equilibrium dynamics of the macroeconomy and vice versa. In general, an affine equilibrium of this type may not exist, or there may be multiple solutions to this fixed point problem. However, when $a = 0$, the model reduces to a standard New Keynesian model. The result in Proposition 1 shows that this equilibrium persists and is locally unique as we depart from risk neutrality. We make use of this insight in our numerical continuation solution algorithm, described in Appendix D.1.

4.3 Localization Hypothesis and Regression Specification

Our model makes precise the channels through which QE may have financial and macroeconomic effects. The immediate and direct effect of a QE purchase shock is a reduction in the amount of assets held by arbitrageurs through market clearing (a decline in $X_t^{(\tau)}$ or $\tilde{X}_t^{(\tau)}$ in equation (8), depending on the type of assets purchased during QE). If arbitrageurs are risk-neutral ($a = 0$), we recover a typical neutrality result: QE changes the arbitrageurs' portfolio, but not asset prices (and thus has no effect on real activity).

On the other hand, when arbitrageurs are risk-averse ($a > 0$), the change in arbitrageurs' portfolio implies changes in risk exposure, which is priced. We can broadly distinguish between three main sources of risk: *duration* or *short-rate* risk (from fluctuations in i_t); *payoff* risk (from fluctuations in d_t); and *habitat demand* risk (from fluctuations in demand factors β_t^k). By reducing arbitrageur exposure to these sources of risk, in equilibrium QE reduces the risk compensation arbitrageurs require, which manifests as a decline in expected returns. As a result, the household effective borrowing rate \hat{r}_t falls, which through the intertemporal decisions of the household leads to lower savings and a jump in consumption, and from the pricing decisions of firms leads to an increase in inflation.

However, the precise mapping from a QE shock (or private demand shocks) to the repricing of risk depends qualitatively on the risk-bearing capacity of arbitrageurs. One of the characteristic predictions of our model (and preferred habitat theory more generally, as discussed in [Vayanos and Vila \(2021\)](#)), is the *localization hypothesis*. When arbitrageur risk-bearing capacity is high, Treasury demand shocks have *global* effects on the yield curve. That is, the relative response of the interest rates across the yield curve does not depend on where in maturity space the demand shock occurs. However, as arbitrageur risk-bearing capacity declines, the spillovers of demand shocks become more *localized*. That is, the relative response of interest rates becomes more concentrated on parts of the yield curve that are closer in maturity space to where the demand shock occurs.

Intuitively, when arbitrageurs are nearly risk-neutral, macroeconomic fundamentals affecting the path of the short rate (duration risk) are the dominant factor in determining of the term structure of interest rates. Hence, when arbitrageurs hold bonds, short-rate fluctuations are their main source of risk. Demand shocks that re-allocate bonds away from arbitrageurs reduce their exposure to short-rate risk, and hence decrease the compensation arbitrageurs require to hold bonds. Since all bonds are sensitive to short-rate risk, any such demand shock will push down yields of all bonds. Importantly, this mechanism is independent of the location (in maturity space) of the demand shock.

As arbitrageur risk aversion increases, habitat demand shocks become more prominent as additional sources of risk. Arbitrageurs try to limit their exposure to these sources of risk, leading to less propagation from the location of the demand shock to other parts of the term structure. Arbitrageurs become less willing to integrate bond markets across maturities, and hence the response of the yield curve becomes more localized around the location (in maturity space) of a given demand shock.

In order to formalize and derive an empirical test of the localization hypothesis, consider a version of the model with the following Treasury demand factors: a “short” maturity factor β_t^s and “long” maturity factor β_t^ℓ such that

$$\int_0^T \theta^s(\tau) d\tau = \int_0^T \theta^\ell(\tau) d\tau, \quad \exists \tau' : \theta^s(\tau) < \theta^\ell(\tau) \iff \tau > \tau'. \quad (23)$$

That is, the factors have the same overall magnitude across maturities, but the short factor is more concentrated in bonds of short maturities relative to the long factor. This assumption does not imply the long factor β_t^ℓ only affects demand for long maturities; indeed, changes in β_t^ℓ will shift demand for bonds of all maturities τ such that $\theta^\ell(\tau) \neq 0$. In other words, we allow for correlated changes in demand across the term structure because both factors directly move demand for both short- and long-maturity bonds. We only require that, relative to the short factor, the long factor has a larger direct effect on demand for bonds with long maturities.

In this context, the localization hypothesis involves the differential responses of the

entire yield curve to movements in the short and long demand factors. We can formally state a version of the localization hypothesis as follows. When arbitrageur risk-bearing capacity is high ($a \approx 0$), the relative response of the yield curve is the same for both factors. On the other hand, when risk-bearing capacity is low ($a \gg 0$), then long demand shocks have relatively larger effects on long-maturity yields and *vice versa* for short demand shocks. This logic implies:

$$\text{if } a \approx 0 : \frac{\partial y_t^{(\tau)} / \partial \beta_t^s}{\partial y_t^{(\tau^*)} / \partial \beta_t^s} \approx \frac{\partial y_t^{(\tau)} / \partial \beta_t^\ell}{\partial y_t^{(\tau^*)} / \partial \beta_t^\ell}, \quad (24)$$

$$\text{if } a \gg 0 : \tau > \tau^* \iff \frac{\partial y_t^{(\tau)} / \partial \beta_t^s}{\partial y_t^{(\tau^*)} / \partial \beta_t^s} < \frac{\partial y_t^{(\tau)} / \partial \beta_t^\ell}{\partial y_t^{(\tau^*)} / \partial \beta_t^\ell}, \quad (25)$$

where τ^* is some arbitrary “baseline” maturity (and unrelated to τ) and $\partial y_t^{(\tau)} / \partial \beta_t^k$ is the response of τ -maturity yields to the demand shock $k \in \{s, \ell\}$.¹² Hence, these expressions make statements about the movements of the yield curve to short and long demand shocks, *relative* to movements in some fixed maturity τ^* . Specifically, equation (24) states that even if $\theta^k(\tau) \neq \theta^k(\tau^*)$ (i.e., direct responses are different across maturities for a given factor) and $\theta^s(\tau) \neq \theta^\ell(\tau)$ (i.e., direct responses for a given maturity are different across factors), arbitrageurs with low risk aversion ($a \approx 0$) ensure that the *equilibrium* scaled responses of yields are approximately the same for short and long factors. In contrast, equation (25) states that when risk aversion is high, arbitrageurs do not smooth out demand shocks and the scaled responses of yields depend on where the direct impact of a factor is concentrated. In particular, if the long factor has a larger direct effect on demand for long maturities than the short factor, then in equilibrium, the scaled response of yields for longer maturities is larger for the long factor than for the short factor.

In order to test the localization hypothesis, we need empirical analogues that are proportional to the model objects $\partial y_t^{(\tau)} / \partial \beta_t^s$ and $\partial y_t^{(\tau)} / \partial \beta_t^\ell$. As shown in Section 3, our high-frequency identification strategy is precisely designed to isolate the reactions of the yield curve to Treasury demand shocks alone, effectively ruling out any other shocks during these small windows around auctions. This insight allows us to arrive at a simple, theory-based regression specification that can test the localization hypothesis using only high-frequency changes in yields around auctions $D_t^{(\tau)} = y_t^{(\tau),post} - y_t^{(\tau),pre}$, which are data

¹²Appendix D.2 discusses sufficient conditions and derives the localization predictions of the model.

analogues proportional to $\partial y_t^{(\tau)} / \partial \beta_t^k$.¹³ Our localization specification is

$$D_t^{(\tau)} = \alpha^{(\tau)} + \gamma_s^{(\tau)} \mathbf{I}(m_t = \text{short}) D_t^{(\tau^*)} + \gamma_\ell^{(\tau)} \mathbf{I}(m_t = \text{long}) D_t^{(\tau^*)} + \varepsilon_t^{(\tau)}, \quad (26)$$

where $\mathbf{I}(m_t = \text{short})$ and $\mathbf{I}(m_t = \text{long})$ are indicator variables equal to one if there is an auction of short-maturity and long-maturity bonds on date t , respectively. We estimate equation (26) for all maturities τ , holding τ^* fixed.

Coefficients $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$ measure the relative effect of demand shocks for short-maturity and long-maturity auctions respectively. Now we can restate the localization hypothesis formally as a function of the coefficients $\gamma_s^{(\tau)}$, $\gamma_\ell^{(\tau)}$, and risk aversion a as follows: i) as risk aversion $a \rightarrow 0$, $|\gamma_s^{(\tau)} - \gamma_\ell^{(\tau)}| \rightarrow 0$ for all maturities τ ; ii) when risk aversion is high ($a \gg 0$), then $\gamma_s^{(\tau)} > \gamma_\ell^{(\tau)}$ if $\tau < \tau^*$ and $\gamma_s^{(\tau)} < \gamma_\ell^{(\tau)}$ if $\tau > \tau^*$.

4.4 Empirical Localization Results

To test the state-dependent localization hypothesis, we estimate specification (26) separately for two subsamples: a “non-crisis” period (risk aversion a is low), and a “crisis” period (risk aversion a is high). Testing for the equality of coefficients $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$ in each subsample shows whether demand shocks have more localized effects when risk aversion is high. In our baseline estimates, we take the “crisis” period to be 2008-2012. We divide the auctions into short-maturity (maturity of 5 years or less) and long-maturity (maturity of 7 years or greater). The results are robust to alternative choices.

Since we construct $D_t^{(\tau)}$ from secondary-market yields, we do not have measures for all maturities τ at all times. Our approach is to run rolling regressions (across maturities), including yields for maturities within ± 2 years for each maturity $\tau \leq 20$ years and within ± 4 years for each maturity $\tau > 20$ year. Given that the choice of benchmark maturity τ^* is arbitrary, we set $\tau^* = 3$, with an eye towards applying our results to QE in order to focus on the differential effects of intermediate and long-maturity yields.

Panel A of Figure 5 plots the estimates of $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$ for the non-crisis sample. The estimated responses follow a similar hump-shaped pattern peaking at intermediate maturities (around roughly 5-7 years), and then declining and stabilizing for longer term maturities (with a possible slight uptick for very long (20+ years) maturities). In general, we cannot reject equality of $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$.

When we estimate specification (26) on the crisis sample, we observe a strikingly

¹³A jump-diffusion process would better match the discrete timing of Treasury auctions, and so our approach based on continuous processes introduces some slippage between the model and the data for the benefit of tractability. To be clear, the discrepancy with auctions in the model are: *i*) The auction reveals the results (which we interpret as the demand shock), but in reality the actual change in holdings occurs a few days later. *ii*) The bidding process can be thought of as “scooping up” changes in demand leading up to the auction, which are only revealed when the auction closes. Formally, the model only allows for contemporaneous, observable changes in demand.

different pattern (Panel B of Figure 5). In response to shocks in demand for short- and long-maturity Treasuries, both $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$ increase rapidly for $\tau < \tau^*$, with the $\hat{\gamma}_s^{(\tau)}$ estimates increasing somewhat more quickly than $\hat{\gamma}_\ell^{(\tau)}$. Once we move to maturities greater than τ^* , the estimates quickly diverge. Specifically, in response to shocks in demand for short-maturity Treasuries, the yields for maturities greater than τ^* fall relative to the yield response for τ^* (as shown by the estimates of $\hat{\gamma}_s^{(\tau)}$). On the other hand, in response shocks in demand for long-maturity Treasuries, yields for maturities $\tau > \tau^*$ continue to increase relative to the benchmark maturity τ^* (as shown by the estimates of $\hat{\gamma}_\ell^{(\tau)}$). For maturities of 20 to 30 years, the relative response of yields to long-maturity demand shocks ($\hat{\gamma}_\ell^{(\tau)}$) is over twice as large as the response of yields to short-maturity demand shocks ($\hat{\gamma}_s^{(\tau)}$). We can strongly (at the 0.1% level) reject the null of $\hat{\gamma}_s^{(\tau)}$ and $\hat{\gamma}_\ell^{(\tau)}$ being equal.

These results are consistent with the key predictions of our preferred habitat framework: during “normal” periods when financial risk-bearing capacity is high, demand shocks for short- and long-maturity securities have relatively similar impacts on the yield curve. During periods of financial distress when risk-bearing capacity is low, the impacts are more localized: the impact of short-maturity demand shocks are largest for short maturities, while the impact of long-maturity demand shocks peaks at the long end of the term structure. These results provide support for the view that during financial crises, arbitrageurs are less willing or able to integrate bond markets.

The localization results are robust to a variety of alternative assumptions. In the interest of space, we provide summaries for a few key robustness specifications in this section. First, we explore the sensitivity of our results to using alternative measures of financial distress. Specifically, we consider two alternatives: i) an aggregate “intermediary capital ratio,” a market-based measure of financial distress (low intermediary capital ratios are associated with lower risk-bearing capacity) described in He et al. (2016); ii) a narrative-based measure of financial crisis from Romer and Romer (2017) (higher values of the crisis indicator are associated with lower risk-bearing capacity). Both of these alternatives generate results similar to our baseline findings (see Appendix Figures B7 through B11). Second, our results are robust to using different cutoffs for separating auctions into short and long maturities. For example, when we use 10 years (rather than 7 years in the baseline) as the cut-off for long-maturity auctions, the results (Appendix Figure B12) still strongly support the localization hypothesis and, if anything, the point estimates for the “non-crisis” period are even more similar than in our baseline specification. Third, as we discussed above, the choice of the benchmark maturity τ^* is arbitrary in our framework. To verify that this choice is indeed immaterial for our results, we experiment with values other than $\tau^* = 3$ and find similar results (e.g. Appendix Figure B13 reports estimates for $\tau^* = 6$). Fourth, our results are nearly identical when dropping auctions that occurred during the weeks of QE announcements (Appendix Figure B14).

We also considered an alternative specification that regresses $D_t^{(\tau)}$ directly on the bid-

to-cover ratio, a crude proxy for demand. Although the formal test of the localization hypothesis is not as straightforward using this specification (recall that the localization hypothesis is about relative movements in yields across the term structure), we continue to see strong patterns of localization in the “crisis” estimates, but little evidence of localization in the “non-crisis” estimates (Appendix Figure B15).

We additionally explore state-dependence in the pass-through of Treasury demand shocks to private borrowing rates. The logic of the localization hypothesis also suggests that the pass-through to risky assets of Treasury demand shocks should lessen when risk-bearing capacity is low. Although our model features only one type of risky asset, in general there are many different assets of varying levels of risk. Panel A of Table 4 estimates a version of equation (26) where we regress the intraday change of various ETF prices on $D_t^{(\tau^*)}$, interacted with whether the auction took place during the crisis period. For very safe or very risky corporate borrowing (LQD and HYG in columns 1 and 2, respectively), we find little evidence of localization. Although the sign of the crisis interaction coefficient in both cases is positive, it is not statistically significant. On the other hand, mortgage borrowing rates (MBB and VMBS in columns 3 and 4, respectively) seem to exhibit substantial localization. In both cases, the interaction coefficient is positive, economically large compared to the non-crisis coefficient, and highly statistically significant. Next, we explore the pass-through to equity indices. The model is not designed to capture the entire range of corporate funding structure, and hence does not make strong predictions about localization from Treasury demand shocks to equity markets. Perhaps consistent with this ambiguity in the model, the results are mixed. For the S&P500 (SPY, column 5), we find little evidence for localization; while for the Russell 2000 (IWM, column 6), there is some support for localization: the coefficient is positive in non-crisis times, but the interaction coefficient suggests that during crisis times the pass-through drops to zero. However, in both cases, the R^2 is low.

Finally, we explore state- and maturity-dependent localization for safe corporate borrowing rates. We again estimate a version of equation (26), but use intraday changes in various corporate bond ETFs as the dependent variable interacted with both the regime (crisis/non-crisis) and maturity (short/long) of the auction. We utilize two sets of ETFs: “BSV,” “BIV,” and “BLV” from Vanguard; and “CSJ,” “CIU,” and “CLY” from iShares. These ETFs track investment-grade bonds with short, intermediate, and long maturities (respectively).¹⁴ The results for this exercise, documented in Panel B of Table 4, are not directly comparable to our baseline Treasury results from Figure 5 because the ETFs are measured as (log) price changes and because we do not observe the entire term structure for corporate debt. Nevertheless, the results are consistent with our findings when analyzing the spillovers across the Treasury yield curve. The first row shows that demand

¹⁴The Vanguard ETFs were introduced in 2007, but include Treasuries in addition to corporate bonds. The iShares ETFs only include corporate bonds, but have shorter time series.

shocks in Treasury auctions also have large effects on corporate bond prices across the entire term structure. The second row shows that this pass-through is similar for demand shocks originating in long-term auctions in non-crisis times (with the one exception of the coefficient for BLV). The third and fourth rows report the additional interaction coefficients for the “crisis” periods. The final row shows that the pass-through of demand shocks for long-maturity Treasuries occurring during crisis periods has the same kind of localization pattern as Figure 5. The coefficient becomes monotonically more negative as we move from short-maturity to long-maturity bond ETFs. In particular, the coefficient for the long-maturity ETFs is negative and statistically significant.

5 Implications for Quantitative Easing

In this section, we use our theoretical framework to make further progress in several directions. First, we use a calibrated version of our model to quantify the role of preferred habitat in rationalizing the response of asset prices to previous QE announcements. Second, we use the model to evaluate the effectiveness of QE for macroeconomic stabilization purposes. Third, we compare our findings for QE with what our model predicts for the most recent rounds of quantitative tightening (QT). Finally, we study the sensitivity of our findings to a wide array of parameterization choices. Besides reassuring us of the robustness of our main results, this also allows for a better understanding of the interactions between the state of the economy and QE transmission. This exercise also allows us to explore different implementations of QE in order to inform policymakers about possible trade-offs associated with designing QE.

5.1 Model Calibration

For our quantitative exercises, we extend the model to allow for additional aggregate shocks while also reducing the number of parameters we must calibrate. For ease of exposition, we collect and restate all of the dynamic processes in our model, along with all parameters to be calibrated. Aggregate demand and cost-push shocks $z_{\pi,t}$, $z_{x,t}$ enter the Phillips and IS curves as follows:

$$\begin{aligned} E_t d\pi_t &= (\rho\pi_t - \delta x_t - z_{\pi,t}) dt, \\ E_t dx_t &= \varsigma^{-1} (\hat{r}_t - \pi_t - \bar{r} - z_{x,t}) dt, \\ dz_{\pi,t} &= -\kappa_{z_{\pi}} z_{\pi,t} dt + \sigma_{z_{\pi}} dB_{z_{\pi},t}, \\ dz_{x,t} &= -\kappa_{z_x} z_{x,t} dt + \sigma_{z_x} dB_{z_x,t}. \end{aligned}$$

The parameters $\kappa_{z_{\pi}}$, κ_{z_x} govern the persistence in these processes, and the terms $B_{z_{\pi},t}$, $B_{z_x,t}$ are standard independent Brownian motions, with respective volatility terms $\sigma_{z_{\pi}}$, σ_{z_x} .

To map the model to our empirical estimates in Section 4, we assume there are three demand factors, corresponding to short- and long-maturity Treasury auctions, and a risky asset. Each factor $\beta^k \in \{\beta_t^s, \beta_t^\ell, \tilde{\beta}_t\}$ evolves according to

$$d\beta_t^k = -(\kappa_\beta \beta_t^k + \phi_{i,\beta} i_t) dt + \sigma_\beta dB_{\beta^k,t},$$

where we impose that the parameters $\kappa_\beta, \phi_{i,\beta}$, and σ_β are identical for each demand factor.

The dynamics of the short rate and payoff process are given by:

$$\begin{aligned} di_t &= -\kappa_i(i_t - \phi_\pi \pi_t - r^*) dt + \sigma_r dB_{r,t}, \\ dd_t &= -\kappa_d(d_t - \psi_x x_t - d^*) dt + \sigma_d dB_{d,t}, \end{aligned}$$

Note that in order to reduce the number of parameters needed to be calibrated, we simplify and assume that the central bank only responds to inflation, and the payoff process only responds to the output gap. We explore sensitivity to these assumptions below.

Finally, we must choose functional forms regarding the effective borrowing weights and the habitat elasticity and demand functions. We assume similar exponential functions as in [Vayanos and Vila \(2021\)](#):

$$\text{habitat elasticity function: } \alpha(\tau) = \alpha_0 \exp(-\alpha_1 \tau), \quad (27)$$

$$\text{habitat demand functions: } \theta^k(\tau) = \theta_0 \tau (\theta_1^k)^2 \exp(-\theta_1^k \tau), \quad (28)$$

$$\text{effective borrowing weights: } \eta(\tau) = \eta_0 \tau \eta_1^2 \exp(-\eta_1 \tau), \quad (29)$$

with analogous functional forms for $\tilde{\alpha}(\tau), \tilde{\theta}^k(\tau), \tilde{\eta}(\tau)$ (and $\tilde{\eta}_0 = 1 - \eta_0$ so that the weights sum to one). Equation (27) implies that the habitat investor elasticity with respect to (log) price is declining with maturity, and is single-peaked with respect to yields. Similarly, equations (28) and (29) imply that the demand factor and borrowing weights are single-peaked functions. In addition to improving numerical properties of the model, these exponential functional forms allow us some flexibility in capturing key modeling features, such as demand shocks targeted in specific areas of maturity space, without significantly increasing the dimensionality of the problem. The parameters α_0, θ_0 govern the overall size of the habitat elasticity and demand functions, while $\alpha_1, \theta_1^k, \eta_1$ govern the shape as a function of maturity: a lower value of these parameters imply that more of the weight of these functions lies at longer maturities.

In order to impose more discipline on the model, we assume that the habitat demand shocks are identical, except for the shape of the demand factor functions $\theta^s(\tau), \theta^\ell(\tau)$, and $\tilde{\theta}(\tau)$. Specifically, we set $\theta_1^s = 0.5$ and $\theta_1^\ell = 0.2$ to match our regression analysis in Section 4. These choices imply that the short factor is concentrated in short maturities less than 5 years (and the mean of $\theta^s(\tau)$ is 4 years), while the long factor has more weight

in intermediate and long maturities above 7 years (and the mean of $\theta^\ell(\tau)$ is 10 years). We set the parameter $\alpha_1 = 0.1$ such that the habitat elasticity with respect to yields ($\equiv \tau \cdot \alpha(\tau)$) is maximized for the 10-year maturity, since this is often taken as a key benchmark yield by investors. We further assume that the habitat demand and elasticity functions are identical for Treasuries and risky assets: $\alpha(\tau) = \tilde{\alpha}(\tau)$ and $\theta^s(\tau) = \tilde{\theta}(\tau)$.

An important input into our model is the effective borrowing rate weights $\eta(\tau), \tilde{\eta}(\tau)$. If household borrowing responds only to movements in the instantaneous short rate, then the macroeconomic dynamics of the model are identical to a textbook New Keynesian model. Thus, the effective borrowing weights can be thought of broadly as capturing the sensitivity of the macroeconomy to borrowing rates besides the federal funds rate. For our baseline calibration, we assume that the effective borrowing rate only depends on risky rate ($\eta_0 = 0$ and hence $\eta(\tau) = 0$ and only $\tilde{\eta}(\tau)$ is non-zero). Further, we set $\eta_1 = 2$, such that $\tilde{\eta}(\tau)$ peaks at 0.5 years and has an average value of 1 year. Our baseline choice puts a heavy weight on short and intermediate maturities because trading volume in debt markets is concentrated at shorter-term maturities. For instance, estimates from the Securities Industry and Financial Markets Association (SIFMA) show that over the last two decades, trading volume for Treasury securities with maturity of 3 years or less made up about 45% of total trading volume on average (and this ratio was relatively stable, with a minimum and maximum annual value of 41% and 52% respectively). Even within coupon-bearing securities (excluding T-bills), trading volume for Treasury notes with maturity of 3 years or less made up 33% of the trading volume in coupon-bearing Treasury notes and bonds. In comparison, trading volume for Treasury bonds with a maturity of greater than 11 years made up only 8% of the trading volume in coupon-bearing Treasury notes and bonds. Trading volume for corporate debt markets across maturities is less readily available. However, comparing trading volume in corporate bond markets and commercial paper markets (from SIFMA and the Federal Reserve, respectively) further suggests an outsized role of short-maturity rates. For instance, for 2020-2021 the trading volume in commercial paper markets was on average 4 times that of trading volume in corporate debt markets (for securities with maturity of at least one year). In short, our calibration implies that household borrowing is a function of risky borrowing rates (rather than the policy rate), largely concentrated at short and intermediate maturities. We explore the sensitivity of our results to alternative calibrations below.

We jointly estimate the remaining parameters through a moment-matching exercise.¹⁵ We target volatility and cross-correlations of Treasury and corporate yields $y_t^{(\tau)}, \tilde{y}_t^{(\tau)}$ as

¹⁵Collecting unknown parameters into a vector $\boldsymbol{\rho}$, we estimate the model by choosing $\hat{\boldsymbol{\rho}}$ to minimize the weighted sum of squares: $L(\boldsymbol{\rho}) = \sum_{n=1}^N w_n (\hat{m}_n - m_n(\boldsymbol{\rho}))^2$, where $\{\hat{m}_n\}_{n=1}^N$ are empirical moments and $\{m_n(\boldsymbol{\rho})\}_{n=1}^N$ are model-implied counterparts as a function of $\hat{\boldsymbol{\rho}}$. The terms $\{w_n\}_{n=1}^N$ are weights placed on each target moment. These weights are set to $1/\mathcal{N}_T$ for moments that are a function of maturity, where \mathcal{N}_T is the number of maturities, and 1 otherwise, so that our estimates are not overly influenced by maturity-based moments. Appendix D.1 derives the model-implied moments.

well as inflation and the output gap π_t, x_t .¹⁶ Specifically, we target the following set of moments: i) the volatility of 1-year Treasury yields, 1-year corporate-Treasury spreads, the output gap, and inflation (in levels, 1-year changes, and 1-month changes); ii) the correlation of inflation and 1-year Treasury yields, the correlation of output gap and 1-year corporate-Treasury spreads, and the correlation of inflation and the output gap (in levels); iii) the volatility of the entire term structure of Treasury yields (1-year changes and 1-month changes); iv) the correlation of the entire term structure of Treasury yields and 1-year Treasury yields (1-year changes and 1-month changes); v) the localization regression coefficients from Figure 5. Besides the localization regression coefficients, the data are monthly. Inflation is defined as the year-over-year log change in the Personal Consumption Expenditure price index. The output gap is defined as the cyclical component of Industrial Production using an HP filter. Zero-coupon Treasury yields are from [Gürkaynak et al. \(2007\)](#). Zero-coupon corporate bond yields are from the Treasury’s High Quality Market (HQM) Corporate Bond Yield Curve data. We utilize the HQM data because it is a long-running measure of the term structure of zero-coupon private borrowing rates which are important for macroeconomic activity; however, these rates reflect relatively safe corporate rates (rated A or above). Besides the localization coefficients, moments are computed starting in 1986 (when 30-year yields are available in [Gürkaynak et al. \(2007\)](#)).

By targeting the localization regression coefficients from Figure 5, our model is informed by our empirical localization results, which are well-suited to identify the preferred habitat parameters of our model. We allow only the habitat risk-adjusted parameters ($a \cdot \alpha_0$, $a \cdot \sigma_\beta \cdot \theta_0$, and $a \cdot \phi_{i,\beta}$) to be different in “crisis”, which we target to match the “crisis” localization regression coefficients from Figure 5. All other parameters are assumed to be the same across “crisis” and “non-crisis” periods. Given that the number of observations in the “non-crisis” period is vastly larger than the number of observations in the “crisis” period, we first estimate all of the parameters from the “non-crisis” sample.

The fit of the model is summarized in Figure 6 (moments which depend on maturity) and Panel A of Table 5 (additional moments). Panel B of Table 5 reports our baseline parameter values. Our parameterized model not only picks up the qualitative features of the data but is also successful at matching the data quantitatively. Besides matching a wide variety of volatility and correlation moments across borrowing rates and aggregate variables, the model localization coefficients are close to the data localization coefficients in “crisis” and “non-crisis” periods (Panels A through D of Figure 6). Nonetheless, given the challenges associated with estimating DSGE models, one should treat this parame-

¹⁶The habitat elasticity functions and demand functions enter the solution multiplicatively with risk aversion and demand shock volatility, so they are only identified up to a scaling factor. If shocks to quantity demand for Treasuries and risky assets can be measured directly across all periods (including outside auction times), one can separately identify these parameters. Because such measures are not available, the literature (e.g., [Vayanos and Vila \(2021\)](#)) typically chooses some normalization, such as $\sigma_\beta = 1$. In our auction data, the bid-to-cover ratio captures this information partially; this information is not necessary for our calibration strategy, but we utilize this information in our QE exercises.

terization with caution, and we run extensive sensitivity analysis in Section 5.5.

5.2 Response of the Yield Curve to QE1

To assess the contribution of preferred habitat theory to the observed reaction of yields to quantitative easing, we feed a “QE1” shock into our model, compute predicted responses of yields at different maturities, and compare predictions to actual changes in yields. We focus on QE1 because it was arguably the “cleanest” QE shock: there are a clear set of policy announcement events, and the observed response to these events are unlikely to be plagued by anticipation issues relative to later rounds of QE. But in order to accurately capture the relevant features of QE1, we do not treat QE as precisely equivalent to a habitat demand shock in our model. Besides the obvious fact that QE1 was significantly larger than typical private demand shocks, QE1 also occurred unexpectedly, and markets had different expectations about the dynamic properties QE1 compared to typical private demand shocks. Moreover, QE1 simultaneously purchased Treasuries and mortgage-backed securities (MBS), and the profile of maturities was different than in auctions. Thus, in our model QE1 is not a simple rescaling of the habitat demand shocks during auctions. We discuss in detail how we mimic the actual QE1 shock in the model.

Persistence: We assume that this shock was completely unexpected (“MIT shock”), and that afterwards markets expected purchases to be unwound slowly and deterministically:

$$d\beta_t^{QE} = -\kappa_{QE}\beta_t^{QE} dt. \quad (30)$$

We set the inertia parameter $\kappa_{QE} = 0.2$. This magnitude roughly implies that markets expected the Fed to unwind its purchases somewhat faster than holding to maturity (more precisely, the half-life of the purchases is roughly 3.5 years). Ex-post, the MBS holdings roughly followed this process until the reintroduction of MBS purchases during QE3. On the other hand, the Treasuries purchased as part of the Fed’s QE programs were held on the balance sheet for a very long time, and holdings remained elevated well beyond that implied by our parameterization. However, this does not imply that markets expected this ex-ante.¹⁷ We explore the sensitivity of this assumption below.

Composition: QE1 involved purchasing a total of roughly \$1.25 trillion mortgage-backed securities (MBS) and \$300 billion Treasuries, concentrated on intermediate and long-term maturity purchases (over 5 years).¹⁸ Given this focus, we assume the same functional

¹⁷The actual purchases of MBS and Treasuries during QE1 were planned to take place over the 6 months following the March 2009 announcement. The FOMC statements during this time do not make any reference to selling these securities off, but state that the FOMC will “carefully monitor the size and composition of the Federal Reserve’s balance sheet in light of evolving financial and economic developments.” Eventually, the FOMC made clear their policy of Treasury reinvestment. For instance, in Chairman Bernanke’s July 2010 report to Congress, he stated that “the proceeds from maturing Treasury securities are being reinvested in new issues of Treasury securities with similar maturities.”

¹⁸In our analysis, we exclude purchases of agency debt (which accounts for a small fraction of the total

form as in equation (28) for the QE demand function $\theta^{QE}(\tau)$ and set $\theta_1^{QE} = 0.35$, such that the model-implied QE1 purchases are of relatively long-term maturity but in between the maturities of the preferred habitat “short” and “long” factor described above (hence the mean of $\theta^{QE}(\tau)$ is roughly 6 years). These purchases are split up such that roughly 80% of QE1 purchases are risky assets in the model, while the remaining 20% are of safe bonds, in order to match the fraction of actual MBS and Treasury purchases during QE1.

Size: Matching the overall magnitude of QE1 requires a few additional steps. As discussed above, our calibration strategy does not separately identify the size of preferred habitat demand shifts and arbitrageur risk aversion. This allows us to compute the response of yields to a “unit” demand shock $\partial y_t^{(\tau)} / \partial \beta_t$. However, our moment-matching exercise provides no information about the dollar magnitude of a “unit” demand shock in the model, since we only can estimate the product $a \cdot \sigma_\beta \cdot \theta_0$. Our model is meant to capture all the volatility of demand shocks, not just those which occur during auctions. However, we can utilize additional information from Treasury auctions to pin down the dollar magnitude of demand shocks. From Table 2, a unit increase in the bid-to-cover for an auction of intermediate maturities moves 10-year yields by roughly 3 basis points. This movement in the bid-to-cover ratio corresponds to roughly \$30 billion, which we denote by $\Delta\beta_t^{(auc)}$. Hence, we have $\Delta\beta_t^{(auc)} \cdot \partial y_t^{(10)} / \partial \beta_t \approx 3bp$ and can use the model to solve for $\Delta\beta_t^{(auc)}$. Finally, since QE1 was roughly \$1.5 trillion, we have that $\Delta\beta_t^{(QE)} \approx 50 \times \Delta\beta_t^{(auc)}$. To be clear, this does not imply the yield curve response to QE1 is hard-wired to be the same as a (scaled-up) auction demand shock.

Panel A of Figure 7 plots the cumulative change observed in the data and predicted in the model. We use the cumulative change in the yield curve reported in [Krishnamurthy and Vissing-Jorgensen \(2011\)](#) following the 5 major QE1 event dates as the empirical response of the yield curve to QE1. The remarkable consistency between the responses suggests that the actual market reaction to QE1 announcements aligns with the predictions of our model in response to observed shifts in private demand for Treasuries. This finding implies that the *net* effect of other channels of QE (e.g., inflation expectations, forward guidance, signaling) could be smaller than thought before.

5.3 Macroeconomic Effects of Quantitative Easing

While there is extensive research documenting the responses of financial markets to rounds of QE, little is known about how QE affected the broader economy because QE events are so infrequent. We cannot shed more light on this using regression analysis or similar tools, but we can use our calibrated model to quantify the macroeconomic effects of QE.

Panel B of Figure 7 shows that our baseline calibration implies that in terms of macroeconomic effects, on impact QE1 increased output by roughly 0.7 percentage points, and purchases during QE1) given the complexities associated with the health of Freddie Mac and Fannie Mae.

inflation by 0.35 percentage points. These effects then monotonically fall towards zero over the next few years. The cumulative effects are $\int_0^\infty E_0 [x_t] dt \approx 0.53$ percentage points and $\int_0^\infty E_0 [\pi_t] dt \approx 0.6$ percentage points. For comparison, these stimulative effects of QE1 are comparable to a rate cut of roughly 50-75 b.p. in the model, undertaken when financial markets are not distressed (and note that conventional monetary policy rate cuts have a faster degree of mean reversion in our model).¹⁹

5.4 Comparing Quantitative Easing and Tightening

To rein in inflation, central banks are beginning the implementation of quantitative tightening (shrinking their balance sheets through asset sales or a reduction in reinvestment of maturing assets). In our linearized model, QE and QT are mirror images of one another. Differences in the macroeconomic impacts of QE and QT can arise only from differences in the financial environment or in the design of the program. These differences are salient in the context of the Fed’s QT policy, which began in June 2022. First, the Fed is conducting QT in a relatively passive, back-loaded fashion: QT began with a monthly reduction of up to \$30 billion in Treasuries and \$17.5 billion in MBS, with both caps doubling after one quarter. The increasing pace of QT (which was announced in advance) differs from how the Fed conducted QE1. Second, the Fed’s QT has focused more on a reduction of Treasury holdings than MBS, again in contrast with QE1. Third, the maturity composition of QT is shorter than QE1. Fourth, although the Fed has not specified the size of QT, this program is likely to be larger than the purchases undertaken during QE1. Finally, risk-bearing capacity of financial markets is higher now than during QE1.

While there is substantial uncertainty associated with how the Fed will conduct QT going forward, we attempt to parsimoniously capture these salient differences within the model. We assume that the QT sales shock β_t^{QT} is composed of 65% Treasuries and 35% MBS, mimicking the composition of the Fed’s QT balance sheet reduction caps. In line with the maturity composition of the Fed’s balance sheet, we also assume that $\theta_1^{QT} = 0.5$ so that the maturity of the assets sold during QT is shorter than the maturity of assets purchased during QE1 (and the mean of $\theta^{QT}(\tau)$ is 4 years; Appendix Figure B16 compares the change in the Fed’s Treasury holdings by maturity following QE1 and QT). Capturing the passive, back-loaded approach of QT while maintaining the mean-reverting properties necessary in the model requires some additional changes. We posit that β_t^{QT}

¹⁹In our model, there is little difference between (1) the Fed buying assets (and thus reducing assets available to the private market) and (2) the Treasury issuing less debt (and thus reducing assets available to the private market). Thus, while comparing our estimated effect of QE1 and actual data, one should keep in mind that the Treasury increased issuance of debt by approximately \$2.7 trillion between December 2008 and October 2010 (the duration of QE1) relative to the pre-crisis trend. The average maturity of debt issued over this period was 6.4 years. If we assume that this shock to the supply of government debt is as persistent as QE1 (i.e., debt is held to maturity), then QE1 was roughly offsetting the increased supply of Treasuries and the combined macroeconomic effect of changes in government debt due to fiscal and monetary policies was a wash.

is a mixture of an “active” component ($\beta_t^{QT,A}$) and a “passive” component ($\beta_t^{QT,P}$) such that $\beta_t^{QT} = \lambda_{QT}\beta_t^{QT,A} + (1 - \lambda_{QT})\beta_t^{QT,P}$ where

$$d\beta_t^{QT,A} = -\kappa_{QT,A}\beta_t^{QT,A} dt, \quad (31)$$

$$d\beta_t^{QT,P} = -\left(\gamma_{QT,A,P}\beta_t^{QT,A} + \kappa_{QT,P}\beta_t^{QT,P}\right) dt. \quad (32)$$

Thus, QT sales initially are driven by the “active” component $\beta_t^{QT,A}$, which reverts back to steady state just as our QE1 shock (and we choose the same inertia $\kappa_{QT,A} = \kappa_{QE}$). However, the “passive” factor $\beta_t^{QT,P}$ then kicks in, capturing the slow increase in the magnitude of QT sales following the announcement of QT (taken into account by market participants). We choose $\gamma_{QT,A,P} = 1.75$, $\kappa_{QT,P} = 2.25$, and $\lambda_{QT} = 0.25$ so that the QT shock doubles in magnitude after one quarter, peaks after 1 year, and then reverts to half of the peak after roughly 4-5 years. The overall magnitude of the initial QT shock is chosen to be double that of QE1: $\Delta\beta_t^{QT,A} = 2 \times \Delta\beta_t^{QE}$. Thus, while QT sales are smaller than QE1 purchases at the beginning of the program, QT sales eventually surpass QE1 in magnitude, remaining elevated so that the cumulative size of QT is larger than QE1.²⁰

Finally, we choose the risk-adjusted parameters to be equal to 75% of our baseline QE1 calibration. On the one hand, despite increased volatility during COVID-19, many broad measures of financial distress (e.g., the Chicago Fed National Financial Conditions Index) remain significantly below the peaks observed during the Great Recession. On the other hand, some measures of intermediary health like [He et al. \(2016\)](#) which are more closely related to the risk-bearing capacity of arbitrageurs show signs of deterioration in the last year (see Appendix Figure B7). Thus, we split the difference for our baseline QT experiment. However, we view this as a lower bound on risk-bearing capacity (and hence the macroeconomic reactions to QT should be viewed as upper bounds).

Panel C of Figure 7 plots the impulse response of inflation and the output gap to our QT shock. Despite the fact that QT is larger in magnitude than QE1, the macroeconomic effects on impact are somewhat smaller. For instance, the initial response of output and inflation is a decline of between 0.25 and 0.3 percentage points. However, the persistent passive component also generates a longer-lasting effect of QT compared to QE1, and implies that the response of the output gap to QT is hump-shaped rather than monotonic.

The design of QT is in part responsible for the relatively muted response of output and

²⁰Appendix Figure B17 compares the dynamics of QE1 and QT shocks in the model. The Fed has been very clear about the initial timing of the Treasury and MBS caps (e.g., see the [March 2022 FOMC statement](#)). Going forward, the FOMC has stated that they intend to “maintain securities holdings in amounts needed to implement monetary policy efficiently and effectively in its ample reserves regime,” although the FOMC has been reticent regarding what this means quantitatively. But if we take the size of the balance sheet pre-COVID as this target level, then the overall size of QT relative to GDP would be roughly twice the size of QE1 (see also [Ennis and Kirk \(2022\)](#)). Hence, these calibration choices represent our best translation into a mean-reverting shock in the model. Because of the linearity of the model, responses scale one-for-one with the overall size of shocks. All other sensitivity analyses are conducted in Section 5.5.

inflation. However, the key difference between QE1 and QT is the risk-bearing capacity of financial markets. As discussed above, when risk-bearing capacity increases ($a \rightarrow 0$), our model collapses to a textbook New Keynesian model and recovers the standard neutrality results regarding asset purchases or sales. In summary, according to our model QT alone is unlikely to bring down inflation from its historically high levels. The differences in the model-implied effects of QE and QT motivate our subsequent sensitivity analysis for the design of these programs.

5.5 Alternative Designs of Quantitative Easing

We now explore how variations in structural parameters and in the implementation of QE influence the ability to move output and inflation. Because in our model output and inflation co-move strongly in response to QE shocks, we focus on the sensitivity analysis for output responses (Figure 8) and relegate results for inflation to the appendix (Appendix Figure B18). For all sensitivity analyses, we study how the macroeconomic effects vary in our baseline calibration (solid line), and also compare with counterfactual “risky-only” and “Treasury-only” QE policies (dashed and dotted lines, respectively), which are identical to our QE1 calibration but only purchase risky or safe assets.

Risk Appetite: As we discussed above, the power of QE to affect yields at target maturities is high in crisis times and weak in non-crisis times. Consistent with this insight, Panel A of Figure 8 shows that the transmission is highly sensitive to the risk aversion of arbitrageurs. Given that our baseline calibration for “crisis” corresponds to the Great Recession, one has to have a financial crisis of truly unprecedented proportions to materially increase the power of QE-based tools. As a result, the balance of risks appears to be somewhat one-sided: it is difficult to raise the power of QE beyond what was achieved during the Great Recession but it is relatively easy to reduce the power as soon as financial panics calm down. This logic suggests that QE is less effective as a “conventional” tool to the extent that “conventional” entails well-functioning financial markets (and was reflected in our analysis of QT). This finding is true regardless of the design of QE purchases: the counterfactual “risky-only” and “Treasury-only” QE policies have the same pattern as a function of risk aversion.

Risky Asset Uncertainty: We next discuss how the transmission of QE depends on the riskiness of risky assets. Panel B of Figure 8 plots the long-run effect of QE on output as we increase σ_d from the baseline calibration. We find that QE policy has larger macroeconomic effects as risky assets become riskier. The intuition for this can be seen by examining the counterfactual “risky-only” and “Treasury-only” QE policies. Unlike the previous sensitivity exercise, these policies act differently as a function of risky asset uncertainty. As uncertainty increases, the effect of risky asset purchases on output increases. However, the impact of Treasury purchases decreases. Intuitively, when risky

asset payoff uncertainty is very low, Treasuries and risky assets are good substitutes (in the limit of no payoff risk, these two assets become perfect substitutes). In this case, “risky-only” and “Treasury-only” QE policies have similar effects on household borrowing rates, and therefore macroeconomic transmission is similar because the payoff risk extraction channel discussed in Section 4 disappears. However, as risky asset uncertainty increases, Treasuries and risky assets become less substitutable. Now, “risky-only” QE policies are highly effective at moving household borrowing rates (and therefore have larger macroeconomic effects), while “Treasury-only” QE policies have smaller effects.

Unwinding: One practical question for policymakers is how long central banks should hold assets accumulated during QE rounds (e.g., Sims and Wu (2020) and Karadi and Nakov (2020)). To this end, we vary κ_{QE} in equation (30), which governs the unwinding process. Panel C of Figure 8 shows that the effects on output nearly double when comparing very fast and very slow unwinding (the x-axis reports results from $\kappa_{QE} \in (0.05, 1.0)$, implying a half-life of about 14 years to 3 quarters, respectively). Intuitively, if the Fed makes large purchases of assets but then quickly sells those securities, we should not observe large and long-term macroeconomic effects. Rather, it is the cumulative size of QE over time that matters. Hence, policymakers should be clear about how long the central bank expects to hold the securities on its balance sheet. Providing a type of “forward guidance” regarding the expected path of purchases can potentially increase the immediate effectiveness of these policies.

Asset Maturity: The maturity of the assets purchased during QE is one of the key decisions policymakers must make. The x-axis of Panel D of Figure 8 is the maturity of the assets purchased (where a higher value implies shorter maturity). The baseline QE policy has larger macroeconomic effects as the maturity of the purchased assets increases. Long-maturity assets are riskier in terms of duration risk, and hence purchasing these assets amplifies the duration risk extraction channel. However, we again see a dichotomy between the counterfactual “Treasury-only” and “risky-only” QE policies. This is because the payoff risk extraction channel is still active when the duration of the risky asset purchases is short. Hence, while Treasury purchases become ineffective as the maturity becomes very short-term, risky asset purchases still have sizable macroeconomic effects.

Effective Borrowing Weights: Panels E and F explore the robustness of our assumptions regarding the effective borrowing weight function $\eta(\tau)$, which as discussed above is an important input into our model. Panel E of Figure 8 plots the long-run macroeconomic effects of QE as the effective borrowing rate weights become more concentrated at short-term rates (larger values of the x-axis) or at long-term rates (smaller values of the x-axis). As expected, if the macroeconomy is more sensitive to longer-term borrowing rates, QE overall becomes more effective. Because the short end of the term structure is pinned down by the Fed’s policy rate, QE will naturally have larger effects on intermediate Treasury yields. Moreover, given the localization results discussed above, longer maturity

purchases will have larger effects on long-term rates when the risk-bearing capacity of financial markets is relatively low.

Panel F instead varies the weights placed on safe and risky borrowing rates. In the baseline, the effective borrowing rate depends entirely on risky rates (corresponding to the x-axis value of 0). We compare with alternative weights placed on safe borrowing rates, up until the effective rate is only a function of safe rates (corresponding to the x-axis value of 1). As expected, when household borrowing is more sensitive to safe rates, the counterfactual “Treasury-only” QE program becomes more powerful. However, the magnitude of the differences here is small.

Interaction with Conventional Policy: Next we turn to how the macroeconomic effects of QE interact with conventional policy via the standard Taylor rule. Panels G, H, and F vary the Taylor coefficients on inflation ϕ_π , the output gap ϕ_x , and inertia κ_i (respectively). In general, if markets expect the Fed to react to the macroeconomy more quickly and aggressively with the policy rate (corresponding to larger values on the x-axis), then the macroeconomic effects of QE are attenuated. However, for a wide range of coefficient values, the macroeconomic effects of QE are quantitatively similar.

QE Uncertainty: Finally, we assumed that QE1 was completely unanticipated by markets. This may be an accurate representation of the first round of quantitative easing, but over a decade later it is likely that markets now consider the possibility of future QE shocks. To model the recurrent nature of QE, we modify equation (30) and instead assume that QE shocks are described by

$$d\beta_t^{QE} = -\kappa_{QE}\beta_t^{QE} dt + \sigma_{QE} dB_{QE,t}. \quad (33)$$

Hence, whenever $\sigma_{QE} > 0$, QE shocks themselves may lead to additional macroeconomic volatility. Further, risk-averse arbitrageurs must hedge against QE risk, in addition to fundamental sources of risk in the economy.

Panel J of Figure 8 explores the change in long-run macroeconomic volatility as a function of the volatility of QE shocks. $\sigma_{QE} = 0$ is our baseline estimate (marked by the vertical dotted line); the x-axis is the volatility of QE shocks relative to the volatility of habitat demand shocks $\frac{\sigma_{QE}}{\sigma_\beta}$; the y-axis is the the long-run (unconditional) variance of output $Var[x_t]$. The results provide an important note of caution for central bankers: increased uncertainty regarding QE leads to increased macroeconomic volatility. In other words, although policymakers may desire the added flexibility of discretionary QE tools, the downside is that this increases the uncertainty surrounding these policy tools. By communicating clearly the expected path of QE purchases, policymakers should be able to reduce market uncertainty and prevent volatility spillovers from QE into the real economy. This provides additional support for the use of QE rules or forward guidance regarding

asset purchases in the spirit of [Greenwood et al. \(2016\)](#).²¹

6 Concluding Remarks

Quantitative easing programs during the Great Recession were a massive policy experiment. The redeployment of QE in response to the COVID-19 crisis and the current reversal through quantitative tightening is a testament to policymakers' belief in their effectiveness. But the precise channels through which QE policies work are still not clear, and so this paper seeks to unbundle QE by isolating one specific channel. Our focus is “preferred habitat,” which hypothesizes that there are investor clienteles with specific preferences for bonds within a given maturity segment. Utilizing Treasury auctions, we identify shifts in *private* demand for Treasuries that mimic QE, but are independent of all other plausible channels of QE. We develop and confirm a key “localization” test of preferred habitat theory: when risk-bearing capacity is low, purchase or sale shocks of specific bonds in a given maturity segment have larger effects on bonds within this range. We then develop a general equilibrium preferred habitat model, using our demand shock results to discipline the model calibration. Our quantitative results are consistent with the view that QE programs worked largely through preferred habitat forces, and that QE is a useful (but modest) policy tool for macroeconomic stabilization during crises. However, the effects of QE weaken if financial markets are well-functioning, the holding period of assets purchases is short, or the program focuses on safer, shorter-duration assets. Further, uncertainty about future QE/QT rounds can lead to excess macroeconomic volatility. Given the design of quantitative tightening as well as the prevailing financial environment, our model predicts rather small effects on output and inflation.

Our results suggest several promising directions for future work. First, the demand shocks we construct are a potentially important input to evaluate a host of quantity-based asset pricing theories. Second, while we have focused on preferred habitat in the market for Treasuries and other debt securities, this channel may be relevant for other arenas, too. For example, we document suggestive evidence supporting state-dependence of demand shock spillovers to mortgage-backed securities, and possibly to equities. In a similar spirit, [Greenwood et al. \(2020\)](#) and [Gourinchas et al. \(2022\)](#) explore preferred habitat effects in currency markets and international bond markets. Finally, preferred habitat is one of many financial frictions relevant for economic agents. It will be interesting to explore how preferred habitat interacts with debt vs. equity structure of firms, liquidity constraints, and banking frictions. Apart from clarifying the distributional aspects of QE-like policies, this extension could also shed more light on how preferred habitat can affect investment.

²¹Additional robustness exercises are reported in Appendix Figures [B19](#) and [B20](#).

Appendix A Proofs

Proof of Lemma 1. Collect all state and jump variables in a vector $\mathbf{Y}_t = [\mathbf{y}_t^\top \ \mathbf{x}_t^\top]^\top$. The interest rate process (12), risky asset payoff process (13), and habitat demand factor processes (11) are all affine functions of \mathbf{Y}_t . Moreover, the (linearized) Phillips curve (14) and IS equation (15) are also affine functions of \mathbf{Y}_t , since from equation (16) $\hat{r}_t = \hat{\mathbf{A}}^\top \mathbf{y}_t + \hat{C}$ is affine in the state variables. Aggregate dynamics can thus be written

$$d\mathbf{Y}_t = -\Upsilon (\mathbf{Y}_t - \bar{\mathbf{Y}}) dt + \mathbf{S} d\mathbf{B}_t. \quad (\text{A1})$$

Note that Υ depends on $\hat{\mathbf{A}}$, but which we currently take as given. Then the rational expectations equilibrium is found immediately from Buiter (1984). Partition the eigenvalues and eigenvectors as follows:

$$\Upsilon = \mathbf{Q}\Lambda\mathbf{Q}^{-1}, \quad \Lambda = \begin{bmatrix} \Lambda_1 & \mathbf{0} \\ \mathbf{0} & \Lambda_2 \end{bmatrix}, \quad \mathbf{Q} = \begin{bmatrix} \mathbf{Q}_{11} & \mathbf{Q}_{12} \\ \mathbf{Q}_{21} & \mathbf{Q}_{22} \end{bmatrix},$$

where the partitions correspond to the state \mathbf{y}_t and jump \mathbf{x}_t variables. If the number of “stable” eigenvalues (non-negative real parts) equals the number of state variables, then the rational expectations equilibrium dynamics are given by (17) and (18), where

$$\Gamma = \mathbf{Q}_{11}\Lambda_1\mathbf{Q}_{11}^{-1}, \quad \Omega = \mathbf{Q}_{21}\mathbf{Q}_{11}^{-1}. \quad (\text{A2})$$

□

Proof of Lemma 2. Since asset prices are given by (19) and the state evolves according to (17), Ito’s Lemma implies that $\frac{dP_t^{(\tau)}}{P_t^{(\tau)}} = \mu_t^{(\tau)} dt + \boldsymbol{\sigma}^{(\tau)} d\mathbf{B}_t$, with $\boldsymbol{\sigma}^{(\tau)} = -\mathbf{A}(\tau)^\top \boldsymbol{\sigma}$ and

$$\mu_t^{(\tau)} = \mathbf{A}'(\tau)^\top \mathbf{y}_t + C'(\tau) + \mathbf{A}(\tau)^\top \Gamma (\mathbf{y}_t - \bar{\mathbf{y}}) + \frac{1}{2} \mathbf{A}(\tau)^\top \Sigma \mathbf{A}(\tau), \quad (\text{A3})$$

where $\Sigma \equiv \boldsymbol{\sigma}\boldsymbol{\sigma}^\top$ and with analogous expressions for $\tilde{P}_t^{(\tau)}$. Then differentiating the arbitrageur budget constraint (7) with respect to holdings $X_t^{(\tau)}$ gives the optimality conditions

$$\mu_t^{(\tau)} - i_t = a \left[\int_0^T X_t^{(\tau)} \mathbf{A}(\tau) + \tilde{X}_t^{(\tau)} \tilde{\mathbf{A}}(\tau) d\tau \right]^\top \Sigma \mathbf{A}(\tau),$$

again with analogous conditions with respect to $\tilde{X}_t^{(\tau)}$.

Substituting equation (19) into the habitat demand equations (10), we can write $Z_t^{(\tau)} = [\alpha(\tau)\mathbf{A}(\tau) - \Theta(\tau)]^\top \mathbf{y}_t$ and $\tilde{Z}_t^{(\tau)} = [\tilde{\alpha}(\tau)\tilde{\mathbf{A}}(\tau) - \tilde{\Theta}(\tau)]^\top \mathbf{y}_t$, where

$$\Theta(\tau) = [\dots \ \theta^k(\tau) \ \dots]^\top, \quad \tilde{\Theta}(\tau) = [\dots \ \tilde{\theta}^k(\tau) \ \dots]^\top. \quad (\text{A4})$$

Then substitute market clearing conditions $X_t^{(\tau)} = -Z_t^{(\tau)}$, $\tilde{X}_t^{(\tau)} = -\tilde{Z}_t^{(\tau)}$ into the optimality conditions and collect terms that are linear in the state \mathbf{y}_t to get:

$$\mathbf{A}'(\tau) + \mathbf{M}\mathbf{A}(\tau) - \mathbf{e}_i = \mathbf{0}, \quad \tilde{\mathbf{A}}'(\tau) + \mathbf{M}\tilde{\mathbf{A}}(\tau) - \mathbf{e}_i = \mathbf{0}, \quad (\text{A5})$$

where \mathbf{M} is given by equation (21). Taking \mathbf{M} as given, this is a linear system of differential equations. To derive initial conditions, note that at maturity, the riskless bonds pay \$1 while the risky asset pays D_t , so the $\tau = 0$ prices are given by $P_t^{(0)} = 1$, $\tilde{P}_t^{(0)} = D_t$. Hence, we have $\mathbf{A}(0) = \mathbf{0}$, $\tilde{\mathbf{A}}(0) = -\mathbf{e}_d$. Then assuming \mathbf{M} is diagonalizable and invertible, the solution is given by equation (20). □

Proof of Proposition 1. In an affine equilibrium where asset prices are given by equation (19), we have that $\hat{r}_t = \int_0^T (\eta(\tau)\mu_t^{(\tau)} + \tilde{\eta}(\tau)\tilde{\mu}_t^{(\tau)}) d\tau$. Substituting equations (A3) and (A5) into this expression and collecting terms which are linear in the state \mathbf{y}_t gives equation (22). Equilibrium is the solution of the fixed point problem implicitly defined by equations (21) and (22). Rewrite these conditions in the following function:

$$f(\hat{\mathbf{A}}; \mathbf{M}; a) = \begin{bmatrix} \mathbf{e}_i + \left(\mathbf{\Gamma}(\hat{\mathbf{A}})^\top - \mathbf{M} \right) \boldsymbol{\nu}(\mathbf{M}) - \hat{\mathbf{A}} \\ \text{vec} \left\{ \mathbf{\Gamma}(\hat{\mathbf{A}})^\top - a \cdot \boldsymbol{\Lambda}(\mathbf{M}) - \mathbf{M} \right\} \end{bmatrix}, \quad (\text{A6})$$

where $\boldsymbol{\Lambda}(\mathbf{M})$ and $\boldsymbol{\nu}(\mathbf{M})$ are the integral terms from equations (21) and (22). In both cases, dependence on \mathbf{M} comes through the affine coefficients $\mathbf{A}(\tau)$, $\tilde{\mathbf{A}}(\tau)$. We have also made explicit the dependence of $\mathbf{\Gamma}$ on $\hat{\mathbf{A}}$, which can be seen in the proof of Lemma 1. If $J \equiv \dim \mathbf{y}_t$, then $\dim \mathbf{M} = J \times J$ and $\dim \hat{\mathbf{A}} = J$ and the function $f : \mathbb{R}^{J(J+1)+1} \rightarrow \mathbb{R}^{J(J+1)}$. For any value of a , equilibrium is defined by $f(\hat{\mathbf{A}}; \mathbf{M}; a) = \mathbf{0}$.

We now analyze the solution in a neighborhood around $a = 0$. For $a = 0$, clearly $\hat{\mathbf{A}} = \mathbf{e}_i$ and $\mathbf{M} = \mathbf{\Gamma}(\mathbf{e}_i)^\top$. The partial derivatives evaluated at this point are given by:

$$\frac{\partial f}{\partial \hat{\mathbf{A}}_j} = \begin{bmatrix} \left[\frac{\partial \mathbf{\Gamma}^\top}{\partial \hat{\mathbf{A}}_j} \right] \boldsymbol{\nu}(\mathbf{M}) - \mathbf{e}_j \\ \text{vec} \left[\frac{\partial \mathbf{\Gamma}^\top}{\partial \hat{\mathbf{A}}_j} \right] \end{bmatrix}, \quad \frac{\partial f}{\partial \mathbf{M}_{kl}} = \begin{bmatrix} \mathbf{e}_k \mathbf{e}_l^\top \boldsymbol{\nu}(\mathbf{M}) \\ - \text{vec} \mathbf{e}_k \mathbf{e}_l^\top \end{bmatrix},$$

where $\mathbf{e}_j, \mathbf{e}_k, \mathbf{e}_l$ are standard normal basis vectors. The matrix $\frac{\partial \mathbf{\Gamma}}{\partial \hat{\mathbf{A}}_j}$ is the derivative of the state dynamics matrix $\mathbf{\Gamma}$ with respect to the j -element of $\hat{\mathbf{A}}$; because this depends on derivatives of the eigendecomposition defined in the proof of Lemma 1, even in the case of $a = 0$ this is a complicated expression. Nevertheless, from this we can show that the Jacobian of f with respect to $\hat{\mathbf{A}}, \mathbf{M}$ evaluated at the $a = 0$ solution has full rank. In fact,

writing this Jacobian in block form, we have

$$Df \equiv \begin{bmatrix} \mathbf{D}_{11} & \mathbf{D}_{12} \\ \mathbf{D}_{21} & -\mathbf{I}_{J^2} \end{bmatrix}, \quad (\text{A7})$$

and $\mathbf{D}_{12} = \begin{bmatrix} \mathbf{I}_J \cdot \nu_1 & \dots & \mathbf{I}_J \cdot \nu_J \end{bmatrix}$, where ν_j is the j -element of $\boldsymbol{\nu}(\mathbf{M})$. Then it can be easily shown that the elementary row operations which transform \mathbf{D}_{12} into the zero matrix simultaneously transform \mathbf{D}_{11} into $-\mathbf{I}_J$. Hence, $\det Df = 1$ and the result follows from the implicit function theorem. □

References

- Beetsma, R., Giuliodori, M., de Jong, F., and Widijanto, D. (2016). Price effects of sovereign debt auctions in the euro-zone: The role of the crisis. *Journal of Financial Intermediation*, 25(C):30–53.
- Beetsma, R., Giuliodori, M., Hanson, J., and de Jong, F. (2018). Bid-to-cover and yield changes around public debt auctions in the euro area. *Journal of Banking & Finance*, 87(C):118–134.
- Bernanke, B. S. and Kuttner, K. N. (2005). What Explains the Stock Market’s Reaction to Federal Reserve Policy? *Journal of Finance*, 60(3):1221–1257.
- Bhattarai, S. and Neely, C. J. (2020). An analysis of the literature on international unconventional monetary policy. *FRB St. Louis Working Paper*, (2016-21C).
- Bretschler, L., Schmid, L., Sen, I., and Sharma, V. (2022). Institutional Corporate Bond Pricing. Swiss Finance Institute Research Paper 21-07, Swiss Finance Institute.
- Buiter, W. H. (1984). Saddlepoint Problems in Continuous Time Rational Expectations Models: A General Method and Some Macroeconomic Examples. *Econometrica*, 52(3):665–680.
- Cahill, M. E., D’Amico, S., Li, C., and Sears, J. S. (2013). Duration risk versus local supply channel in Treasury yields: evidence from the Federal Reserve’s asset purchase announcements. Finance and Economics Discussion Series 2013-35, Board of Governors of the Federal Reserve System (U.S.).
- Cammack, E. B. (1991). Evidence on Bidding Strategies and the Information in Treasury Bill Auctions. *Journal of Political Economy*, 99(1):100–130.
- Campbell, J. R., Evans, C. L., Fisher, J. D., and Justiniano, A. (2012). Macroeconomic Effects of Federal Reserve Forward Guidance. *Brookings Papers on Economic Activity*, 43(1):1–80.
- Carlstrom, C. T., Fuerst, T. S., and Paustian, M. (2017). Targeting Long Rates in a Model with Segmented Markets. *American Economic Journal: Macroeconomics*, 9(1):205–242.
- Chen, H., Cúrdia, V., and Ferrero, A. (2012). The Macroeconomic Effects of Large-scale Asset Purchase Programmes. *Economic Journal*, 122(564):289–315.
- Chodorow-Reich, G. (2014). Effects of Unconventional Monetary Policy on Financial Institutions. *Brookings Papers on Economic Activity*, 45(1):155–227.

- Cúrdia, V. and Woodford, M. (2011). The central-bank balance sheet as an instrument of monetary policy. *Journal of Monetary Economics*, 58(1):54–79.
- D’Amico, S. and King, T. B. (2013). Flow and stock effects of large-scale treasury purchases: Evidence on the importance of local supply. *Journal of Financial Economics*, 108(2):425–448.
- Di Maggio, M., Kermani, A., and Palmer, C. J. (2020). How Quantitative Easing Works: Evidence on the Refinancing Channel. *Review of Economic Studies*, 87(3):1498–1528.
- Ennis, H. and Kirk, K. (2022). Projecting the Evolution of the Fed’s Balance Sheet. 22-15, Federal Reserve Bank of Richmond Economic Brief.
- Fieldhouse, A. J., Mertens, K., and Ravn, M. O. (2018). The Macroeconomic Effects of Government Asset Purchases: Evidence from Postwar U.S. Housing Credit Policy. *Quarterly Journal of Economics*, 133(3):1503–1560.
- Fleming, M. J. (2007). Who buys treasury securities at auction? *Federal Reserve Bank of New York Current Issues in Economics and Finance*, 13(1).
- Fleming, M. J. and Liu, W. (2016). Intraday pricing and liquidity effects of us treasury auctions.
- Forest, J. J. (2018). The Effect of Treasury Auction Results on Interest Rates: The 1990s Experience. Technical report, University of Massachusetts - Amherst.
- Gali, J. (2015). *Monetary Policy, Inflation, and the Business Cycle: An Introduction to the New Keynesian Framework and its Applications*. Princeton University Press.
- Garbade, K. D. and Ingber, J. F. (2005). The Treasury auction process: objectives, structure, and recent acquisitions. *Current Issues in Economics and Finance*, 11(Feb).
- Gertler, M. and Karadi, P. (2011). A model of unconventional monetary policy. *Journal of Monetary Economics*, 58(1):17 – 34. Carnegie-Rochester Conference Series on Public Policy: The Future of Central Banking April 16-17, 2010.
- Gorodnichenko, Y. and Ray, W. (2017). The Effects of Quantitative Easing: Taking a Cue from Treasury Auctions. NBER Working Papers 24122, National Bureau of Economic Research, Inc.
- Gourinchas, P.-O., Ray, W., and Vayanos, D. (2022). A Preferred-Habitat Model of Term Premia, Exchange Rates, and Monetary Policy Spillovers. Working paper 29875, NBER.
- Greenlaw, D., Hamilton, J. D., Harris, E., and West, K. D. (2018). A Skeptical View of the Impact of the Feds Balance Sheet. NBER Working Papers 24687, National Bureau of Economic Research, Inc.
- Greenwood, R., Hanson, S., Stein, J., and Sunderam, A. (2020). A Quantity Driven Theory of Risk Premiums and Exchange Rates. Working paper 27615, NBER.
- Greenwood, R., Hanson, S. G., and Vayanos, D. (2016). Forward Guidance in the Yield Curve: Short Rates versus Bond Supply. In Albagli, E., Saravia, D., and Woodford, M., editors, *Monetary Policy through Asset Markets: Lessons from Unconventional Measures and Implications for an Integrated World*, Central Banking, Analysis, and Economic Policies Book Series, pages 11–62. Central Bank of Chile.
- Greenwood, R. and Vayanos, D. (2014). Bond supply and excess bond returns. *Review of Financial Studies*, 27(3):663–713.
- Gürkaynak, R. S., Sack, B., and Wright, J. H. (2007). The U.S. Treasury yield curve: 1961 to the present. *Journal of Monetary Economics*, 54(8):2291 – 2304.
- Hamilton, J. D. and Wu, J. C. (2012). The Effectiveness of Alternative Monetary Policy Tools in a Zero Lower Bound Environment. *Journal of Money, Credit and Banking*, 44:3–46.

- He, Z., Kelly, B., and Manela, A. (2016). Intermediary asset pricing: New evidence from many asset classes. Working Paper 21920, National Bureau of Economic Research.
- He, Z. and Krishnamurthy, A. (2013). Intermediary Asset Pricing. *American Economic Review*, 103(2):732–770.
- Kaminska, I. and Zinna, G. (2020). Official demand for u.s. debt: Implications for u.s. real rates. *Journal of Money, Credit and Banking*, 52(2-3):323–364.
- Karadi, P. and Nakov, A. (2020). Effectiveness and addictiveness of quantitative easing. *Journal of Monetary Economics*.
- King, T. (2019a). Duration Effects in Macro-Finance Models of the Term Structure. Technical report.
- King, T. B. (2019b). Expectation and duration at the effective lower bound. *Journal of Financial Economics*, 134(3):736–760.
- Koijen, R. S., Koulischer, F., Nguyen, B., and Yogo, M. (2021). Inspecting the mechanism of quantitative easing in the euro area. *Journal of Financial Economics*, 140(1):1–20.
- Koijen, R. S. J. and Yogo, M. (2019). A Demand System Approach to Asset Pricing. *Journal of Political Economy*, 127(4):1475–1515.
- Koijen, R. S. J. and Yogo, M. (2022). Understanding the Ownership Structure of Corporate Bonds. NBER Working Papers 29679, National Bureau of Economic Research, Inc.
- Krishnamurthy, A. and Vissing-Jorgensen, A. (2011). The effects of quantitative easing on interest rates: Channels and implications for policy. *Brookings Papers on Economic Activity*, (2):215–265.
- Krishnamurthy, A. and Vissing-Jorgensen, A. (2012). The aggregate demand for Treasury debt. *Journal of Political Economy*, 120(2):233–267.
- Kuttner, K. N. (2001). Monetary policy surprises and interest rates: Evidence from the Fed funds futures market. *Journal of Monetary Economics*, 47(3):523–544.
- Kyle, A. S. and Xiong, W. (2001). Contagion as a Wealth Effect. *Journal of Finance*, 56(4):1401–1440.
- Li, C. and Wei, M. (2013). Term Structure Modeling with Supply Factors and the Federal Reserve’s Large-Scale Asset Purchase Programs. *International Journal of Central Banking*, 9(1):3–39.
- Lou, D., Yan, H., and Zhang, J. (2013). Anticipated and Repeated Shocks in Liquid Markets. *Review of Financial Studies*, 26(8):1891–1912.
- Martin, C. and Milas, C. (2012). Quantitative easing: a sceptical survey. *Oxford Review of Economic Policy*, 28(4):750–764.
- Peng, C. and Wang, C. (2022). Factor Demand and Factor Returns. Technical report.
- Ray, W. (2019). Monetary policy and the limits to arbitrage: Insights from a new keynesian preferred habitat model. Working paper.
- Romer, C. D. and Romer, D. H. (2017). New evidence on the aftermath of financial crises in advanced countries. *American Economic Review*, 107(10):3072–3118.
- Sims, E. and Wu, J. C. (2020). Evaluating central banks tool kit: Past, present, and future. *Journal of Monetary Economics*.
- Vayanos, D. and Vila, J. (2021). A Preferred-Habitat Model of the Term Structure of Interest Rates. *Econometrica*, 89(1):77–112.
- Wright, J. H. (2012). What does monetary policy do to long-term interest rates at the zero lower bound? *Economic Journal*, 122(564):F447–F466.

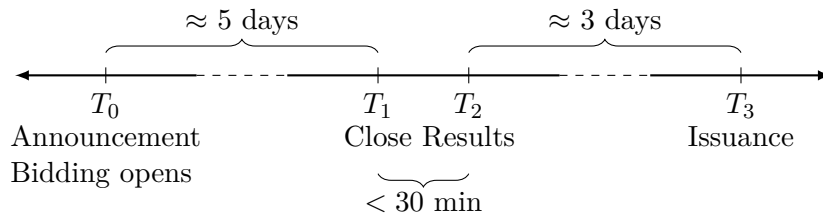


Figure 1: Auction Timing

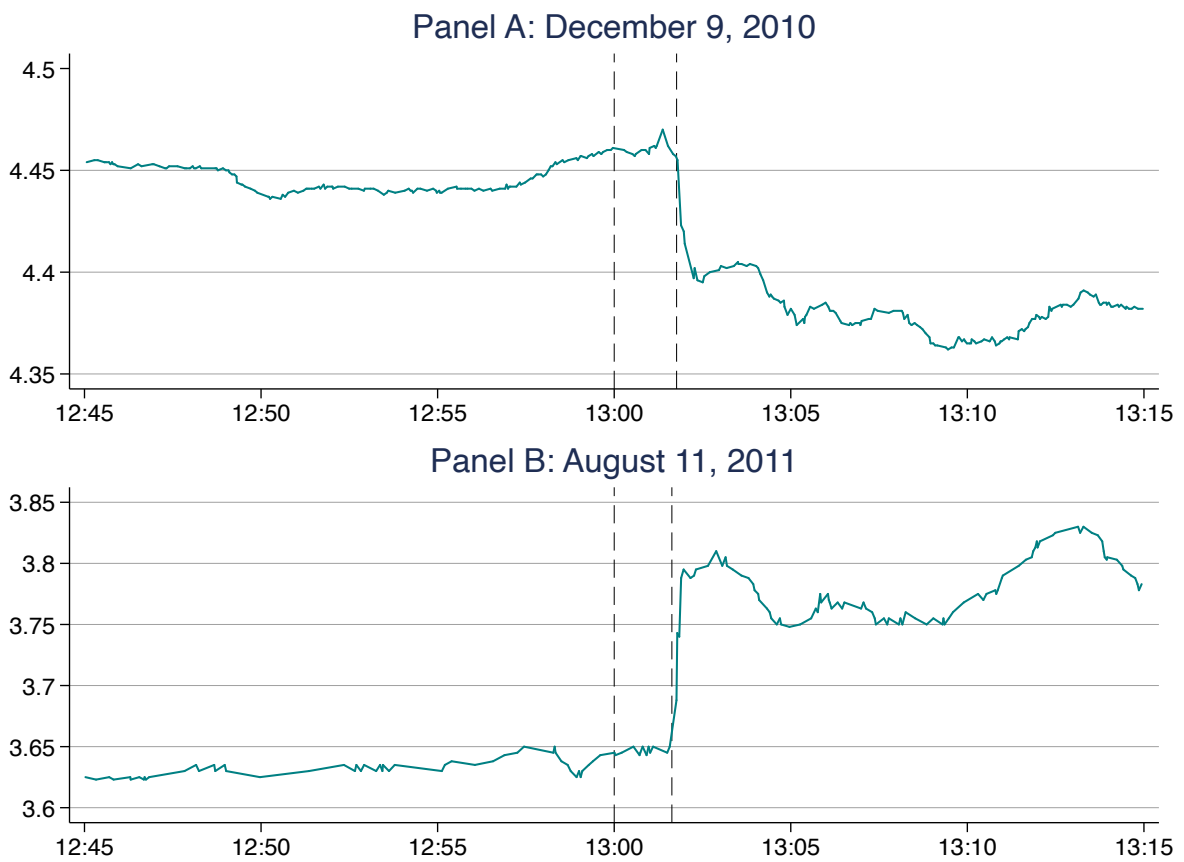


Figure 2: Intraday Treasury Yield Movements

Notes: Intraday movements in 30-year Treasury yields around the announcement of auction results for two selected auction dates. Dashed vertical lines denote the close of an auction and release of results. In both auctions considered, auctions closed at 1:00pm and results were released a few minutes thereafter.

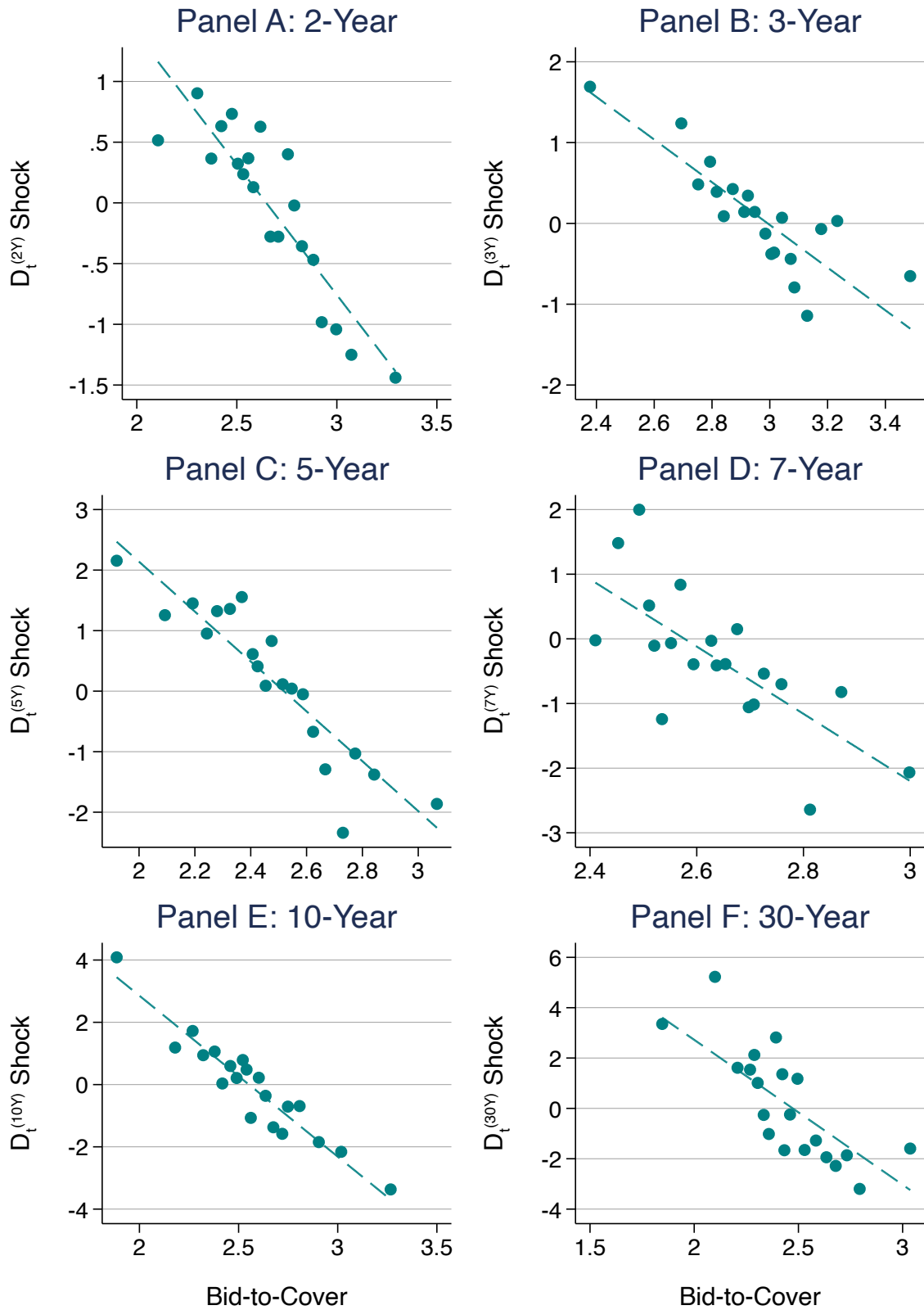


Figure 3: Demand Shocks and the Bid-to-Cover

Notes: Binned scatter plots examining the relationship between demand shocks and the bid-to-cover ratio across auctions. The bid-to-cover is the ratio of the dollar value of bids received to those accepted at a given auction. Each figure controls for four lags of the bid-to-cover.

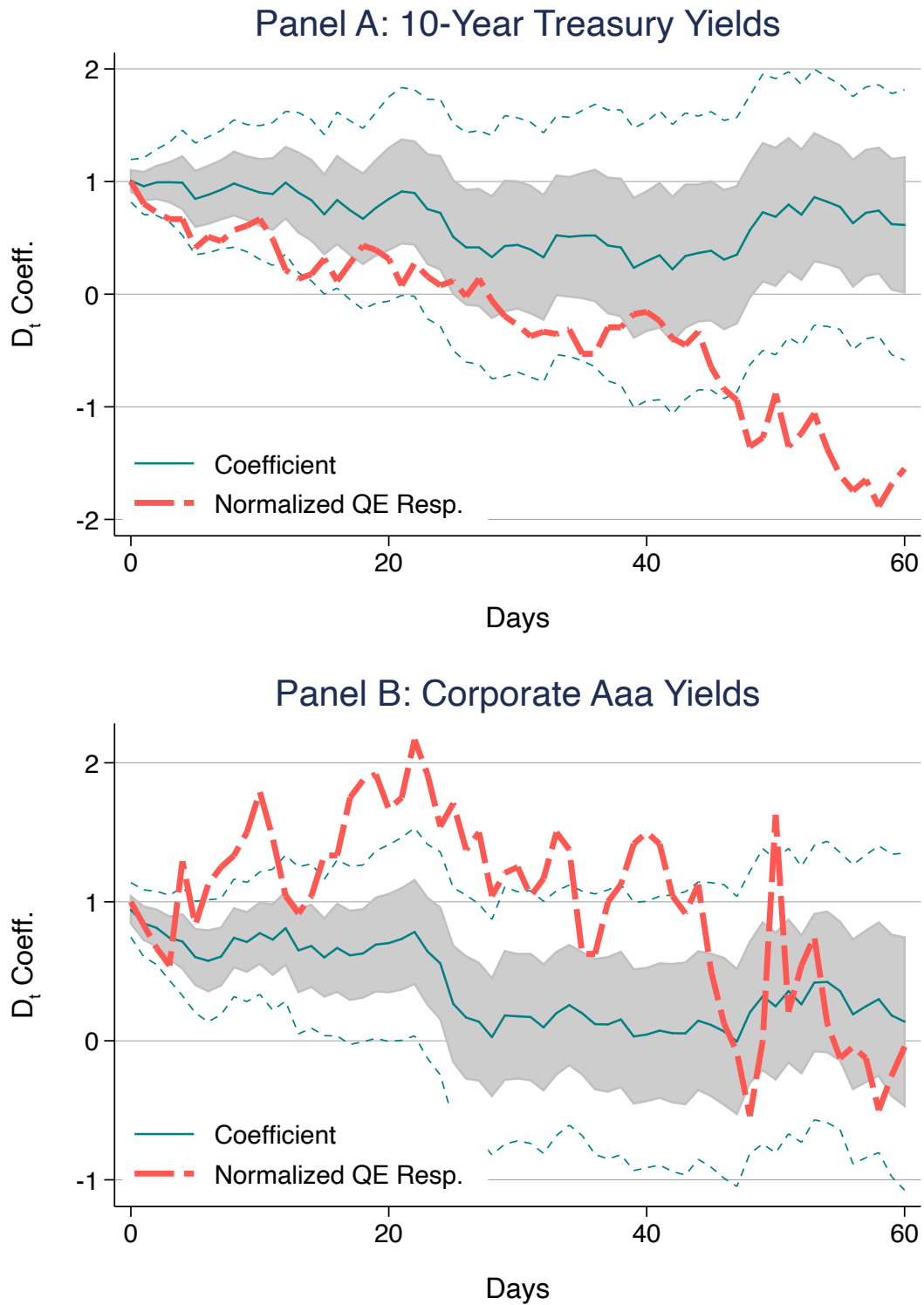


Figure 4: Long-Difference Response to Demand Shocks

Notes: Responses of 10-year Treasury spot rates (Panel A) and Moody's Aaa yields (Panel B) to demand shocks D_t (pooled across maturities). We compute "long-difference" regressions: on an auction date t , the dependent variable is $y_{t+h} - y_{t-1}$, the change h days after the auction relative to the day before the auction. The solid line plots the coefficients from regressions for $h = 0, \dots, 60$; the shaded region and dotted lines correspond to one- and two-standard error (Newey-West, 9 lags) confidence bands. The dashed line compares the long-horizon effects of the March 2009 QE1 FOMC announcement (normalized so that the impact on announcement is one).

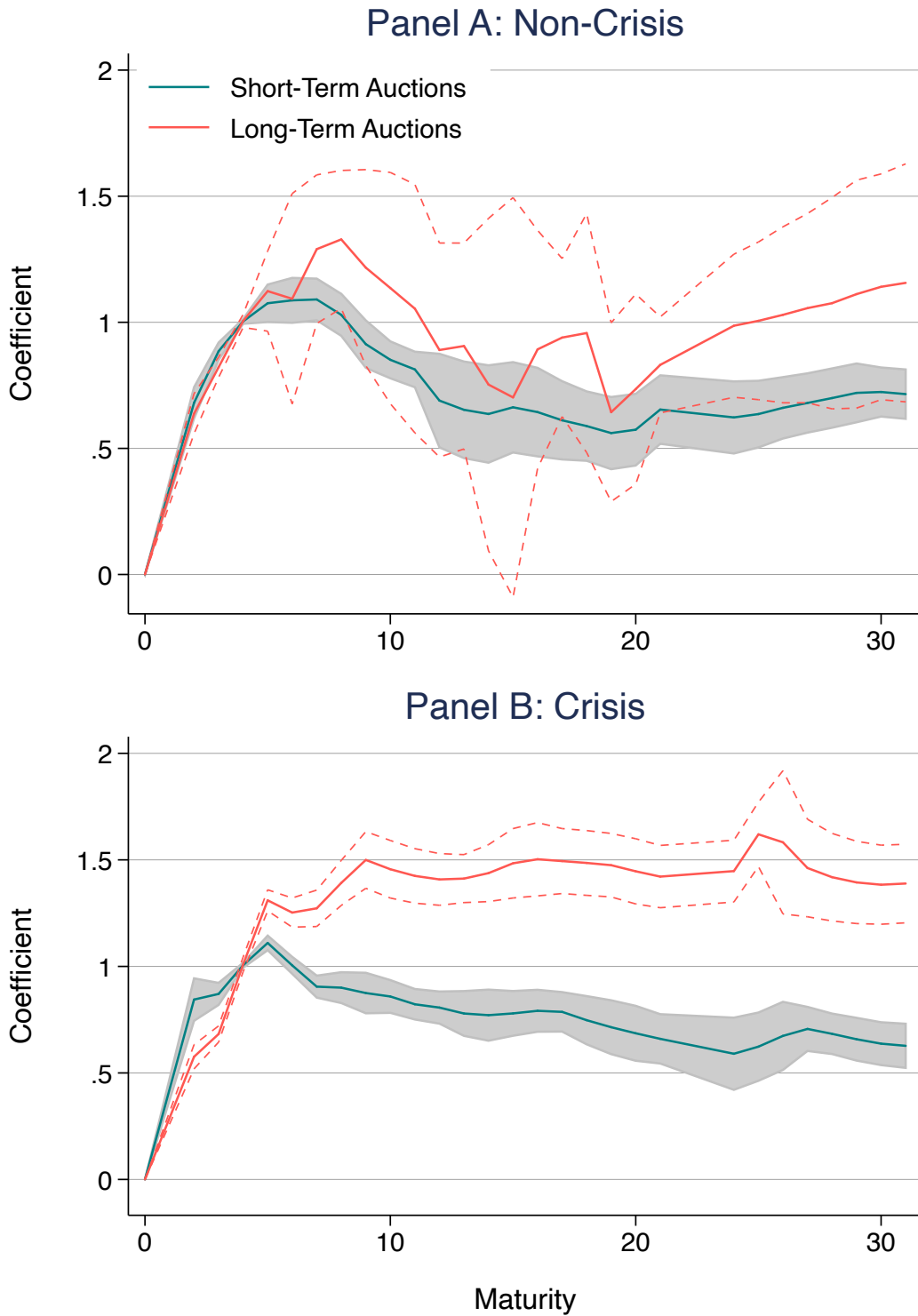


Figure 5: Localization Regression Results

Notes: Plots of the regression coefficients from regression equation (26). The top panel compares estimates from short- and long-maturity auctions during non-crisis periods; the bottom panel compares these estimates during crisis periods. 2 standard error (Newey-West, 9 lags) confidence intervals are included. Appendix Figure B6 reports p-values for the equality of estimates.

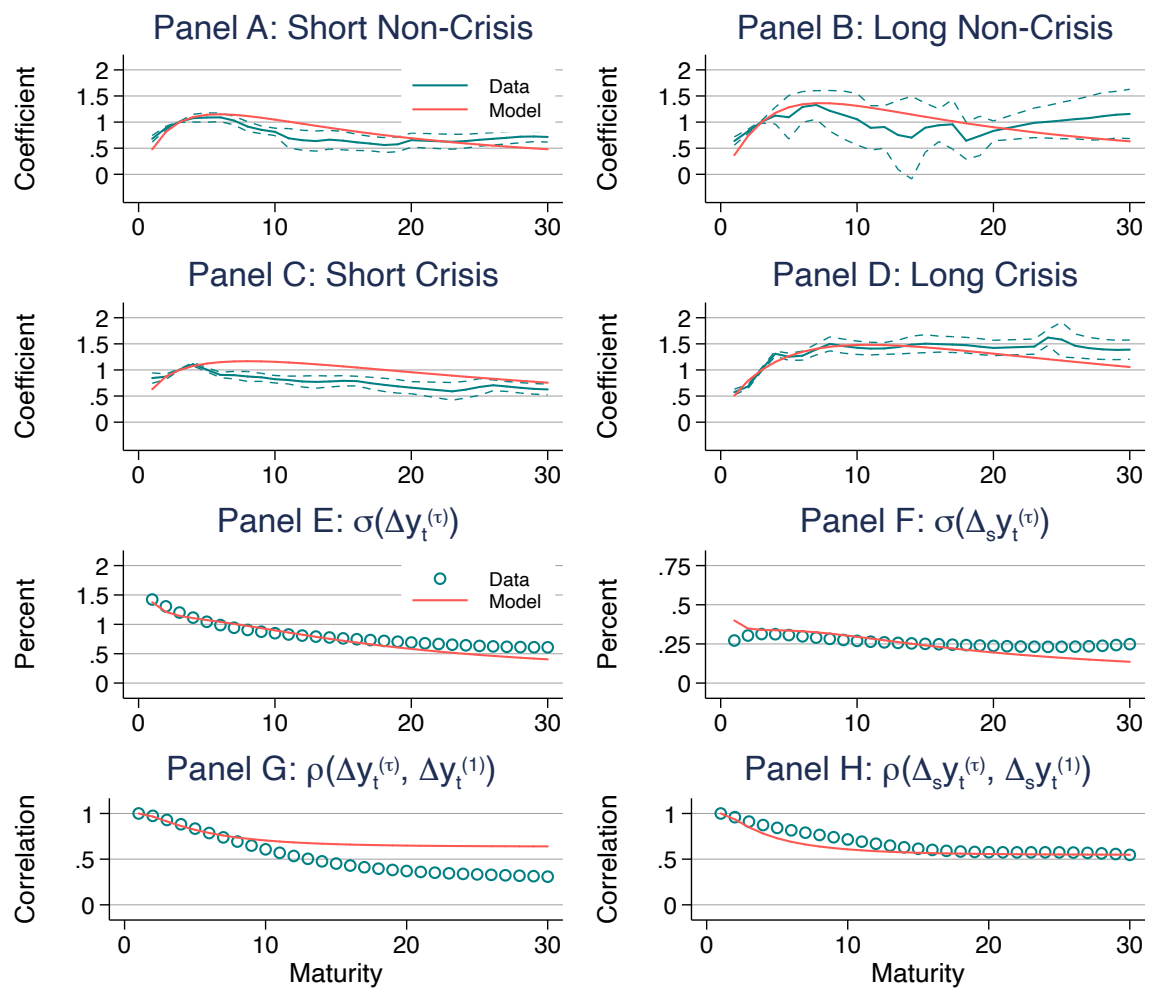


Figure 6: Model Fit

Notes: Panels A through D plot the model-implied and empirical coefficients from regression equation (26); th panels A and B plot the coefficients from the model calibrated to non-crisis periods, while the panels C and D plot the coefficients from the model calibrated to crisis periods. Panels E through H compare additional targeted volatility and correlation moments in the model (solid lines) with the data (scatter points) as a function of maturity.

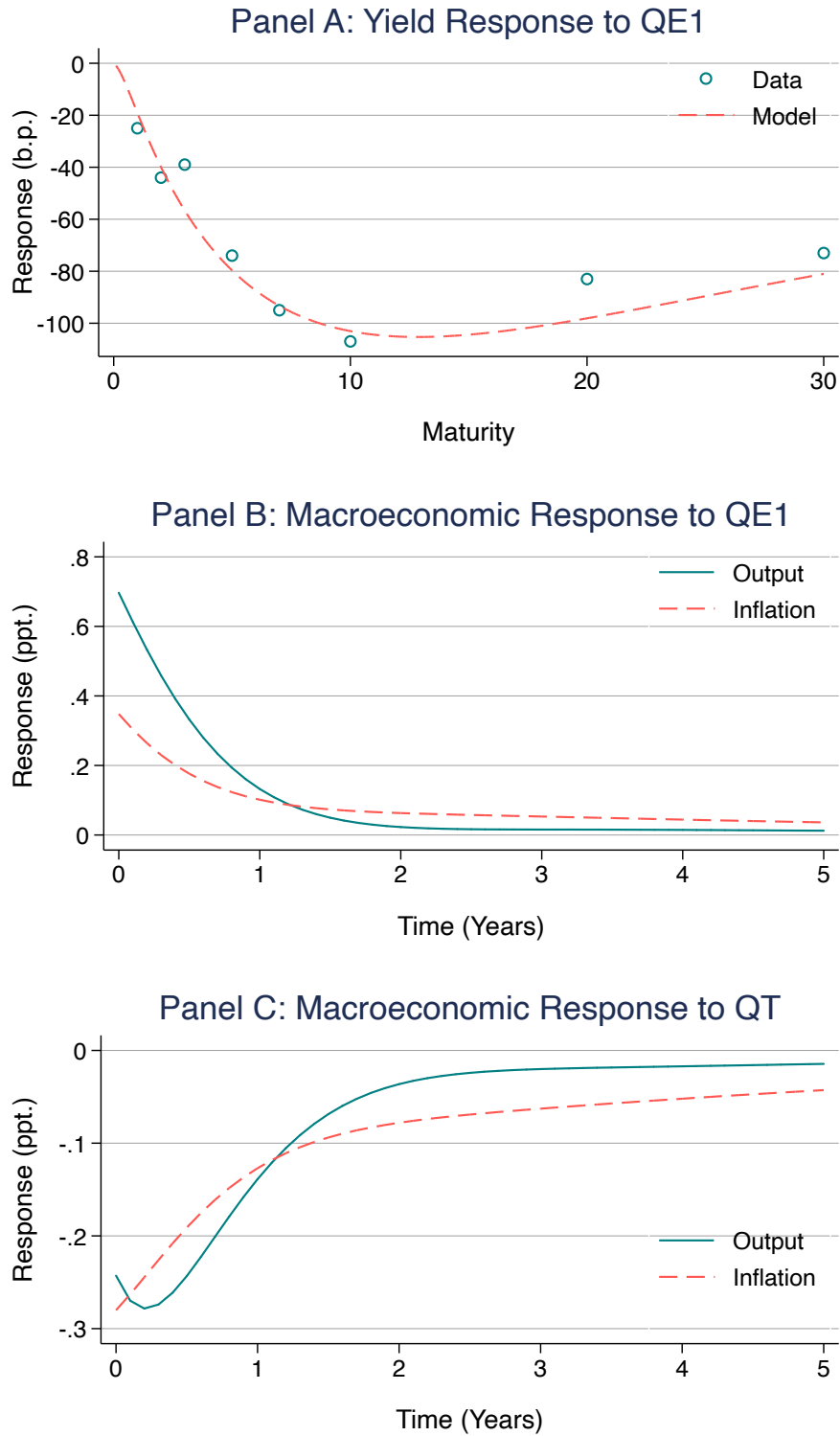


Figure 7: Model-Implied Response to QE1 and QT

Notes: Panel A compares the observed (cumulative) yield reactions and the model-implied change in yields following a QE1 shock (in basis points). Panels B and C plot the model-implied IRFs of output and inflation following QE1 and QT, respectively (in percentage points).

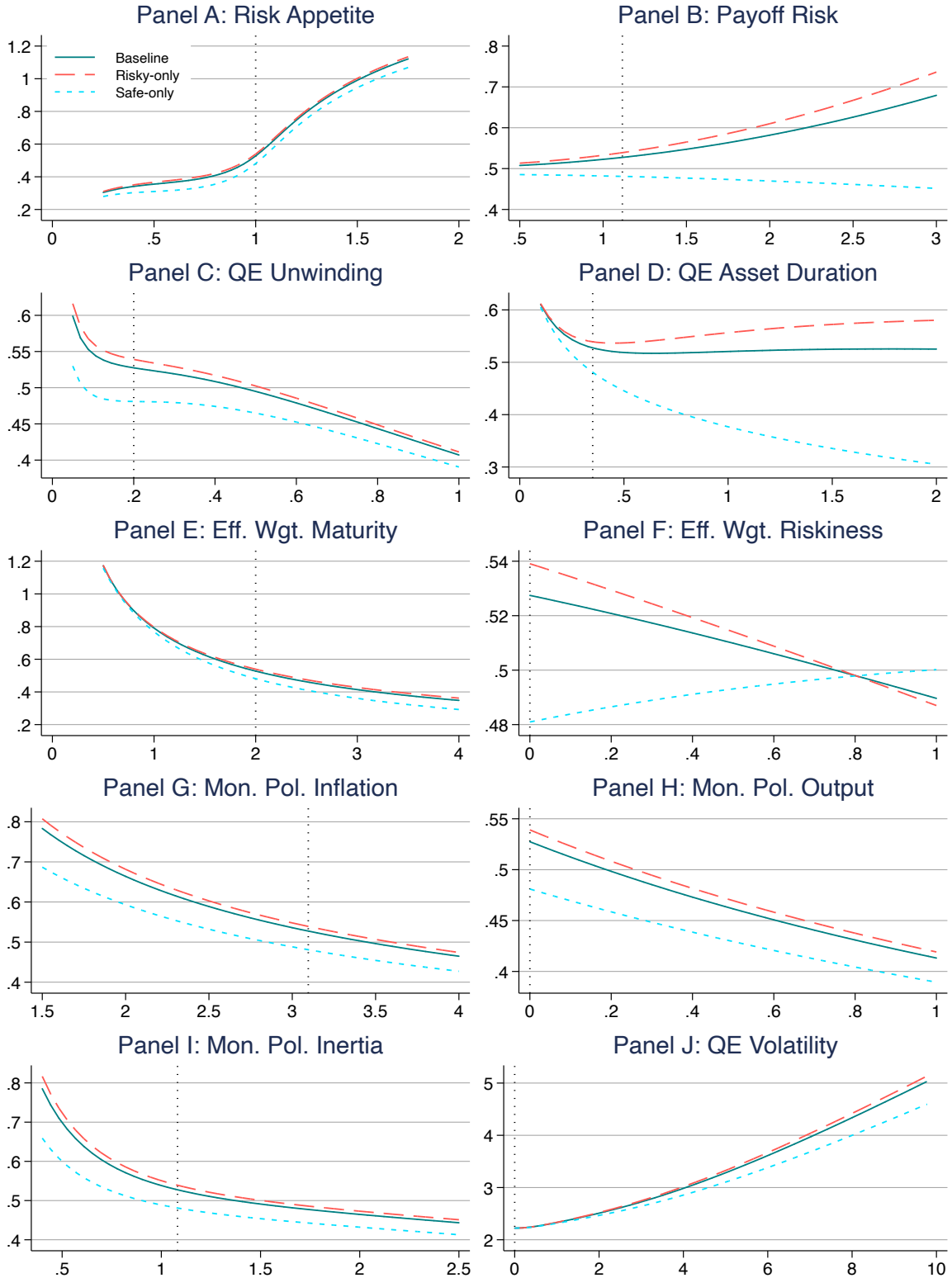


Figure 8: QE Sensitivity Analysis: Output

Notes: Response of output to a QE shock as a function of various model parameters. Panel A: arbitrageur risk aversion (a). Panel B: risky payoff uncertainty (σ_d). Panel C: QE mean reversion (κ_{QE}). Panel D: QE maturity duration (θ_1^{QE}). Panel E: effective borrowing maturity weights (η_1). Panel F: effective borrowing risky/safe weights (η_0). Panel G: inflation Taylor coefficient (ϕ_π). Panel H: output gap Taylor coefficient (ϕ_x). Panel I: inertia Taylor coefficient (κ_i). Panel J: QE volatility (σ_{QE}). In each panel, the vertical dashed line corresponds to the baseline QE calibration. The dashed orange line shows results for a hypothetical QE policy which purchases risky assets only; similarly, the dotted blue line is for Treasury-only purchases. Panel J reports the long-run volatility $Var[x_t]$, while all other panels report the cumulative effect following the QE shock $\int_0^\infty E_0[x_t] dt$.

Table 1: Auction and Shock Summary Statistics

	Mean	Median	Std. Dev.	Min	Max	Obs.
Panel A: Auction Summary Statistics						
Offering Amount (billions)	22.48	22.00	9.02	5.00	44.00	1047
Total Tendered (billions)	61.98	57.91	29.91	11.35	160.96	1047
Term (Years)	8.23	5.00	8.68	2.00	30.25	1047
High Yield	3.01	2.68	1.83	0.22	7.79	1047
Bid-to-Cover	2.60	2.58	0.45	1.22	4.07	1047
Bid-to-Cover by type [#]						
Direct Bidders	0.22	0.21	0.16	0.00	0.80	827
Indirect Bidders	0.54	0.53	0.17	0.03	1.05	827
Primary Dealers	1.92	1.87	0.34	0.98	3.12	827
Fraction Accepted by type [†]						
Depository Institutions	0.01	0.00	0.02	0.00	0.32	896
Individuals	0.01	0.00	0.02	0.00	0.19	896
Dealers	0.53	0.53	0.16	0.12	0.98	896
Pensions	0.00	0.00	0.01	0.00	0.21	896
Investment Funds	0.26	0.23	0.17	0.00	0.74	896
Foreign	0.19	0.18	0.09	0.00	0.61	896
Other	0.00	0.00	0.01	0.00	0.13	896
Panel B: Shock Summary Statistics						
D_t	0.03	0.00	2.12	-8.30	17.80	1047
$D_t^{(2Y)}$	-0.06	0.00	1.39	-5.20	4.40	256
$D_t^{(3Y)}$	0.15	0.10	1.32	-5.30	5.00	134
$D_t^{(5Y)}$	0.20	0.30	1.94	-5.55	8.50	233
$D_t^{(7Y)}$	-0.28	0.05	2.10	-8.30	5.50	106
$D_t^{(10Y)}$	-0.04	-0.05	2.55	-6.80	12.20	186
$D_t^{(30Y)}$	0.09	-0.15	3.28	-7.40	17.80	132
Panel C: Shocks Across Regimes						
Non-ZLB	0.08	0.10	2.02	-7.40	12.20	563
ZLB	-0.03	0.00	2.23	-8.30	17.80	484
Expansion	0.03	0.00	2.03	-8.30	17.80	963
Recession	-0.07	-0.05	2.95	-7.10	9.50	84
Panel D: Non-Auction Shocks						
$\tilde{D}_t^{(2Y)}$	-0.07	0.00	1.32	-19.20	11.00	1225
$\tilde{D}_t^{(5Y)}$	-0.01	0.00	1.13	-17.40	12.90	1924
$\tilde{D}_t^{(10Y)}$	-0.01	0.00	1.03	-13.30	8.90	2151
$\tilde{D}_t^{(30Y)}$	0.01	0.00	0.92	-8.50	5.60	1914

Notes: Panel A presents summary statistics for Treasury note and bond auctions from 1995-2017 for which we have intraday data. [†] indicates that the moments are computed for 2000 onward, the period for which these data are available. [#] indicates that the moments are computed from 2003 onward, the period for which these data are available. Panel B summarizes demand shocks $D_t = y_{t,post} - y_{t,pre}$, the intraday change in Treasury yields before and after the close of an auction (in basis points). For newly issued securities, the yields are from when-issued trades. For reopened securities, the yields are from secondary-market trades. Panel B also reports statistics for shocks $D_t^{(m)} = y_{t,post}^{(m)} - y_{t,pre}^{(m)}$ separately for major maturities $m = 2, 3, 5, 7, 10, 30$ years. Panel C reports statistics separately for binding/non-binding ZLB periods and recessions/expansions. Panel D reports synthetic shocks on non-auction dates $\tilde{D}_t^{(m)} = y_{t,post}^{(m)} - y_{t,pre}^{(m)}$ using the same intraday windows around 1PM on non-auction dates. The yields are from secondary-market trades for on-the-run securities for maturities $m = 2, 5, 10, 30$ years.

Table 2: Demand Shocks and Measures of Demand

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$D_t^{(2Y)}$	$D_t^{(3Y)}$	$D_t^{(5Y)}$	$D_t^{(7Y)}$	$D_t^{(10Y)}$	$D_t^{(30Y)}$	Pool D_t
Panel A: Total Bid-to-Cover Ratio							
Bid-to-Cover	-0.57*** (0.15)	-0.91** (0.37)	-2.50*** (0.51)	-3.06*** (0.72)	-3.05*** (0.49)	-4.69*** (1.09)	-1.68*** (0.22)
Obs.	256	134	233	106	186	132	1047
R^2	0.06	0.11	0.20	0.09	0.26	0.20	0.12
Panel B: Expected and Unexpected Bid-to-Cover							
Fitted	-0.03 (0.14)	-0.09 (0.37)	0.27 (0.62)	1.72 (2.44)	-0.40 (0.51)	-2.58 (1.89)	-0.11 (0.16)
Residual	-2.25*** (0.43)	-2.62*** (0.34)	-4.15*** (0.56)	-6.40*** (1.17)	-5.40*** (0.83)	-5.36*** (1.71)	-3.97*** (0.37)
Obs.	252	130	229	102	182	128	1023
R^2	0.22	0.26	0.34	0.22	0.43	0.22	0.26
Panel C: Bid-to-Cover by Bidder Type							
Indirect	-4.72*** (0.62)	-3.01*** (0.71)	-8.82*** (1.24)	-13.22*** (1.71)	-8.38*** (0.90)	-15.79*** (2.68)	-8.42*** (0.84)
Direct	-2.51** (1.00)	-3.24*** (0.97)	-2.75 (1.78)	-4.88** (2.42)	-3.66** (1.63)	-6.38*** (1.91)	-3.61*** (0.72)
Primary	-0.42 (0.52)	-1.35** (0.61)	-2.97*** (0.77)	-0.09 (1.49)	-3.36*** (0.68)	-4.10** (1.73)	-2.22*** (0.42)
Obs.	159	117	168	102	146	111	803
R^2	0.46	0.39	0.48	0.59	0.50	0.53	0.39
Panel D: Fraction Accepted by Bidder Type							
Invest. Fund	-6.61*** (1.37)	-6.33*** (1.48)	-9.78*** (1.94)	-15.10*** (2.70)	-9.62*** (1.65)	-17.83*** (4.40)	-10.49*** (1.17)
Foreign	-6.89*** (1.52)	-3.90** (1.60)	-10.43*** (2.04)	-16.35*** (2.56)	-9.61*** (2.41)	-17.56*** (5.15)	-9.50*** (1.15)
Misc.	-6.35** (2.88)	-6.87 (7.58)	-6.89*** (2.31)	3.92 (6.53)	11.98 (10.66)	-13.00** (6.44)	-6.88*** (2.12)
Obs.	197	117	181	102	160	115	872
R^2	0.27	0.22	0.30	0.49	0.31	0.41	0.24

Notes: Regressions of demand shocks $D_t^{(m)}$ on the bid-to-cover ratio and fractions accepted, total and broken up by bidder type. Columns (1)-(6) restrict the sample to include only auctions of maturities $m = 2, 3, 5, 7, 10, 30$ years; column (7) pools across all auctions. In Panels A, C, and D, four lags of the dependent variables are included but not reported; in Panel B, the fitted values and residuals of an AR(4) are both used as dependent variables. Newey-West (9 lags) standard errors in parentheses.

Table 3: Asset Price Reactions to Demand Shocks

Asset type	Estimate	Std. Err.	Obs.	R^2	Sample
	(1)	(2)	(3)	(4)	(5)
Panel A: Corporate and Private Debt					
LQD	-3.93***	(0.15)	830	0.59	2002-2017
HYG	-0.34	(0.30)	678	0.01	2007-2017
MBB	-1.42***	(0.18)	662	0.34	2007-2017
VMBS	-1.46***	(0.33)	371	0.13	2009-2017
Corp. Aaa [†]	0.94***	(0.10)	1040	0.14	1995-2017
Corp. Baa [†]	0.96***	(0.10)	1040	0.15	1995-2017
Corp. C [†]	0.23	(0.39)	973	0.00	1997-2017
Panel B: Equities					
SPY	-0.23	(0.52)	1033	0.00	1995-2017
IWM	0.18	(0.58)	876	0.00	2000-2017
SP500 [†]	3.61	(2.74)	974	0.00	1995-2016
Russell 2000 [†]	6.26*	(3.25)	974	0.01	1995-2016
Panel C: Swaps, Commodities, and Spreads					
GLD	-1.16***	(0.36)	775	0.02	2004-2017
GSCI [†]	-1.20	(2.74)	974	0.00	1995-2016
10Y Infl. Swap [†]	0.02	(0.08)	724	0.00	2004-2016
2Y Infl. Swap [†]	0.04	(0.17)	724	0.00	2004-2016
LIBOR-OIS [†]	0.03	(0.04)	737	0.00	2003-2016
Auto CDS [†]	-0.60	(2.65)	733	0.00	2004-2016
Bank CDS [†]	-0.23	(0.16)	733	0.01	2004-2016
VIX [†]	-3.82	(3.37)	1040	0.00	1995-2017
Panel D: Federal Funds Futures					
1-Month Ahead [†]	0.03	(0.02)	1040	0.00	1995-2017
2-Month/1-Month Slope [†]	0.00	(0.01)	1040	0.00	1995-2017

Notes: Regressions of asset price changes on demand shocks D_t (pooled across maturities). [†] denotes daily series; otherwise, intraday changes are measured over the same window as auction demand shocks. Intraday changes are from ETFs that track securities or indices: LQD (investment grade corporate debt); HYG (high yield corporate debt); MBB and VMBS (mortgage indices); SPY (S&P 500); IWM (Russell 2000); GLD (gold bullion). Daily series: Aaa, Baa, C (Moody's & BoA corporate debt yield indices); S&P 500, Russell 2000 (equity indices); GSCI (S&P Total Commodity Index); 10- and 2-year inflation swaps; Auto and Bank credit default swap indices; LIBOR-OIS (3-month USD LIBOR-Overnight Index Swap spread); VIX (implied volatility index); Federal funds futures (h -month ahead continuous contracts). Newey-West (9 lags) standard errors in parentheses. All regressions are estimated with OLS. We report very similar instrumental variable estimates (using unexpected changes in the bid-to-cover ratio as instruments) in Appendix Table B1.

Table 4: Localization Regression Results, Private Borrowing

	(1)	(2)	(3)	(4)	(5)	(6)
	LQD	HYG	MBB	VMBS	SPY	IWM
Panel A: Crisis Localization						
$D_t^{(\tau^*)}$	-4.98*** (0.58)	-0.18 (0.56)	-3.41*** (0.41)	-2.83*** (0.42)	-0.03 (1.22)	2.85*** (1.02)
Crisis $\times D_t^{(\tau^*)}$	0.30 (0.72)	0.19 (0.69)	1.80*** (0.43)	4.51*** (1.58)	0.97 (1.56)	-2.64* (1.42)
Obs.	794	661	647	376	941	811
R^2	0.40	0.00	0.35	0.15	0.01	0.01
Sample	2002-2017	2007-2017	2007-2017	2009-2017	1995-2017	2001-2017
	(1)	(2)	(3)	(4)	(5)	(6)
	BSV	BIV	BLV	CSJ	CIU	CLY
Panel B: Crisis and Maturity Localization						
$D_t^{(\tau^*)}$	-1.54*** (0.18)	-5.20*** (0.37)	-8.74*** (0.93)	-0.84*** (0.17)	-2.98*** (0.25)	-4.32*** (1.24)
Long $\times D_t^{(\tau^*)}$	-0.22 (0.38)	-0.88 (1.46)	-4.45* (2.31)	0.23 (0.28)	-0.58 (0.62)	-4.37 (3.37)
Crisis $\times D_t^{(\tau^*)}$	0.19 (0.25)	0.95 (0.58)	1.72 (1.36)	-0.15 (0.30)	0.79* (0.46)	-2.23 (2.85)
Long \times Crisis $\times D_t^{(\tau^*)}$	0.04 (0.51)	-2.72* (1.61)	-5.73* (3.15)	-0.11 (0.52)	-0.54 (0.81)	-21.22** (10.82)
Obs.	664	653	569	647	642	401
R^2	0.36	0.62	0.38	0.14	0.28	0.19
Sample	2007-2017	2007-2017	2007-2017	2007-2017	2007-2017	2010-2017

Notes: The table reports results for the specification where we regress intraday changes in ETFs which proxy for various private borrowing rates on our demand shocks. Panel A includes interactions with whether the auction took place in a “non-crisis” or “crisis” period, while panel B additionally includes interactions with the maturity of the auction (using the same definitions as in Figure 5). The ETFs used in Panel A are the same as in Table 3. In panel B, the Vanguard ETFs “BSV,” “BIV,” and “BLV” track investment-grade bonds with short, intermediate, and long maturities (respectively). The BlackRock iShares ETFs “CSJ,” “CIU,” and “CLY” track investment-grade corporate bonds with short, intermediate, and long maturities (respectively). Newey-West (9 lags) standard errors in parentheses.

Table 5: Model Calibration and Targeted Moments

Panel A: Matched Moments			
Target Moment	Data		Model
$\sigma(y_t^{(1)})$	1.993		1.978
$\sigma(\tilde{y}_t^{(1)} - y_t^{(1)})$	0.542		0.549
$\sigma(\pi_t)$	0.973		0.882
$\sigma(x_t)$	1.992		1.996
$\sigma(\Delta y_t^{(1)})$	1.423		1.376
$\sigma(\Delta(\tilde{y}_t^{(1)} - y_t^{(1)}))$	0.615		0.617
$\sigma(\Delta\pi_t)$	0.900		0.935
$\sigma(\Delta x_t)$	2.190		2.137
$\sigma(\Delta_s y_t^{(1)})$	0.272		0.399
$\sigma(\Delta_s(\tilde{y}_t^{(1)} - y_t^{(1)}))$	0.258		0.218
$\sigma(\Delta_s \pi_t)$	0.232		0.362
$\sigma(\Delta_s x_t)$	0.499		0.745
$\rho(\tilde{y}_t^{(1)} - y_t^{(1)}, x_t)$	-0.171		-0.158
$\rho(y_t^{(1)}, \pi_t)$	0.549		0.615
$\rho(\pi_t, x_t)$	0.268		0.271
Panel B: Calibrated Parameters			
Parameter	Value	(Crisis)	Description
σ_i	2.567		Monetary Policy Vol.
κ_i	1.082		Monetary Policy Inertia
σ_d	1.116		Risky Payoff Vol.
κ_d	0.879		Risky Payoff Inertia
$\sigma_{z,\pi}$	2.039		Cost-Push Shock Vol.
$\kappa_{z,\pi}$	0.801		Cost-Push Shock Inertia
$\sigma_{z,x}$	1.749		Agg. Demand Shock Vol.
$\kappa_{z,x}$	0.253		Agg. Demand Shock Inertia
ϕ_π	3.096		Inflation Taylor Coeff.
ψ_x	0.393		Risky Payoff Output Coeff.
δ	0.705		Nominal Rigidity
ρ	0.04		Discount Factor
ς^{-1}	1.00		Intertemporal Elasticity
κ_β	1.367		Habitat Demand Inertia
$a \cdot \alpha_0$	0.008	(0.018)	Habitat Elasticity Size
$a \cdot \sigma_\beta \cdot \theta_0$	2.509	(5.123)	Habitat Demand Size
$a \cdot \phi_{i,\beta}$	0.491	(4.620)	Habitat Demand Short Rate Response
θ_1^s	0.50		Short Treasury Factor Maturity Wgt.
θ_1^ℓ	0.20		Long Treasury Factor Maturity Wgt.
$\hat{\theta}_1$	0.50		Risky Factor Maturity Wgt.
α_1	0.10		Habitat Elasticity Maturity Wgt.
Panel C: QE/QT Parameters			
θ_1^{QE}	0.35		QE1 Maturity Wgt.
κ_{QE}	0.20		QE1 Inertia
θ_1^{QT}	0.50		QT Maturity Wgt.
$\kappa_{QT,A}$	0.20		QT Inertia, Active Comp.
$\kappa_{QT,P}$	2.25		QT Inertia, Passive Comp.
$\gamma_{QT,A,P}$	1.75		QT Passive Comp. Response

Notes: Panel A presents the targeted moments which are not a function of maturity which we use to calibrate the model. The targeted moments are volatility and correlations across short-term rates and macroeconomic variables. Δ denotes a 1-year change, while Δ_s denote a 1-month change. $\sigma(\cdot)$ denotes standard deviation (reported in percentage points), while $\rho(\cdot, \cdot)$ denotes correlation. Panel B presents calibrated parameters used in our quantitative exercises. Panel C reports the parameterization of our QE and QT shocks.

Online Appendix for
“Unbundling Quantitative Easing:
Taking a Cue from Treasury Auctions”

by Michael Droste, Yuriy Gorodnichenko, and Walker Ray

Appendix B Additional Figures and Tables

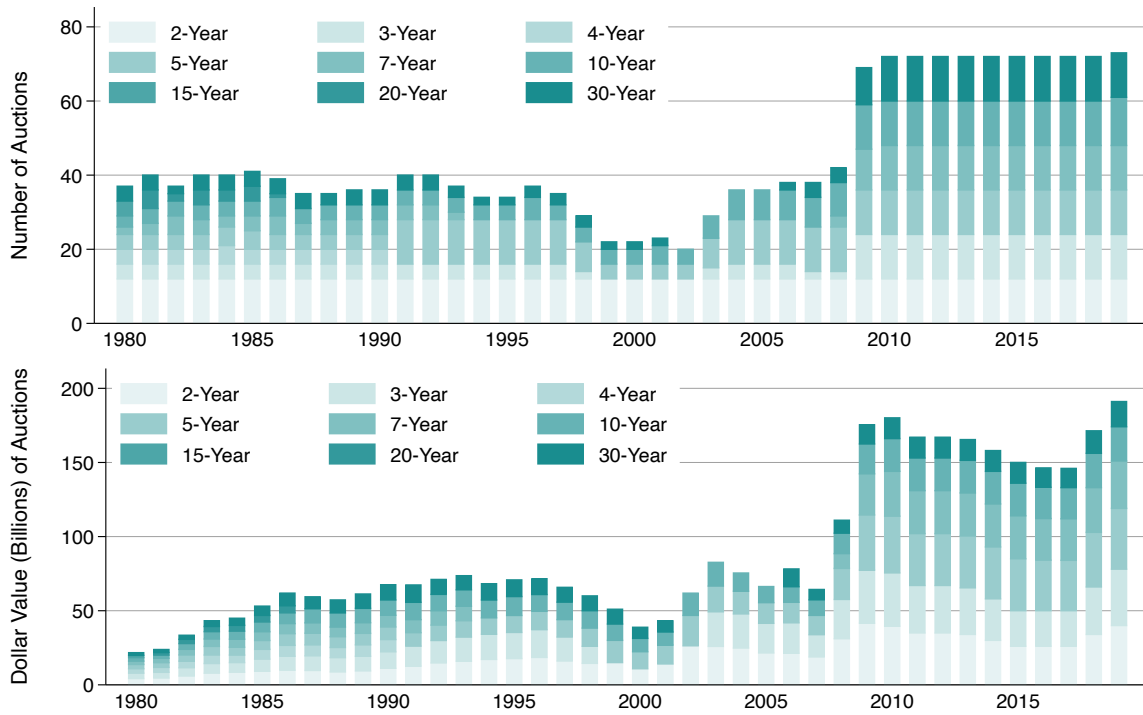


Figure B1: Number and Size of Auctions per Year

Notes: the number (top panel) and dollar value (bottom panel) of note and bond Treasury auctions per year by term length. The number of auctions temporarily fell in the late 1990s and early 2000s (during which time the Treasury ceased issuing 7- and 30-year securities). After the Great Recession, the number and size of auctions increased sharply. Since 2010, the Treasury has held auctions every month for maturities $m = 2, 3, 5, 7, 10, 30$ years.

TREASURY OFFERING ANNOUNCEMENT¹

Term and Type of Security 30-Year Bond
 Offering Amount \$16,000,000,000
 Currently Outstanding \$0
 CUSIP Number 912810Q50
 Auction Date August 11, 2011
 Original Issue Date August 15, 2011
 Issue Date August 15, 2011
 Maturity Date August 15, 2041
 Dated Date August 15, 2011
 Series Bonds of August 2041
 Yield Determined at Auction
 Interest Rate Determined at Auction
 Interest Payment Dates February 15 and August 15
 Accrued Interest from 08/15/2011 to 08/15/2011 None
 Premium or Discount Determined at Auction
 Minimum Amount Required for STRIPS \$100
 Corpus CUSIP Number 912803DT7
 Additional TINT(s) Due Date(s) and August 15, 2041
 CUSIP Number(s) 912834KP2
 Maximum Award \$5,600,000,000
 Maximum Recognized Bid at a Single Yield \$5,600,000,000
 NLP Reporting Threshold \$5,600,000,000
 NLP Exclusion Amount \$0
 Minimum Bid Amount and Multiples \$100
 Competitive Bid Yield Increments² 0.001%
 Maximum Noncompetitive Award \$5,000,000
 Eligible for Holding in Treasury Direct Systems Yes
 Eligible for Holding in Legacy Treasury Direct No
 Estimated Amount of Maturing Coupon Securities Held by the Public \$24,430,000,000
 Maturity Date August 15, 2011
 SOMA Holdings Maturing \$2,205,000,000
 SOMA Amounts Included in Offering Amount No
 FIMA Amounts Included in Offering Amount³ Yes
 Noncompetitive Closing Time 12:00 Noon ET
 Competitive Closing Time 1:00 p.m. ET

TREASURY AUCTION RESULTS

Term and Type of Security 30-Year Bond
 CUSIP Number 912810Q50
 Series Bonds of August 2041
 Interest Rate 3-3/4%
 High Yield¹ 3.750%
 Allotted at High 41.74%
 Price 100.000000
 Accrued Interest per \$1,000 None
 Median Yield² 3.629%
 Low Yield³ 3.537%
 Issue Date August 15, 2011
 Maturity Date August 15, 2041
 Original Issue Date August 15, 2011
 Dated Date August 15, 2011

Competitive	Tendered	Accepted
Noncompetitive	\$33,305,800,000	\$15,985,160,000
FIMA (Noncompetitive)	\$14,855,600	\$14,855,600
	\$0	\$0
Subtotal⁴	\$33,320,655,600	\$16,000,015,600⁵
SOMA	\$489,928,400	\$489,928,400
Total	\$33,810,584,000	\$16,489,944,000
Primary Dealer ⁶	Tendered	Accepted
Direct Bidder ⁷	\$23,734,000,000	\$10,921,532,000
Indirect Bidder ⁸	\$6,567,000,000	\$3,119,654,000
Total Competitive	\$33,301,000,000	\$14,041,186,000

(a) Announcement

(b) Results

Figure B2: Example of Auction Press Releases

Notes: Press releases from the Treasury for an auction of 30-year bonds. Source: TreasuryDirect.

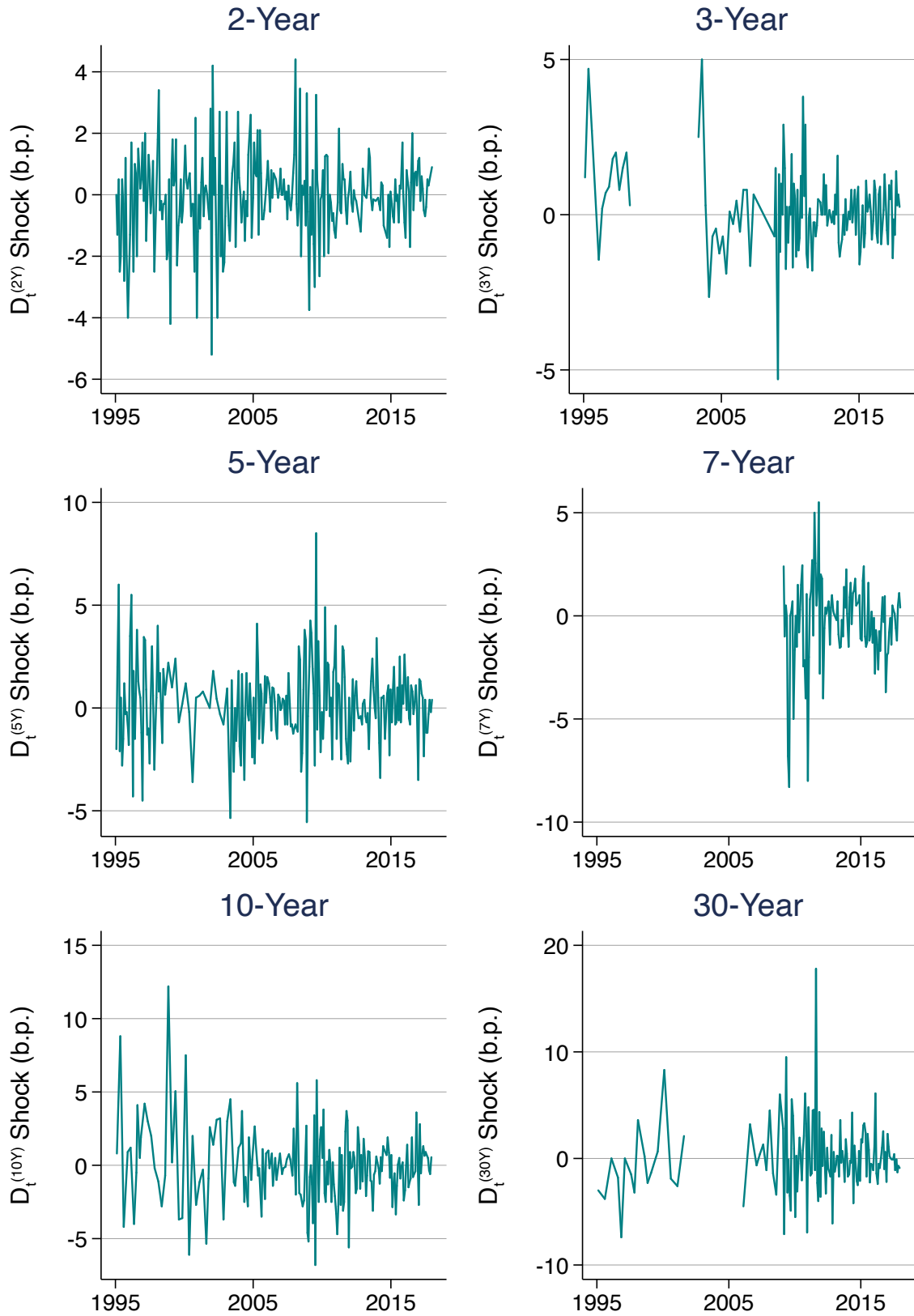


Figure B3: Time Series of Surprise Movements in Treasury Yields

Notes: Plots of the times series of intraday yield shocks following the close of Treasury auctions. Shocks $D_t^{(m)}$ are plotted separately for auctions of maturities $m = 2, 3, 5, 7, 10, 30$ years (in basis points). Gaps in the time series of 3-year, 7-year, and 30-year shocks correspond to temporary halts of newly issued securities of these maturities; see Figure B1.

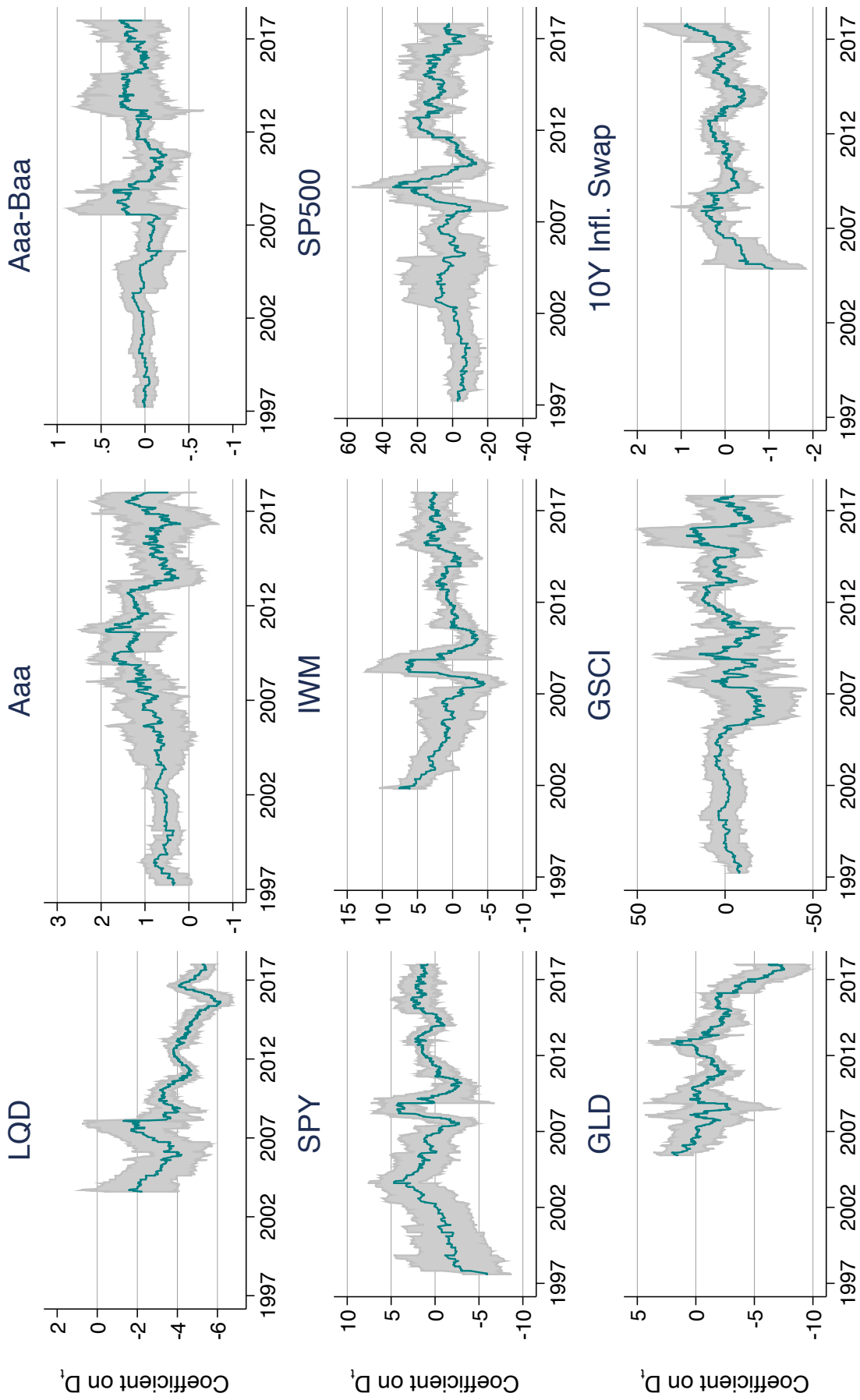


Figure B4: Rolling Regressions, Asset Prices

Notes: Rolling coefficient estimates of asset prices on auction demand shocks D_t (pooled across maturities). Each data point is from rolling estimates of the regressions reported in Table 3, using the 75 most recent auctions.

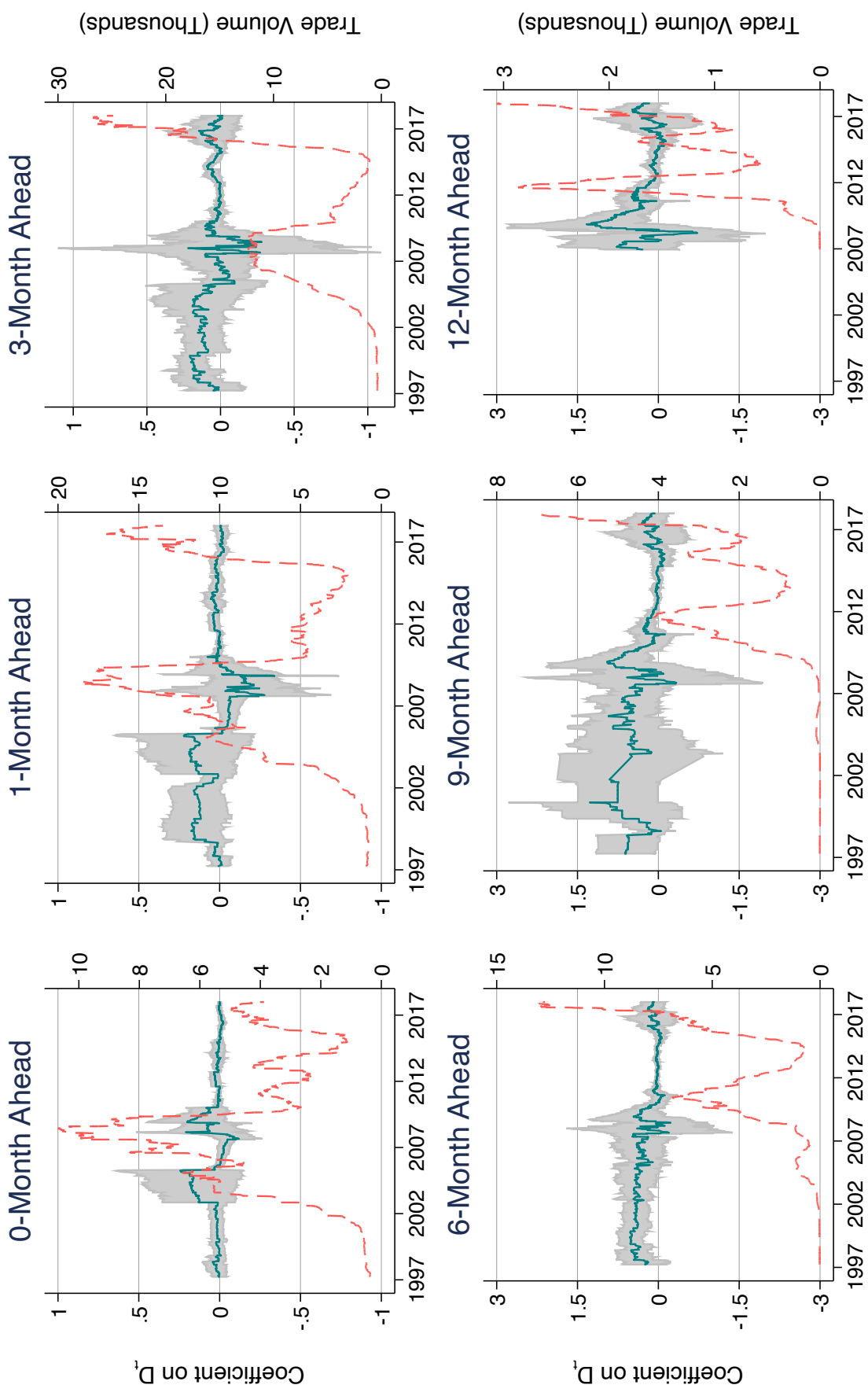


Figure B5: Rolling Regressions, Federal Funds Futures

Notes: Rolling coefficient estimates of h -month ahead expected federal funds rates on auction demand shocks D_t (pooled across maturities). Each data point presents rolling estimates using the 75 most recent auctions. The red line, indexed to the right y-axis, documents the average trade volume (in thousands) over the same 75-auction window

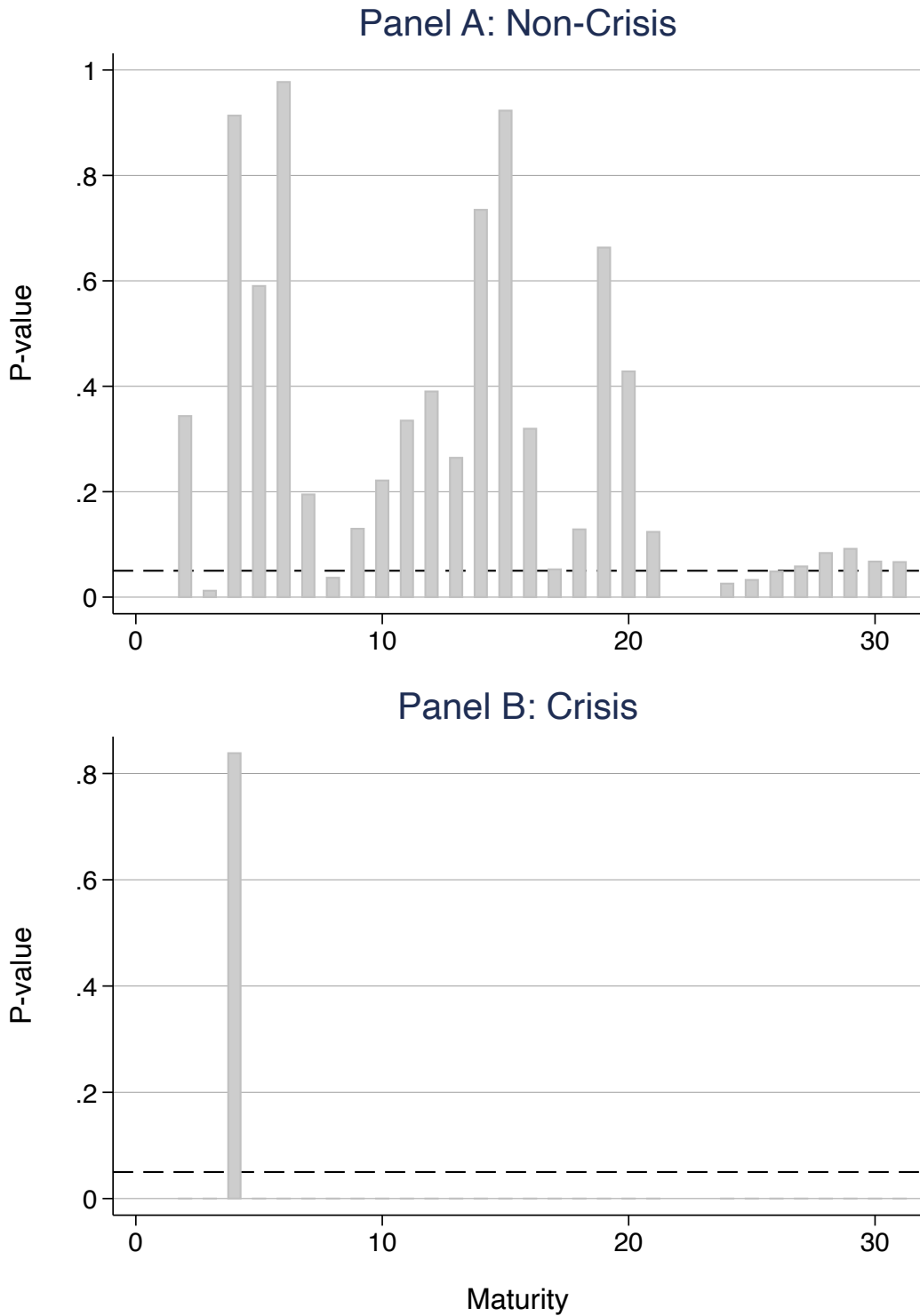


Figure B6: Localization Regression P-Values

Notes: P-values testing equality of coefficients from Figure 5.

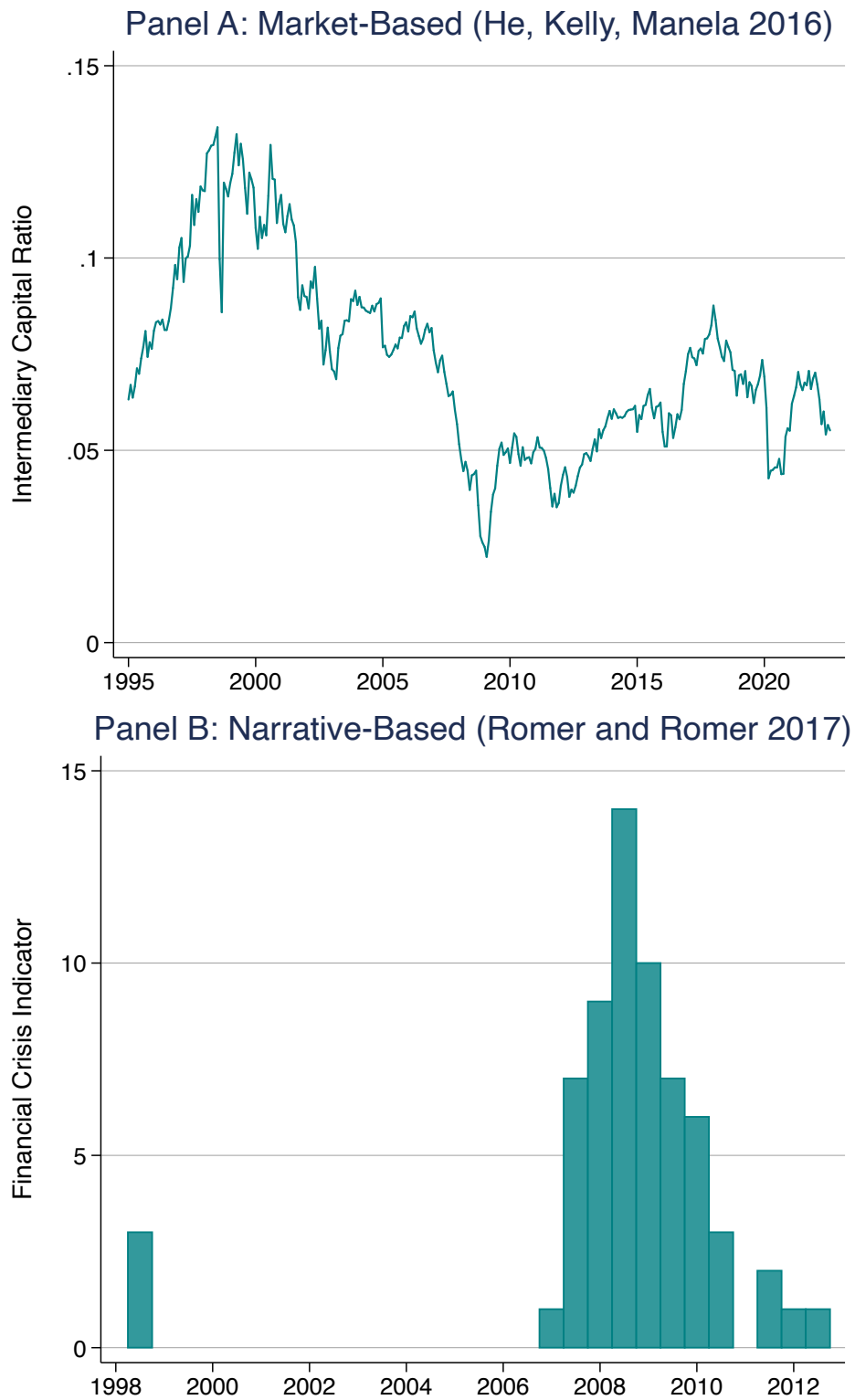


Figure B7: Alternative Measures of Financial Crises

Notes: Alternative measures of financial crises from [He et al. \(2016\)](#) (top panel) and [Romer and Romer \(2017\)](#) (bottom panel).

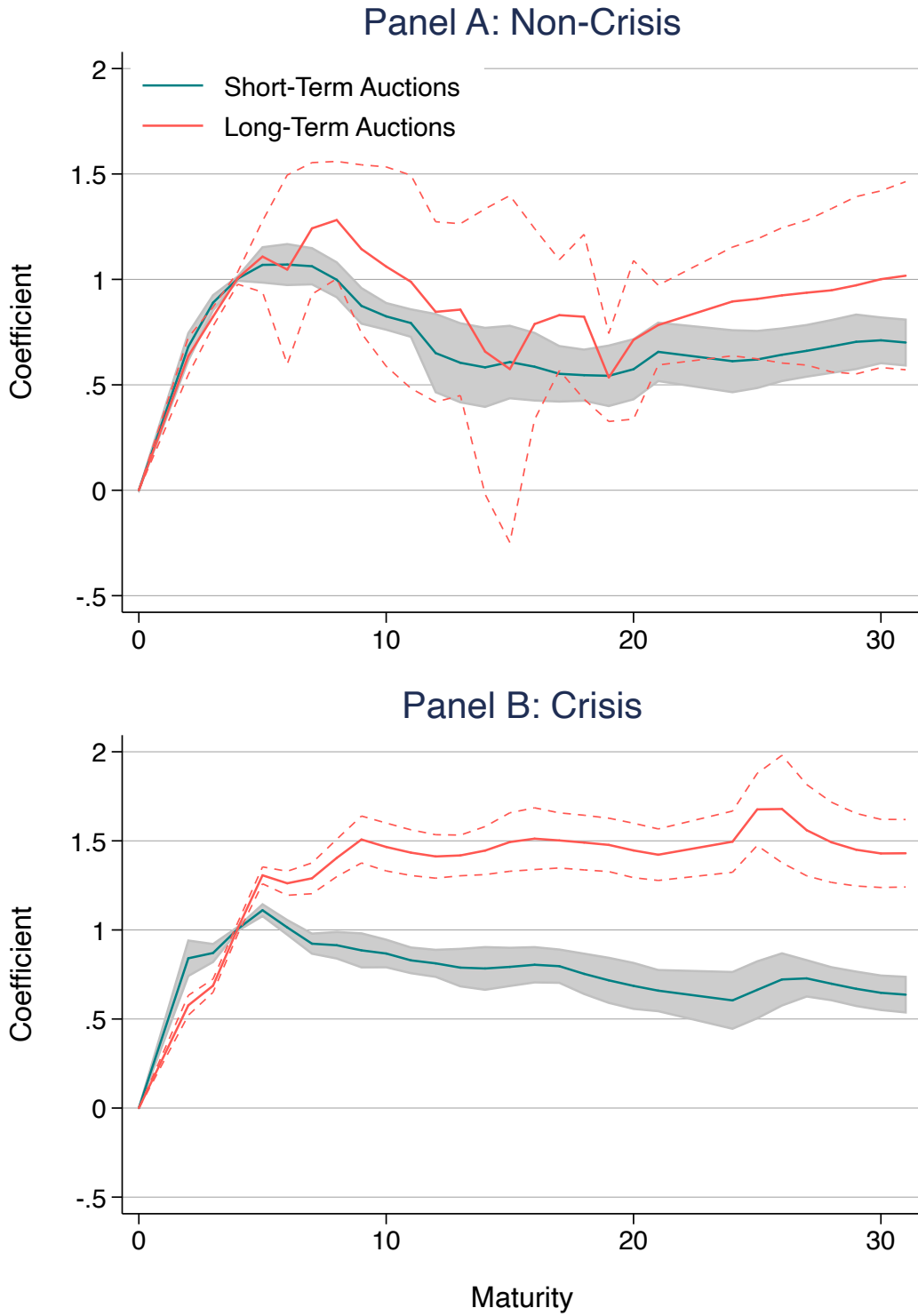


Figure B8: Localization Robustness: Market-Based Crises

Notes: Estimates of regression equation (26), identifying financial crises as periods in which the aggregate capital ratio from He et al. (2016) is low (≤ 0.055).

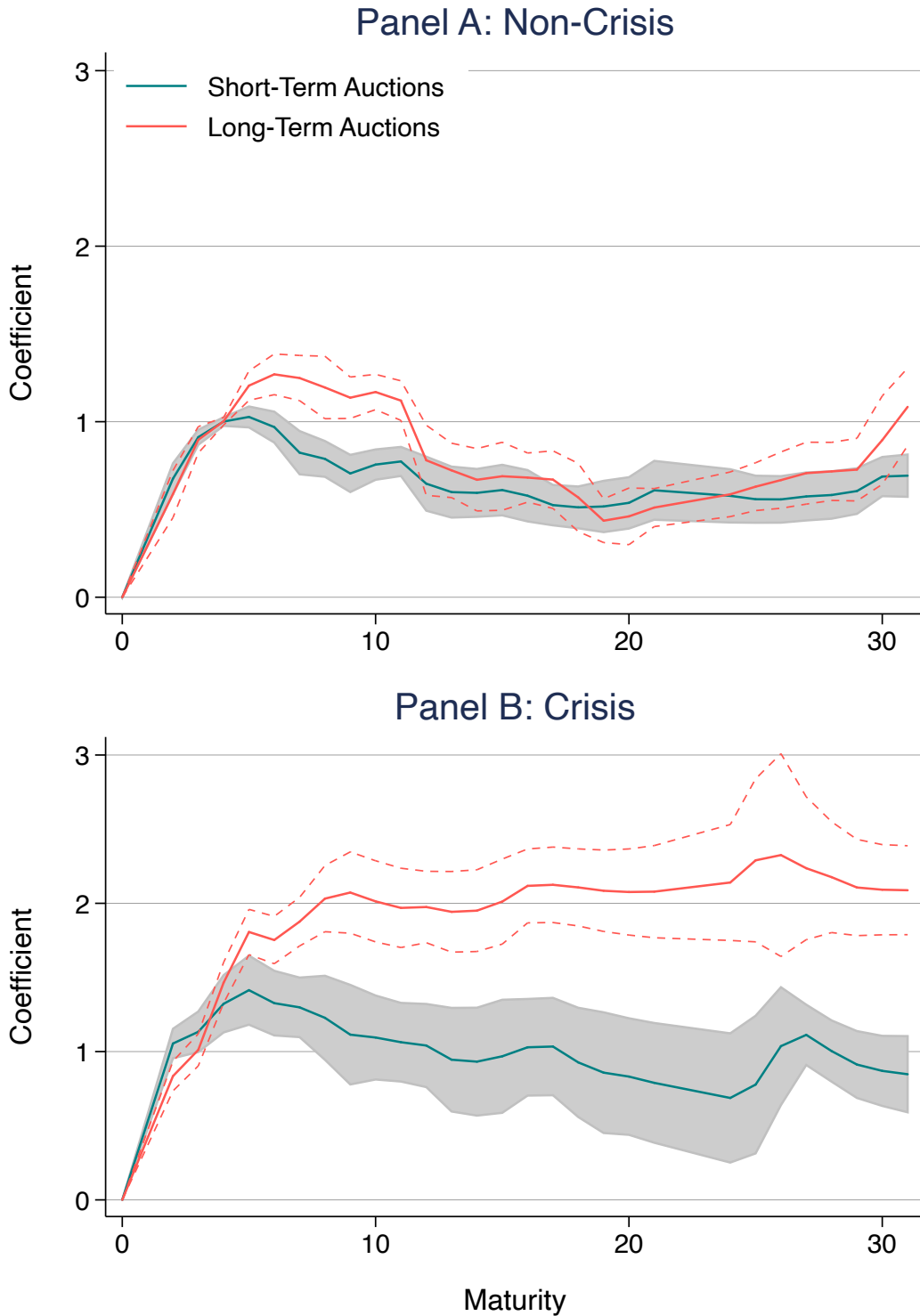


Figure B9: Localization Robustness: Market-Based Crises (Continuous)

Notes: Alternative specification of regression equation (26), where the crisis measure is treated as continuous (as measured by the aggregate capital ratio from He et al. (2016)). The measure is transformed to range from 0 to 1, and truncated so that values below 0.04 are set to 1 while values above 0.075 are set to 0.

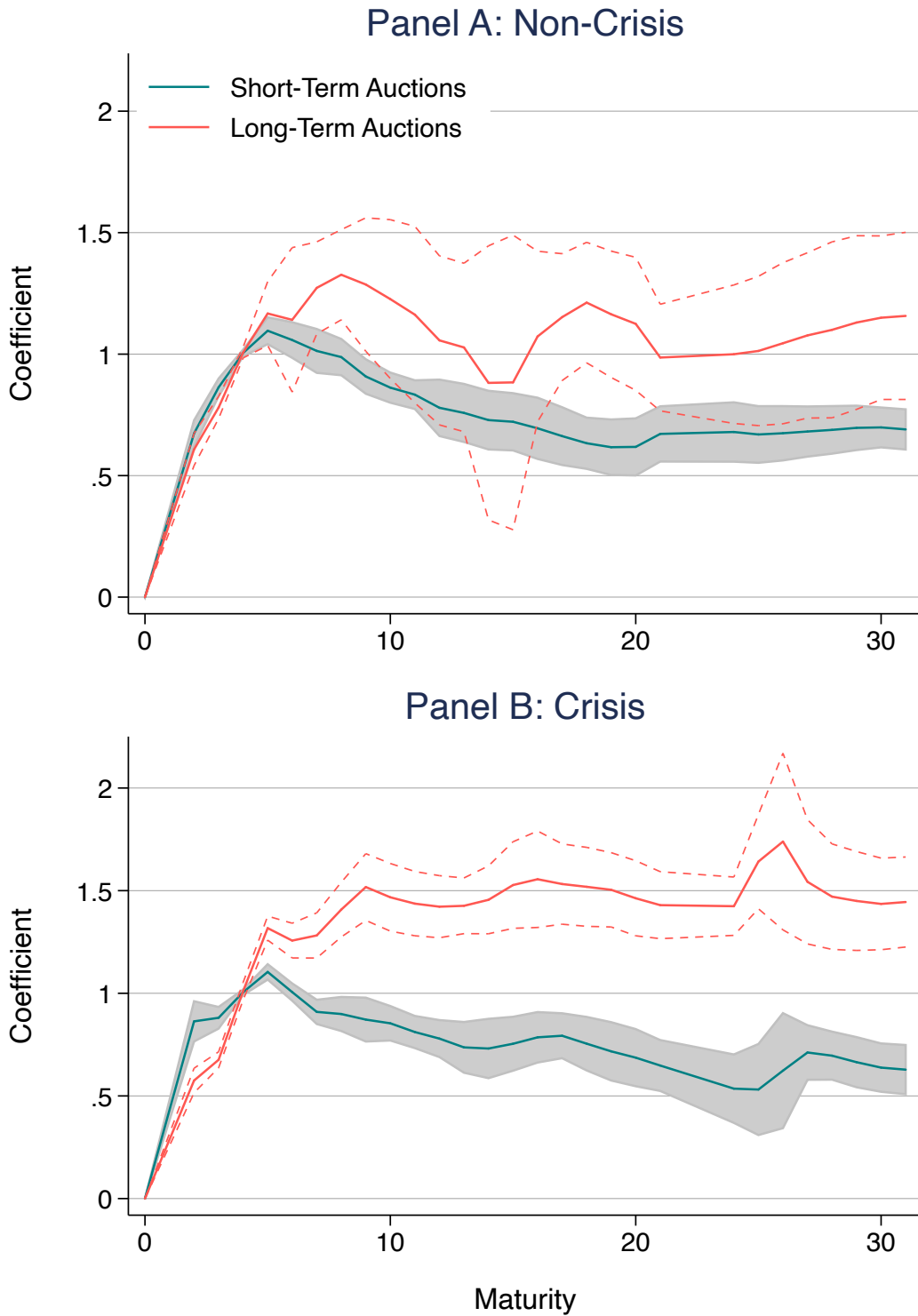


Figure B10: Localization Robustness: Narrative-Based Crises

Notes: Estimates of regression equation (26), identifying financial crises as periods identified by Romer and Romer (2017).

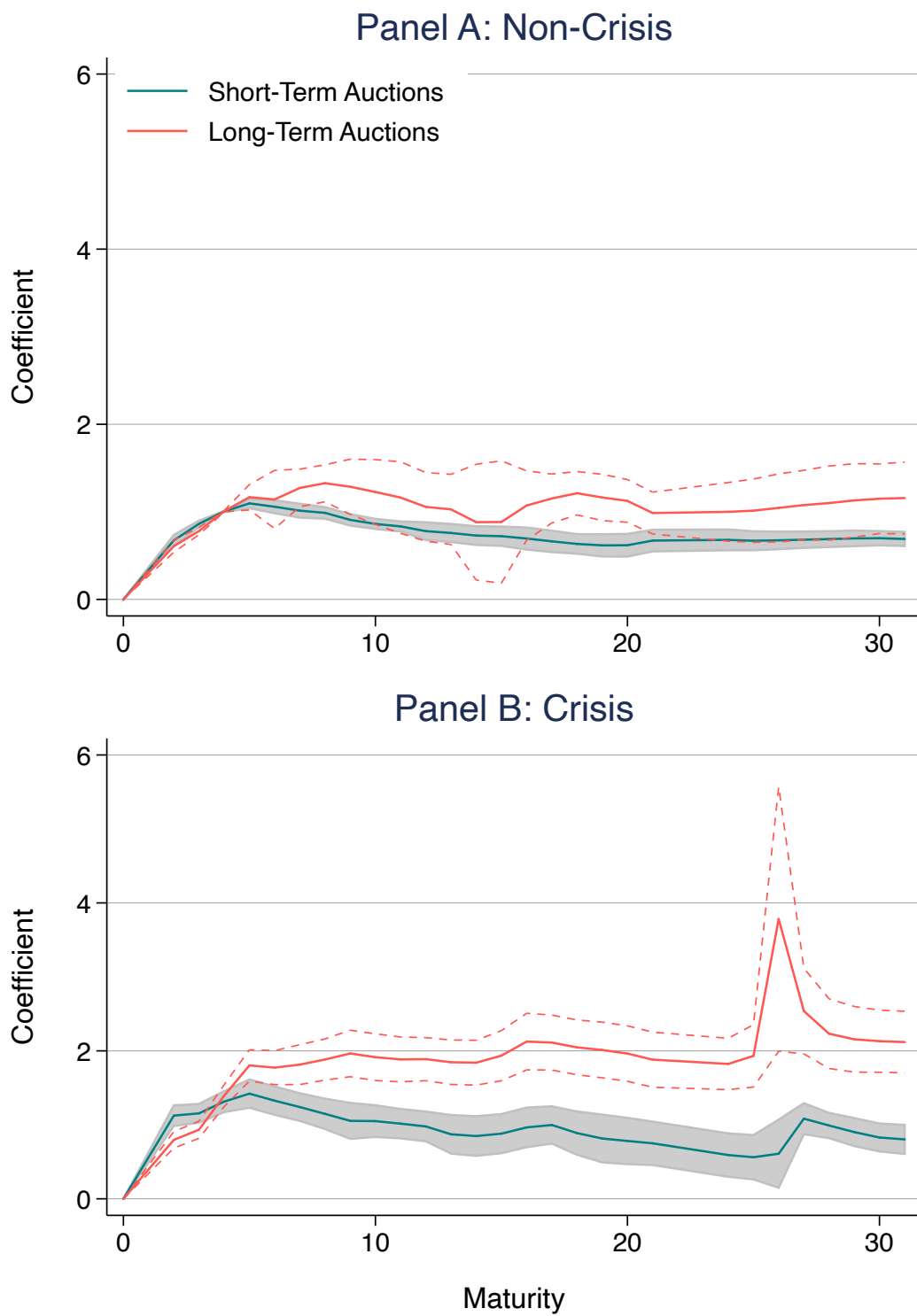


Figure B11: Localization Robustness: Narrative-Based Crises (Continuous)

Notes: Alternative specification of regression equation (26), where the crisis measure is treated as continuous (as measured by Romer and Romer (2017)). The measure is transformed to range from 0 to 1, and truncated so that values above 10 are set to 1.

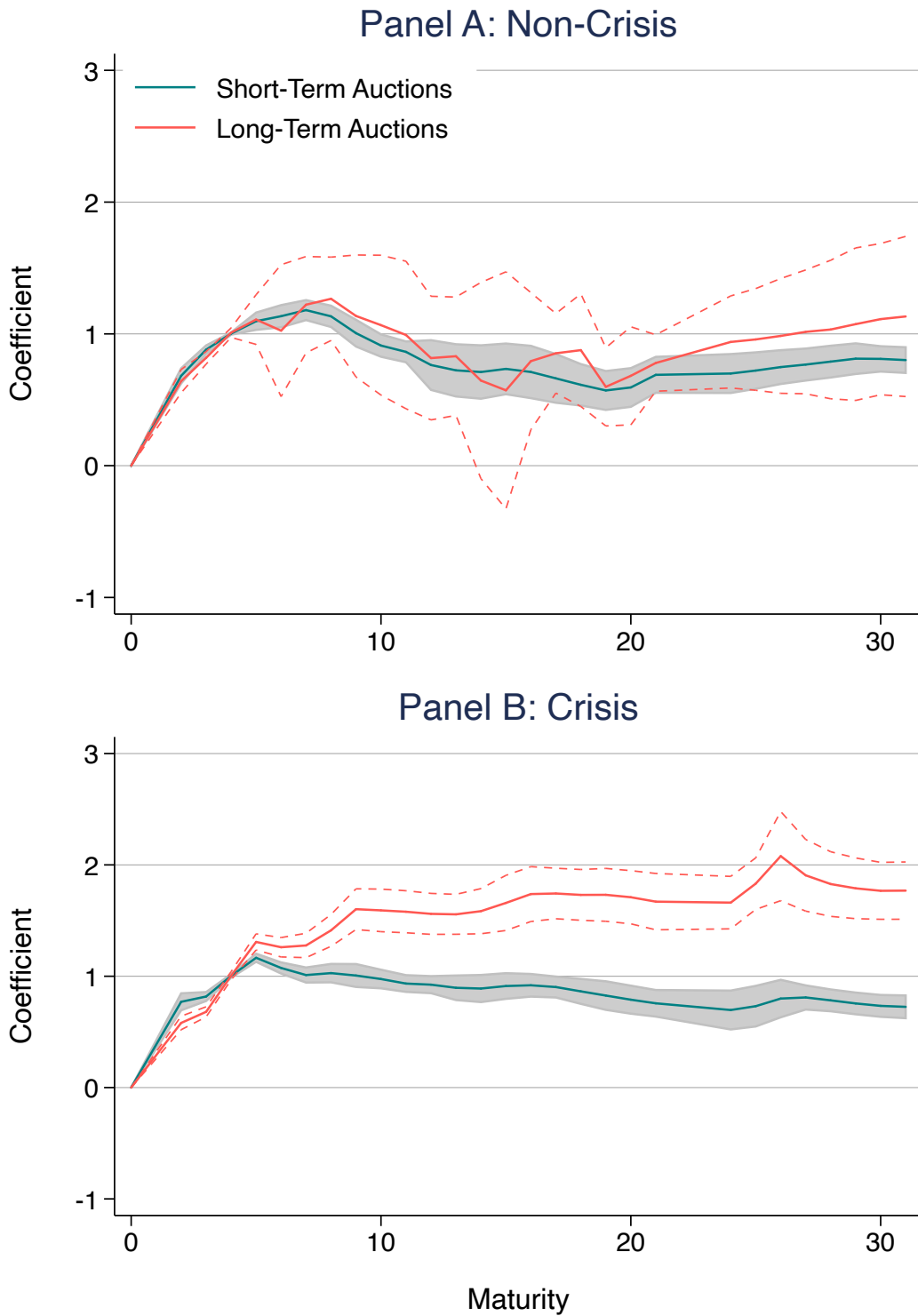
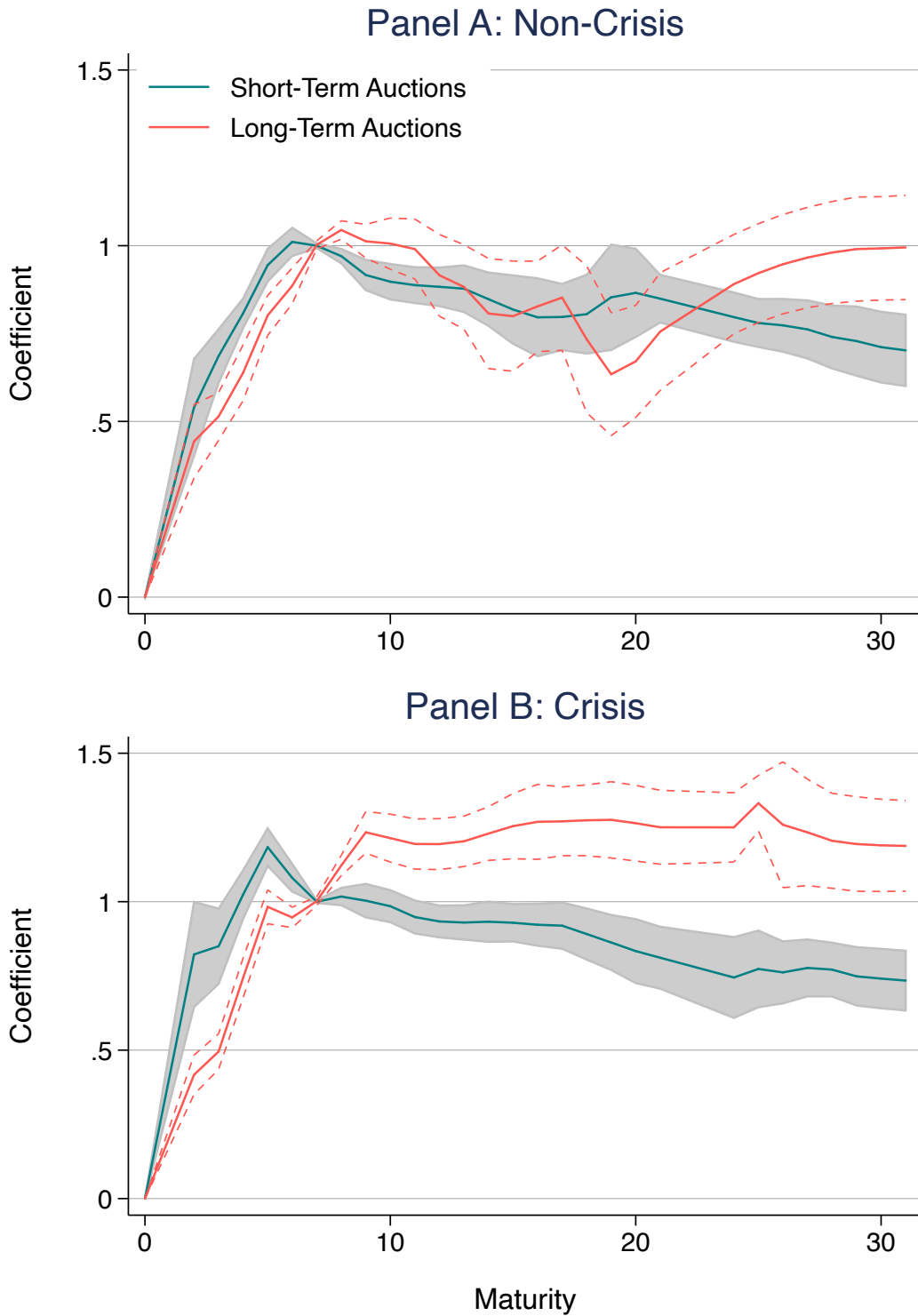


Figure B12: Localization Robustness: Long/Short Auctions

Notes: Estimates of regression equation (26), where short-maturity auctions are those with maturities 7 years or below, while long-maturity auctions are 10 years and above.



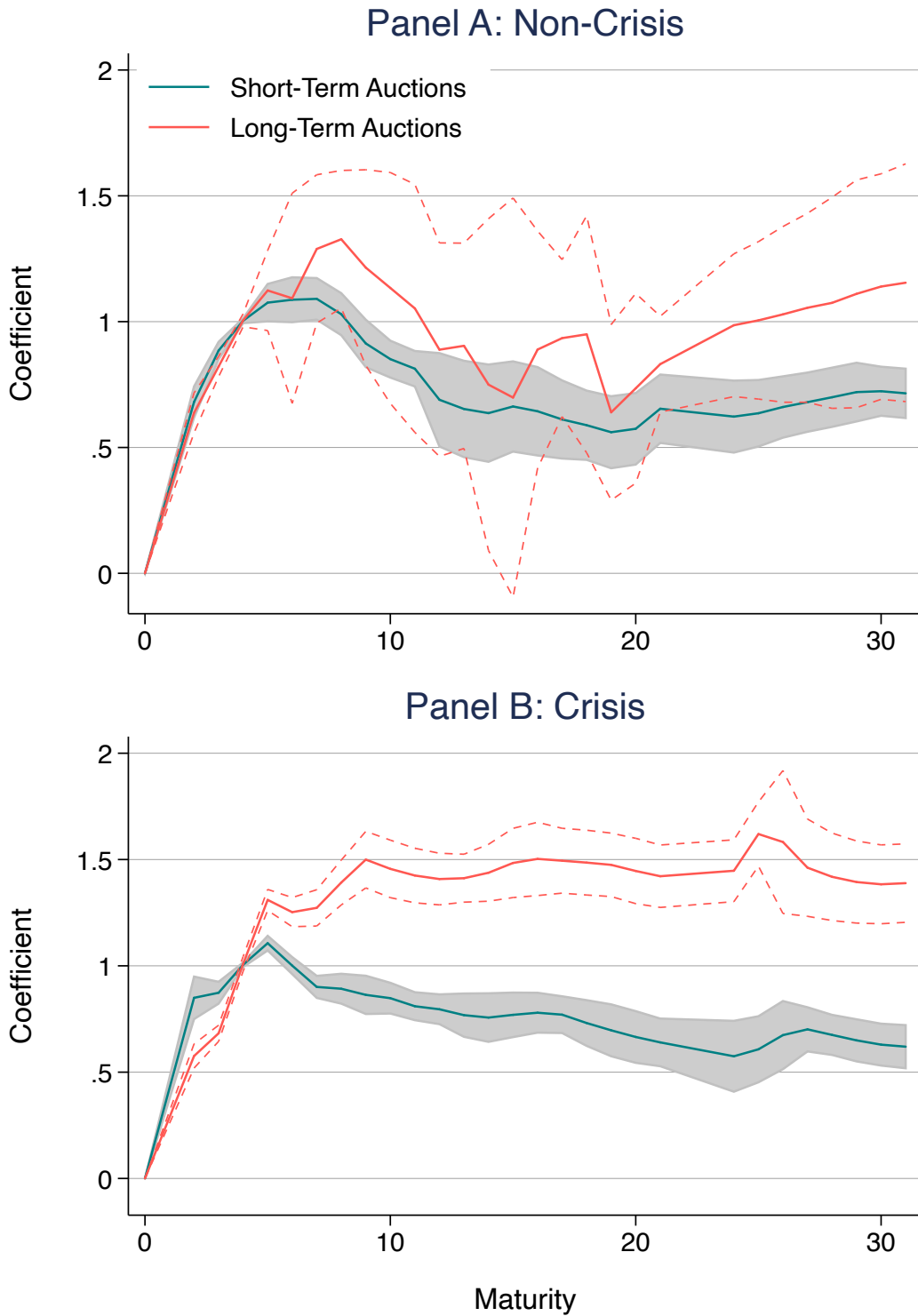


Figure B14: Localization Robustness: No QE Event Weeks

Notes: Estimates of regression equation (26), dropping auctions that occurred during the weeks of QE announcements.

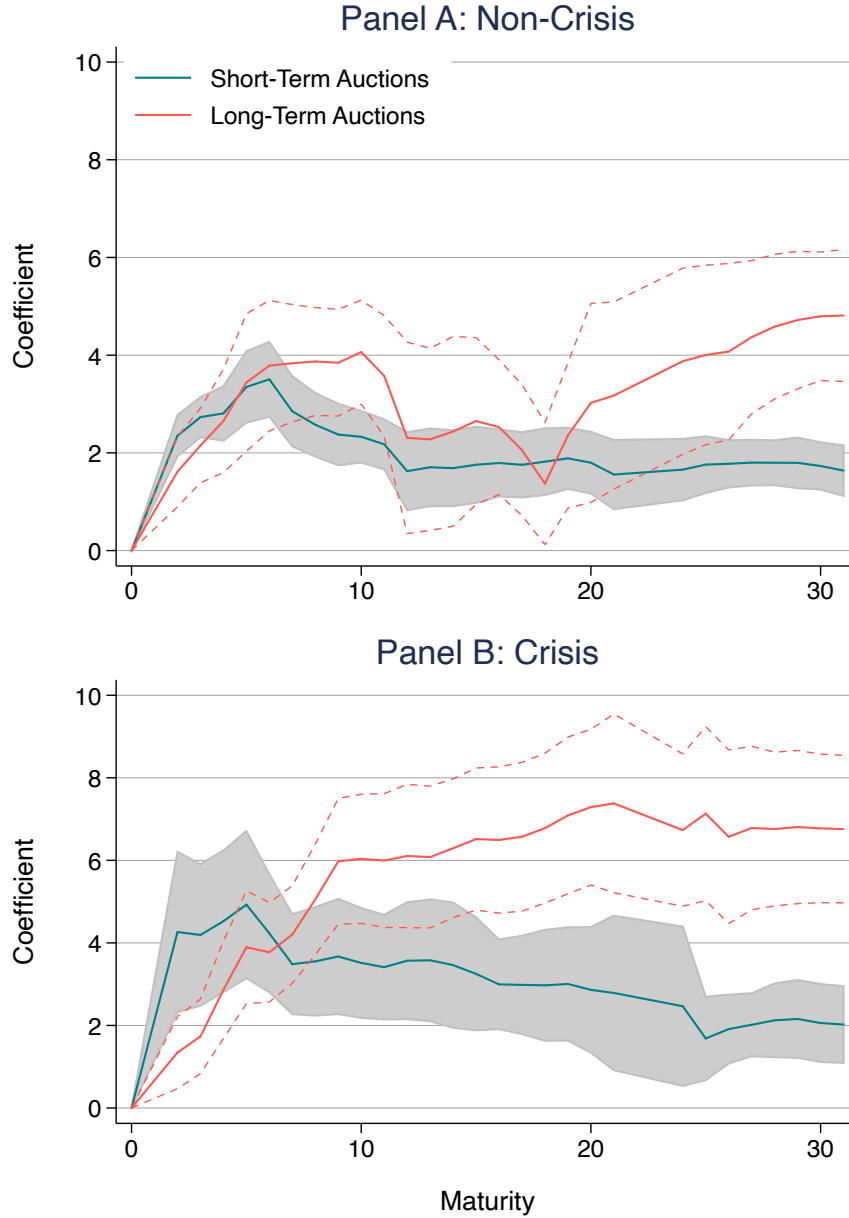


Figure B15: Localization Robustness: Bid-to-Cover

Notes: Estimates of the alternative localization regression, using the bid-to-cover ratio as a proxy of structural demand shocks (after controlling for its own four lags and flipping the sign). The estimate specification is given by: $D_t^{(\tau)} = \alpha^{(\tau)} + \nu_s^{(\tau)} \mathbf{I}(m_t = \text{short}) \tilde{\beta}_t + \nu_\ell^{(\tau)} \mathbf{I}(m_t = \text{long}) \tilde{\beta}_t + \varepsilon_t^{(\tau)}$ where $\tilde{\beta}_t$ is the residualized (“surprise”) bid-to-cover ratio following an auction at date t (controlling for its own four lags, as in Table 2). We further flip the sign of the bid-to-cover ratio, in order to make the estimates more comparable to our baseline specification. 2 standard error (Newey-West, 9 lags) confidence intervals are included. Note that unlike specification (26), the estimates $\hat{\nu}_s^{(\tau)}, \hat{\nu}_\ell^{(\tau)}$ measure the absolute response of the yield curve to the short and long demand factors (proxies), as opposed to the relative response. In the non-crisis subsample estimates (Panel A), the response to both short- and long-maturity demand follows a similar hump-shaped pattern: the response is increasing from short to intermediate maturities, peaking around $\tau = 5$ to $\tau = 10$ before declining (though there is some evidence that long demand shocks have larger effects on very long-maturity yields). On the other hand, the estimates from the crisis subsample (Panel B) exhibit significant differences across short and long estimates: the response to short demand shocks remains hump-shaped, but peaks for short maturities before quickly declining. Conversely, the response to long demand shocks increases almost without fail as the maturity increases, peaking at very long maturities.

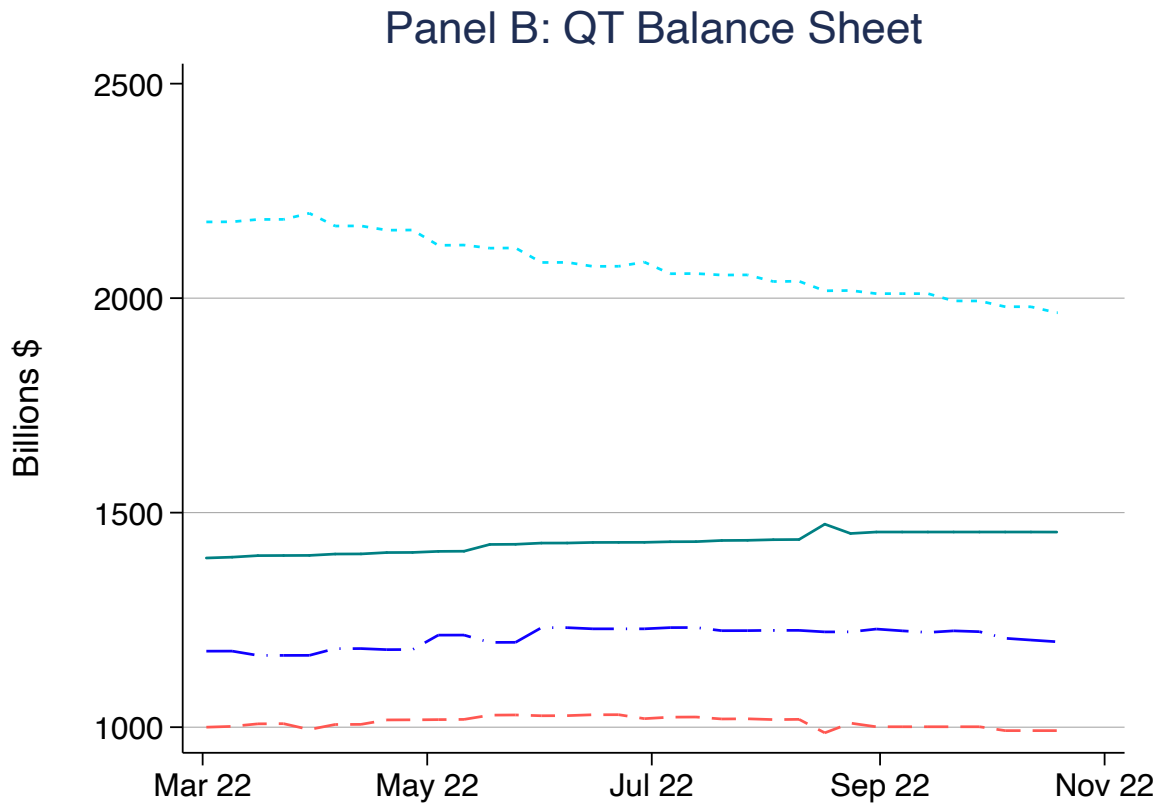
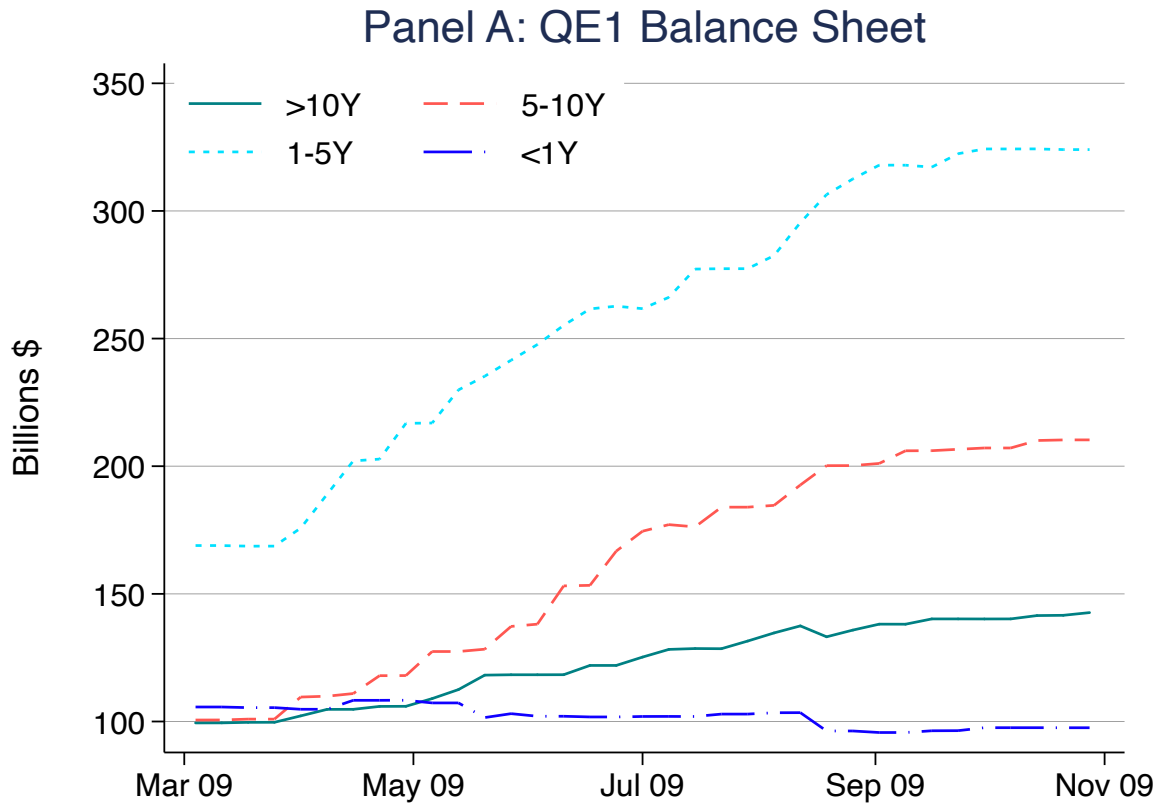


Figure B16: Fed Treasury Holdings: QE1 vs. QT

Notes: Changes in the Fed's holdings of Treasuries following QE1 (Panel A) and QT (Panel B). Following QE1, the Fed increased holdings of both intermediate- and long-term Treasuries. Thus far, the reduction in Treasury holdings following QT has concentrated on intermediate maturities.

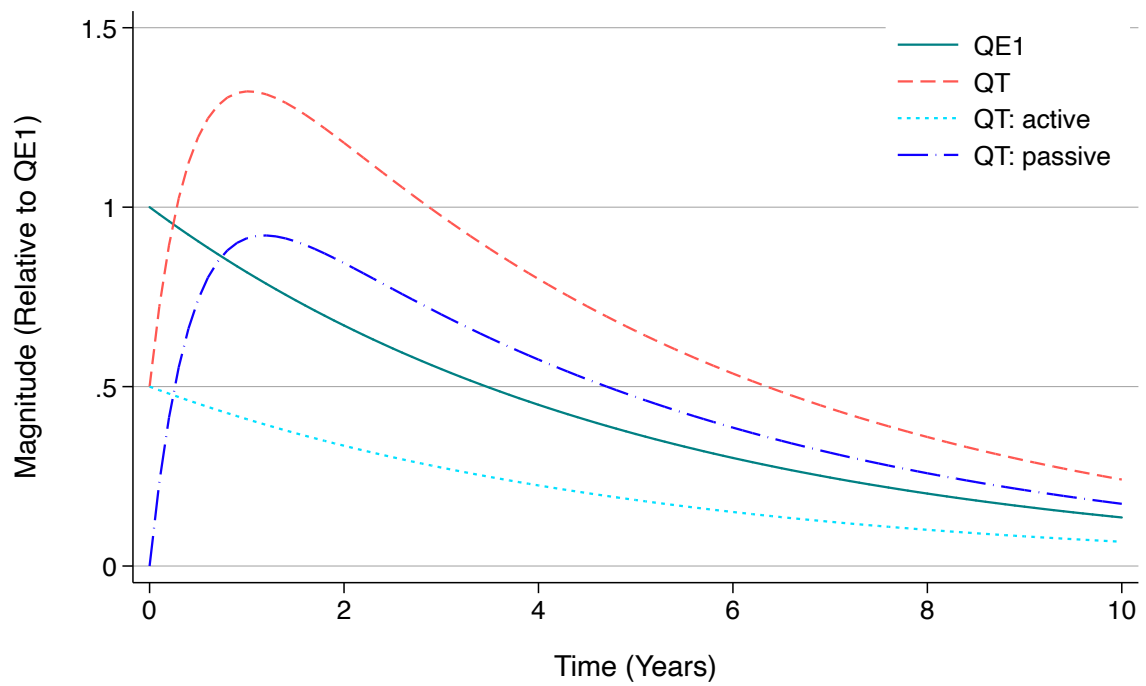


Figure B17: QE1 vs. QT Shocks

Notes: Comparison of the QE1 and QT shocks in the model (β_t^{QE} , solid line; and β_t^{QT} , dashed line). The magnitude is relative to the initial size of QE1 (and with signs flipped so that all numbers are positive). The dotted and dashed-dotted lines plot the contribution of the “active” and “passive” components of the QT shock.

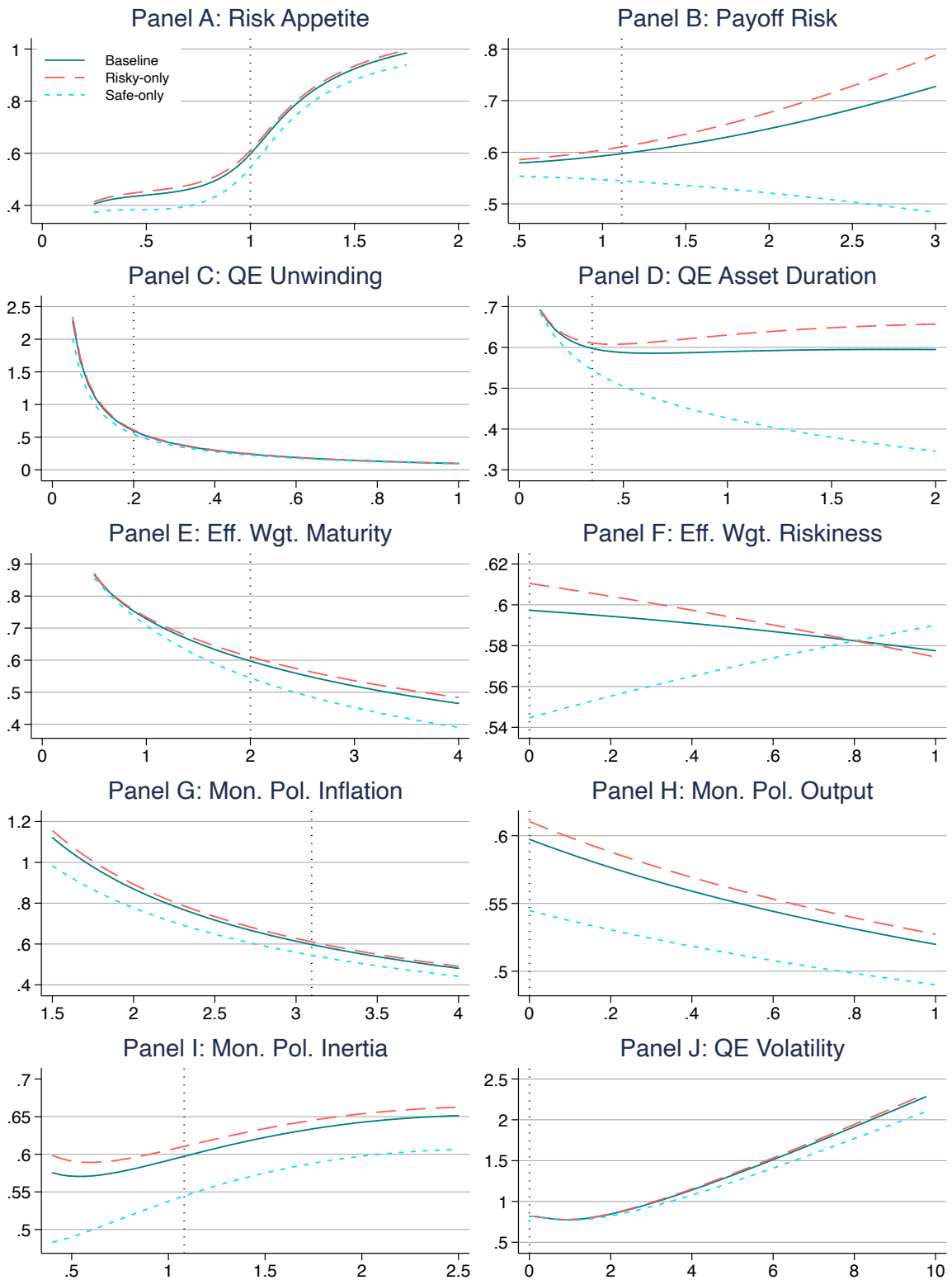


Figure B18: QE Sensitivity Analysis: Inflation

Notes: Response of inflation to a QE shock as a function of various model parameters. This figure conducts the same experiments as Figure 8, but plots the response of inflation π_t rather than the output gap x_t .

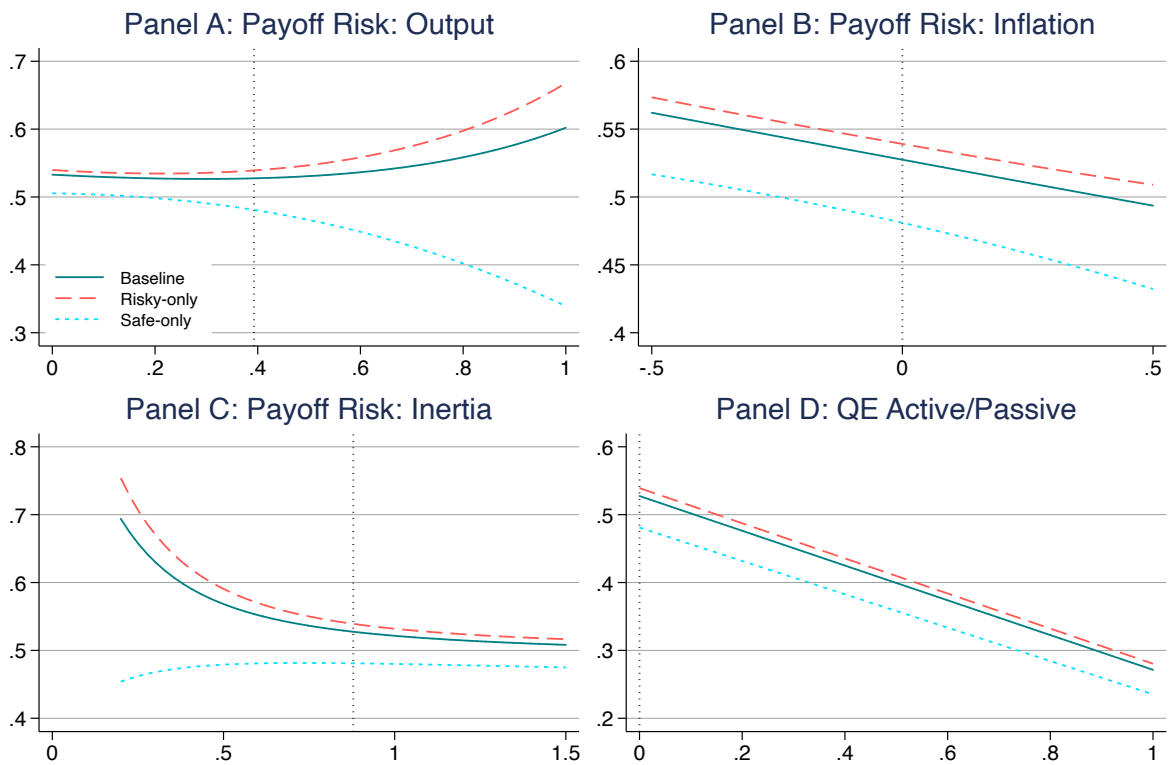


Figure B19: Additional QE Sensitivity Analysis: Output

Notes: Response of output to a QE shock as a function of additional model parameters (as in Figure 8). Panel A: payoff process d_t response to the output gap (ψ_x). Panel B: payoff process d_t response to inflation (ψ_π). Panel C: payoff process d_t inertia (κ_d). Panel D: active and passive QE weights (λ).

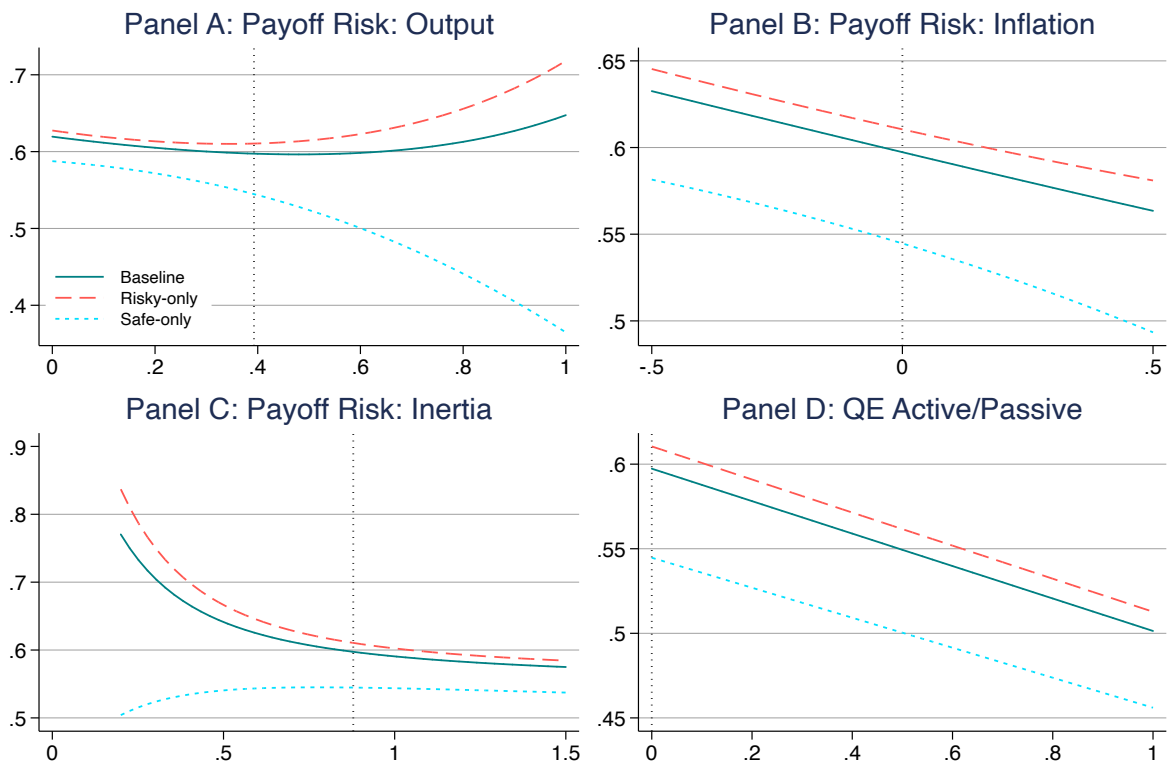


Figure B20: Additional QE Sensitivity Analysis: Inflation

Notes: Response of inflation to a QE shock as a function of additional model parameters. This figure conducts the same experiments as Figure B19, but plots the response of inflation π_t rather than the output gap x_t .

Table B1: Asset Price Reactions to Demand Shocks (IV Specification)

Asset type	Estimate	Std. Err.	Obs.	F-stat	Sample
	(1)	(2)	(3)	(4)	(5)
Panel A: Corporate and Private Debt					
LQD	-4.25***	(0.33)	826	92.2	2002-2017
HYG	0.09	(0.52)	674	91.2	2007-2017
MBB	-1.33***	(0.23)	658	149.5	2007-2017
VMBS	-1.30***	(0.38)	371	129.3	2009-2017
Corp. Aaa [†]	1.10***	(0.15)	1016	147.5	1995-2017
Corp. Baa [†]	1.14***	(0.14)	1016	147.5	1995-2017
Corp. C [†]	0.36	(0.47)	969	134.6	1997-2017
Panel B: Equities					
SPY	-1.04	(0.68)	1020	145.9	1995-2017
IWM	-0.84	(0.94)	872	108.0	2000-2017
SP500 [†]	1.65	(4.24)	950	142.0	1995-2016
Russell 2000 [†]	5.45	(4.40)	950	142.0	1995-2016
Panel C: Swaps, Commodities, and Spreads					
GLD	-1.63***	(0.58)	771	67.1	2004-2017
GSCI [†]	-5.80	(3.99)	950	142.0	1995-2016
10Y Infl. Swap [†]	0.04	(0.13)	720	67.1	2004-2016
2Y Infl. Swap [†]	0.09	(0.33)	720	67.1	2004-2016
LIBOR-OIS [†]	0.22	(0.15)	733	70.8	2003-2016
Auto CDS [†]	1.72	(2.66)	729	69.5	2004-2016
Bank CDS [†]	-0.40	(0.26)	729	69.5	2004-2016
VIX [†]	5.35	(5.56)	1016	147.5	1995-2017
Panel D: Federal Funds Futures					
1-Month Ahead [†]	0.01	(0.05)	1016	147.5	1995-2017
2-Month/1-Month Slope [†]	0.00	(0.02)	1016	147.5	1995-2017

Notes: The table repeats the regressions from Table 3, but instruments the demand shocks D_t with the surprise component of the bid-to-cover ratio. First-stage F-statistics are reported in column (3). Newey-West (9 lags) standard errors in parentheses.

Appendix C Microfoundation Details

In a rational expectations equilibrium, the state variables \mathbf{y}_t and non-predetermined (jump) variables \mathbf{x}_t evolve according to

$$d\mathbf{y}_t = \mathbf{h}(\mathbf{y}_t) dt + \mathbf{r}(\mathbf{y}_t) d\mathbf{B}_t \quad (\text{C1})$$

$$\mathbf{x}_t \equiv \mathbf{x}(\mathbf{y}_t) \quad (\text{C2})$$

where we have collected all Brownian terms into a vector \mathbf{B}_t . The functions $\mathbf{h}(\mathbf{y}_t)$, $\mathbf{r}(\mathbf{y}_t)$ are of course endogenous, but taken as given by optimizing agents (households, firms, and arbitrageurs) in the model. The non-predetermined (jump) variables are a function of the state $\mathbf{x}(\mathbf{y}_t)$, and this endogenous mapping is also taken as given by agents.

Given the vector of Brownian components \mathbf{B}_t , we can decompose the dynamic processes of the model into usual drift and diffusion terms (determined in equilibrium). We use the following notation:

$$\frac{dP_t^{(\tau)}}{P_t^{(\tau)}} = \mu_t^{(\tau)} dt + \boldsymbol{\sigma}_t^{(\tau)} d\mathbf{B}_t \quad (\text{C3})$$

$$\frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} = \tilde{\mu}_t^{(\tau)} dt + \tilde{\boldsymbol{\sigma}}_t^{(\tau)} d\mathbf{B}_t \quad (\text{C4})$$

$$dF_t \equiv \mu_t^F dt + \boldsymbol{\sigma}_t^F d\mathbf{B}_t \quad (\text{C5})$$

Equations (C3) and (C4) give the dynamics of the realized returns for safe and risky assets, respectively. From these expressions, we also can write the effective borrowing rate faced by households as

$$\begin{aligned} \int_0^T \left(\eta(\tau) \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \tilde{\eta}(\tau) \frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} \right) d\tau &= \int_0^T \left(\eta(\tau) \mu_t^{(\tau)} + \tilde{\eta}(\tau) \tilde{\mu}_t^{(\tau)} \right) d\tau dt \\ &\quad + \int_0^T \left(\eta(\tau) \boldsymbol{\sigma}_t^{(\tau)} + \tilde{\eta}(\tau) \tilde{\boldsymbol{\sigma}}_t^{(\tau)} \right) d\tau d\mathbf{B}_t \\ &\equiv \hat{r}_t dt + \hat{\boldsymbol{\sigma}}_t d\mathbf{B}_t \end{aligned} \quad (\text{C6})$$

Finally, equation (C5) is the process for household transfers. All of the drift and diffusion terms will be functions of the state variables \mathbf{y}_t in equilibrium, which we derive now.

C.1 Aggregation and Market Clearing

In a symmetric equilibrium, $Y_{j,t} = Y_t, P_{j,t} = P_t, N_{j,t} = N_t, \pi_{j,t} = \pi_t$. Note also that the price level is (locally) non-stochastic:

$$dP_t = P_t \pi_t dt$$

Because the price adjustment costs are paid to households, market clearing implies:

$$Y_t = C_t = N_t \tag{C7}$$

For instantaneous short-term bonds (with $\tau = 0$) the total supply ($S_t^{(0)}$) is determined endogenously such that the targeted policy rate i_t is the equilibrium outcome. We assume a passive fiscal authority simply balances the budget each period, paying interest i_t on short-term bond holdings and levying lump-sum taxes $P_t T_t$ on households. Thus we have $P_t T_t = -S_t^{(0)} i_t$. Note that the fiscal authority therefore does not supply any long-term bonds, so that $S_t^{(\tau)} = 0$ for $\tau > 0$. Thus, in a zero-net supply equilibrium for $\tau > 0$, asset markets clear when arbitrageurs and habitat funds take opposite positions:

$$X_t^{(\tau)} + Z_t^{(\tau)} = 0, \quad \tilde{X}_t^{(\tau)} + \tilde{Z}_t^{(\tau)} = 0$$

and for $\tau = 0$, arbitrageurs and τ -maturity habitat funds holdings of short-term bonds are given by:

$$\begin{aligned} W_t - \int_0^T X_t^{(\tau)} d\tau \\ W_t^{(\tau)} - Z_t^{(\tau)} + \eta(\tau) A_t \\ \tilde{W}_t^{(\tau)} - \tilde{Z}_t^{(\tau)} + \tilde{\eta}(\tau) A_t \end{aligned}$$

Summing across arbitrageurs and habitat investors and imposing market clearing for $\tau > 0$ gives the total demand for short-term bonds:

$$S_t^{(0)} = W_t + \int_0^T W_t^{(\tau)} d\tau + \int_0^T \tilde{W}_t^{(\tau)} d\tau + A_t$$

Thus, the fiscal authority's per-period budget constraint is given by

$$P_t T_t = - \left[W_t + \int_0^T W_t^{(\tau)} d\tau + \int_0^T \tilde{W}_t^{(\tau)} d\tau + A_t \right] i_t$$

Nominal firm profits and price adjustment costs are given by:

$$\begin{aligned} \int_0^1 \Pi_{j,t} dj + \int_0^1 \Theta(\pi_{j,t}) dj &= P_t \int_0^1 Y_{j,t} \left(1 - w_t - \frac{\theta}{2} \pi_{j,t}^2 \right) dj + \int_0^1 P_{j,t} Y_{j,t} \frac{\theta}{2} \pi_{j,t}^2 dj \\ &= P_t Y_t - \mathcal{W}_t Y_t \end{aligned}$$

where $w_t = \frac{\mathcal{W}_t}{P_t}$ is the real wage.

Total transfers from the financial sector:

$$\begin{aligned} dW_t + \int_0^T \left(dW_t^{(\tau)} + d\tilde{W}_t^{(\tau)} \right) d\tau &= \left[W_t + \int_0^T \left(dW_t^{(\tau)} + d\tilde{W}_t^{(\tau)} \right) d\tau + A_t \right] i_t dt \\ &\quad - A_t \int_0^T \left(\eta(\tau) \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \tilde{\eta}(\tau) \frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} \right) d\tau \end{aligned}$$

Hence, total nominal transfers to the household sector are given by

$$dF_t = [P_t Y_t - \mathcal{W}_t Y_t] dt - A_t \int_0^T \left(\eta(\tau) \frac{dP_t^{(\tau)}}{P_t^{(\tau)}} + \tilde{\eta}(\tau) \frac{d\tilde{P}_t^{(\tau)}}{\tilde{P}_t^{(\tau)}} \right) d\tau$$

Combining with the household wealth dynamics, we obtain:

$$\begin{aligned} dA_t &= 0 \\ da_t &= -a_t \pi_t dt \end{aligned}$$

Thus, if initial household wealth $A_0 = 0$, then $dA_t = 0, da_t = 0 \implies A_t = 0, a_t = 0$ as well. In this case, we have $\sigma_t^F = 0$, which the household takes as given. Moreover, if initial arbitrageur wealth $W_0 = 0$ and habitat fund wealth $W_0^{(\tau)} = 0, \tilde{W}_0^{(\tau)} = 0$, then we also have that the supply of short-term bonds $S_t^{(0)} = 0$.

C.2 Optimality Conditions

Households: In addition to the aggregate state variables given by equation (C1), household wealth is also an idiosyncratic state variable. Defining real wealth $a_t \equiv \frac{A_t}{P_t}$, the household budget constraint (5) and Ito's Lemma imply (dropping notational dependence on time t for convenience)

$$da = \left(wN - C + a(\hat{r} - \pi) + \frac{1}{P} \mu^F \right) dt + (a\hat{\sigma} + \sigma^F) dB$$

where the real wage $w \equiv \frac{\mathcal{W}}{P}$ and we have defined the drift and diffusion terms from equations (C6) and (C6). From the household lifetime utility function and budget constraint given by equations (4) and (5), we form the household HJB equation for the value function

$V(a; \mathbf{y}) \equiv V$:

$$\begin{aligned} \rho V &= \max_{C, N} u(C, N) + V_a \left(wN - C + a(\hat{r} - \pi) + \frac{1}{P} \mu^F \right) + V_{\mathbf{y}^\top} \mathbf{h}(\mathbf{y}) + S^{HH} \\ S^{HH} &\equiv \frac{1}{2} \text{Tr} \begin{bmatrix} a\hat{\boldsymbol{\sigma}} + \boldsymbol{\sigma}^F \\ \mathbf{r}(\mathbf{y}) \end{bmatrix}^\top \begin{bmatrix} V_{aa} & V_{a\mathbf{y}} \\ V_{a\mathbf{y}^\top} & V_{\mathbf{y}\mathbf{y}^\top} \end{bmatrix} \begin{bmatrix} a\hat{\boldsymbol{\sigma}} + \boldsymbol{\sigma}^F \\ \mathbf{r}(\mathbf{y}) \end{bmatrix} \end{aligned}$$

where subscripts denote the gradient of a given function.

The optimality conditions are standard:

$$C^{-\varsigma} = V_a \tag{C8}$$

$$N^\phi = wV_a \tag{C9}$$

The envelope theorem combined with Ito's Lemma imply that the co-state V_a evolves according to

$$\begin{aligned} dV_a &= (\rho + \pi - \hat{r}) V_a dt + (V_{aa}(a\hat{\boldsymbol{\sigma}} + \boldsymbol{\sigma}^F) + V_{a\mathbf{y}^\top} \mathbf{r}(\mathbf{y})) d\mathbf{B} \\ &= (\rho + \pi - \hat{r}) V_a dt + V_{a\mathbf{y}^\top} \mathbf{r}(\mathbf{y}) d\mathbf{B} \end{aligned} \tag{C10}$$

where the second line uses the conditions derived above that $a\hat{\boldsymbol{\sigma}} + \boldsymbol{\sigma}^F = 0$.

Firms: Define the relative price of firm j as $\tilde{P}_j = \frac{P_j}{P}$. Then the firm problem can be written as

$$\max E_0 \int_0^\infty e^{-\rho t} QY \left(\tilde{P}_j^{1-\epsilon} - w\tilde{P}_j^{-\epsilon} - \frac{\theta}{2} \pi_j^2 \right) dt, \quad \text{s.t.} \quad d\tilde{P}_j = \tilde{P}_j(\pi_j - \pi) dt$$

where since households own firms, $Q \equiv V_a$ is the real stochastic discount factor of the household.

We first solve the firm problem with no price adjustment costs. When $\theta = 0$, we have the standard solution

$$P_j^n = \frac{\epsilon}{\epsilon - 1} \mathcal{W}^n \implies w^n = \frac{\epsilon - 1}{\epsilon} \tag{C11}$$

where the superscript n denotes outcomes under flexible prices. Combined with the household optimality conditions (C8) and (C9) as well as market clearing conditions (C7), we find that output under flexible prices is given by

$$Y^n = \left(\frac{\epsilon - 1}{\epsilon} \right)^{\frac{1}{\varsigma + \phi}} \tag{C12}$$

When $\theta > 0$, we form the firm HJB equation for the value function $U(\tilde{P}_j; \mathbf{y}) \equiv U$:

$$\begin{aligned} \rho U &= \max_{\tilde{\pi}_j} QY \left(\tilde{P}_j^{1-\epsilon} - w\tilde{P}_j^{-\epsilon} - \frac{\theta}{2}\tilde{\pi}_j^2 \right) + U_{\tilde{P}_j}\tilde{P}_j(\pi_j - \pi) + U_{\mathbf{y}^\top}\mathbf{h}(\mathbf{y}) + S^F \\ S^F &\equiv \frac{1}{2} \text{Tr} \begin{bmatrix} 0 \\ \mathbf{r}(\mathbf{y}) \end{bmatrix}^\top \begin{bmatrix} U_{\tilde{P}_j\tilde{P}_j} & U_{\tilde{P}_j\mathbf{y}} \\ U_{\tilde{P}_j\mathbf{y}^\top} & U_{\mathbf{y}\mathbf{y}^\top} \end{bmatrix} \begin{bmatrix} 0 \\ \mathbf{r}(\mathbf{y}) \end{bmatrix} \end{aligned}$$

The firm optimality conditions are

$$\theta QY \pi_j = U_{\tilde{P}_j}\tilde{P}_j \quad (\text{C13})$$

The envelope theorem combined with Ito's Lemma imply that the co-state $U_{\tilde{P}_j}$ evolves according to

$$dU_{\tilde{P}_j} = \left((\rho - (\pi_j - \pi))U_{\tilde{P}_j} - QY \left[(1 - \epsilon) + \epsilon w\tilde{P}_j^{-1} \right] \tilde{P}_j^{-\epsilon} \right) dt + U_{\tilde{P}_j\mathbf{y}^\top}\mathbf{r}(\mathbf{y}) d\mathbf{B}$$

In a symmetric equilibrium, all firms make the same choices so that $\pi_j = \pi$ and $\tilde{P}_j = 1$. We therefore have

$$dU_{\tilde{P}_j} = QY (\rho\theta\pi - [(1 - \epsilon) + \epsilon w]) dt + U_{\tilde{P}_j\mathbf{y}^\top}\mathbf{r}(\mathbf{y}) d\mathbf{B} \quad (\text{C14})$$

Arbitrageurs: Using equations (C3) and (C4), we rewrite the arbitrageur budget constraint (8) as

$$\begin{aligned} dW &= \left[Wi + \int_0^T \left(X^{(\tau)}(\mu^{(\tau)} - i) + \tilde{X}^{(\tau)}(\tilde{\mu}^{(\tau)} - i) \right) d\tau \right] dt \\ &\quad + \left[\int_0^T \left(X^{(\tau)}\boldsymbol{\sigma}^{(\tau)} + \tilde{X}^{(\tau)}\tilde{\boldsymbol{\sigma}}^{(\tau)} \right) d\tau \right] d\mathbf{B} \end{aligned}$$

The optimality conditions with respect to holdings $X^{(\tau')}$, $\tilde{X}^{(\tau')}$ are given by

$$\begin{aligned} \frac{\partial E dW}{\partial X^{(\tau')}} &= \frac{a}{2} \frac{\partial Var dW}{\partial X^{(\tau')}} \\ \frac{\partial E dW}{\partial \tilde{X}^{(\tau')}} &= \frac{a}{2} \frac{\partial Var dW}{\partial \tilde{X}^{(\tau')}} \end{aligned}$$

Thus, the optimality conditions with respect to holdings $X^{(\tau')}$ imply

$$\begin{aligned} \frac{\partial E dW}{\partial X^{(\tau')}} &= [\mu^{(\tau')} - i] dt, \quad \frac{\partial Var dW}{\partial X^{(\tau')}} = 2 \int_0^T \left(X^{(\tau)}\boldsymbol{\sigma}^{(\tau)} + \tilde{X}^{(\tau)}\tilde{\boldsymbol{\sigma}}^{(\tau)} \right) d\tau \left[\boldsymbol{\sigma}^{(\tau')} \right]^\top dt \\ \implies \mu^{(\tau')} - i &= a \int_0^T \left(X^{(\tau)}\boldsymbol{\sigma}^{(\tau)} + \tilde{X}^{(\tau)}\tilde{\boldsymbol{\sigma}}^{(\tau)} \right) d\tau \left[\boldsymbol{\sigma}^{(\tau')} \right]^\top \end{aligned}$$

and analogously the optimality conditions with respect to holdings $\tilde{X}^{(\tau')}$ imply

$$\tilde{\mu}^{(\tau')} - i = a \int_0^T \left(X^{(\tau)} \boldsymbol{\sigma}^{(\tau)} + \tilde{X}^{(\tau)} \tilde{\boldsymbol{\sigma}}^{(\tau)} \right) d\tau \left[\tilde{\boldsymbol{\sigma}}^{(\tau')} \right]^\top$$

C.3 Steady State

The deterministic steady state is found by setting the diffusion terms $\mathbf{r}(\mathbf{y}) = 0$. We focus on the deterministic steady state with zero inflation and where output is at potential: $\bar{\pi} = 0, \bar{Y} = \bar{Y}^n$. Combining market clearing conditions, household optimality conditions (C8) and (C9), and firm conditions (C11) we find

$$\bar{w} = \frac{\epsilon - 1}{\epsilon}, \quad \bar{Y} = \bar{w}^{\frac{1}{\varsigma + \phi}}$$

We further assume that the habitat demand in the steady state is zero:

$$\begin{aligned} \overline{Z^{(\tau)}} &= -\alpha(\tau) \log \overline{P^{(\tau)}} - \overline{\beta^{(\tau)}} = 0 \\ \overline{\tilde{Z}^{(\tau)}} &= -\tilde{\alpha}(\tau) \log \overline{\tilde{P}^{(\tau)}} - \overline{\tilde{\beta}^{(\tau)}} = 0 \end{aligned}$$

Hence, arbitrageur optimality conditions imply:

$$\overline{\mu^{(\tau')}} = \bar{r}, \quad \overline{\tilde{\mu}^{(\tau')}} = \bar{r}$$

Thus from equation (C6), we have

$$\begin{aligned} \bar{r} &= \int_0^T \left(\eta(\tau) \overline{\mu^{(\tau')}} + \tilde{\eta}(\tau) \overline{\tilde{\mu}^{(\tau')}} \right) d\tau \\ &= \bar{r} \int_0^T (\eta(\tau) + \tilde{\eta}(\tau)) d\tau = \bar{r} \end{aligned}$$

Hence we must have that the long-run central bank target is given by

$$\bar{r} = \rho$$

so that the dynamics of the household co-state (C10) are consistent with a zero output gap, zero inflation deterministic steady.

C.4 Log-linearization

From the household and firm optimality conditions (along with market clearing conditions), we have that

$$c = y \equiv \log Y = -\varsigma^{-1} \log V_a, \quad w = Y^{\varsigma+\phi}, \quad \pi = \frac{1}{\theta} U_{\tilde{P}_j} \frac{1}{QY}, \quad \frac{1}{QY} = V_a^{\varsigma^{-1}-1}$$

Define the (log) output gap $x \equiv \log\left(\frac{Y}{\bar{Y}}\right)$. We use the household co-state equation (C10) to derive the dynamics of the output gap:

$$\begin{aligned} E dx &= \varsigma^{-1} ((\hat{r} - \pi - \rho) + S^c) dt \\ S^c &\equiv \frac{1}{2} \frac{1}{V_a^2} \text{Tr} [\mathbf{r}^\top V_{a\mathbf{y}} V_{a\mathbf{y}^\top} \mathbf{r}] \end{aligned}$$

We log-linearize around the deterministic steady state ($\mathbf{y} = \bar{\mathbf{y}}$ derived above and no risk $\mathbf{r}(\mathbf{y}) = 0$). Note that to a first-order, the term $S^c \approx 0$. Hence we have

$$E dx \approx \varsigma^{-1} (\hat{r} - \pi - \bar{r}) dt$$

Using the firm co-state dynamics (C14), we find the dynamics of inflation:

$$\begin{aligned} E d\pi &= \left(\rho\pi - \frac{(\epsilon-1)}{\theta} [e^{x(\varsigma+\phi)} - 1] + (\varsigma^{-1} - 1)\pi(\rho + \pi - \hat{r}) + S^\pi \right) dt \\ S^\pi &\equiv \frac{1}{2} \text{Tr} \begin{bmatrix} U_{\tilde{P}_j \mathbf{y}^\top} \mathbf{r} \\ V_{a\mathbf{y}^\top} \mathbf{r} \end{bmatrix}^\top \begin{bmatrix} 0 & \pi(\varsigma^{-1} - 1)U_{\tilde{P}_j}^{-1}V_a^{-1} \\ \pi(\varsigma^{-1} - 1)U_{\tilde{P}_j}^{-1}V_a^{-1} & \pi(\varsigma^{-1} - 1)(\varsigma^{-1} - 2)V_a^{-2} \end{bmatrix} \begin{bmatrix} U_{\tilde{P}_j \mathbf{y}^\top} \mathbf{r} \\ V_{a\mathbf{y}^\top} \mathbf{r} \end{bmatrix} \end{aligned}$$

To a first-order, the term $S^\pi \approx 0$. Further, a first-order approximation gives

$$\begin{aligned} (\varsigma^{-1} - 1)\pi(\rho + \pi - \hat{r}) &\approx 0 \\ \frac{(\epsilon-1)}{\theta} [e^{x(\varsigma+\phi)} - 1] &\approx \frac{(\epsilon-1)(\varsigma+\phi)}{\theta} x \end{aligned}$$

since $\bar{\pi} = 0$ and $\bar{\hat{r}} = \rho$. Then we have

$$E d\pi \approx (\rho\pi - \delta x) dt$$

where $\delta \equiv \frac{(\epsilon-1)(\varsigma+\phi)}{\theta}$.

Appendix D Numerical and Localization Details

D.1 Numerical Solution: Laplace Transforms

Using the functional forms assumed in Section 5, we can solve the model by assuming that $T \rightarrow \infty$ and using Laplace transforms

The differential equations (20) are characterize the coefficient functions $\mathbf{A}(\tau), \tilde{\mathbf{A}}(\tau)$. Define the Laplace transform $\mathcal{A}(s) \equiv \mathcal{L}\{\mathbf{A}(\tau)\}(s)$. Then equation (20) implies:

$$\begin{aligned} s\mathcal{A}(s) + \mathbf{M}\mathcal{A}(s) - \frac{1}{s}\mathbf{e}_i &= \mathbf{0} \\ \implies \mathcal{A}(s) &= [s\mathbf{I} + \mathbf{M}]^{-1} \left[\frac{1}{s}\mathbf{e}_i \right] \end{aligned}$$

using the fact that $\mathbf{A}(0) = \mathbf{0}$. Similarly, we have

$$\begin{aligned} s\tilde{\mathcal{A}}(s) + \mathbf{e}_d + \mathbf{M}\tilde{\mathcal{A}}(s) - \frac{1}{s}\mathbf{e}_i &= \mathbf{0} \\ \implies \tilde{\mathcal{A}}(s) &= [s\mathbf{I} + \mathbf{M}]^{-1} \left[\frac{1}{s}\mathbf{e}_i - \mathbf{e}_d \right] \end{aligned}$$

using the fact that $\tilde{\mathbf{A}}(0) = -\mathbf{e}_d$.

Note that the derivative with respect to the Laplace parameter s is given by

$$\begin{aligned} \mathcal{A}'(s) &= [s\mathbf{I} + \mathbf{M}]^{-1} \left[-\frac{1}{s^2}\mathbf{e}_i - \mathcal{A}(s) \right] \\ \tilde{\mathcal{A}}'(s) &= [s\mathbf{I} + \mathbf{M}]^{-1} \left[-\frac{1}{s^2}\mathbf{e}_i - \tilde{\mathcal{A}}(s) \right] \end{aligned}$$

Additionally, define $\mathbf{X}(\tau) \equiv \mathbf{A}(\tau)\mathbf{A}(\tau)^\top$. Note that from equation (20) we can write

$$\begin{aligned} \mathbf{A}'(\tau)\mathbf{A}(\tau)^\top + \mathbf{A}(\tau)\mathbf{A}'(\tau)^\top + \mathbf{M}\mathbf{X}(\tau) + \mathbf{X}(\tau)\mathbf{M}^\top - \mathbf{e}_i\mathbf{A}(\tau)^\top - \mathbf{A}(\tau)\mathbf{e}_i^\top &= \mathbf{0} \\ \iff \mathbf{X}'(\tau) + \mathbf{M}\mathbf{X}(\tau) + \mathbf{X}(\tau)\mathbf{M}^\top - \mathbf{e}_i\mathbf{A}(\tau)^\top - \mathbf{A}(\tau)\mathbf{e}_i^\top &= \mathbf{0} \end{aligned}$$

Define the Laplace transform $\mathcal{X}(s) \equiv \mathcal{L}\{\mathbf{X}(\tau)\}(s)$. Then we have

$$\left[\frac{1}{2}s\mathbf{I} + \mathbf{M} \right] \mathcal{X}(s) + \mathcal{X}(s) \left[\frac{1}{2}s\mathbf{I} + \mathbf{M} \right]^\top = \mathbf{e}_i\mathcal{A}(s)^\top + \mathcal{A}(s)\mathbf{e}_i^\top$$

since $\mathbf{X}(0) = \mathbf{0}$. This is a Lyapunov equation. A sufficient condition for a unique solution $\mathcal{X}(s)$ is if all the eigenvalues of $\left[\frac{1}{2}s\mathbf{I} + \mathbf{M} \right]$ have positive real parts.

Analogously, define $\tilde{\mathbf{X}}(\tau)$ and $\tilde{\mathcal{X}}(s)$, and the same steps as above imply

$$\left[\frac{1}{2}s\mathbf{I} + \mathbf{M} \right] \tilde{\mathcal{X}}(s) + \tilde{\mathcal{X}}(s) \left[\frac{1}{2}s\mathbf{I} + \mathbf{M} \right]^\top = \mathbf{e}_i\tilde{\mathcal{A}}(s)^\top + \tilde{\mathcal{A}}(s)\mathbf{e}_i^\top + \mathbf{e}_d\mathbf{e}_d^\top$$

since $\tilde{\mathbf{X}}(0) = (-\mathbf{e}_d)(-\mathbf{e}_d^\top) = \mathbf{e}_d\mathbf{e}_d^\top$.

With this notation, we have that

$$\begin{aligned}\int_0^T \alpha(\tau; \alpha_0, \alpha_1) \mathbf{A}(\tau) \mathbf{A}(\tau)^\top d\tau &= \alpha_0 \mathcal{X}(\alpha_1) \\ \int_0^T \theta(\tau; \theta_0, \theta_1) \mathbf{A}(\tau)^\top d\tau &= -\theta_0 \theta_1^2 \mathcal{A}'(\theta_1)^\top\end{aligned}$$

and similarly for terms involving $\tilde{\mathbf{A}}(\tau)$.

With a slight abuse of notation, define the following matrices:

$$\begin{aligned}\mathcal{X} &\equiv \alpha_0 \mathcal{X}(\alpha_1) \\ \tilde{\mathcal{X}} &\equiv \tilde{\alpha}_0 \tilde{\mathcal{X}}(\tilde{\alpha}_1) \\ \mathcal{Y} &\equiv \begin{bmatrix} \vdots \\ -\theta_{0k} \theta_{1k}^2 \mathcal{A}'(\theta_{1k})^\top \\ \vdots \end{bmatrix} \\ \tilde{\mathcal{Y}} &\equiv \begin{bmatrix} \vdots \\ -\tilde{\theta}_{0k} \tilde{\theta}_{1k}^2 \tilde{\mathcal{A}}'(\tilde{\theta}_{1k})^\top \\ \vdots \end{bmatrix}\end{aligned}$$

Using the parameterization of $\eta(\tau), \tilde{\eta}(\tau)$ defined in equation (29), we define:

$$\begin{aligned}\mathcal{N} &\equiv \int_0^T \eta(\tau) \mathbf{A}(\tau) d\tau = -\eta_1^2 \mathcal{A}'(\eta_1) \\ \tilde{\mathcal{N}} &\equiv \int_0^T \tilde{\eta}(\tau) \tilde{\mathbf{A}}(\tau) d\tau = -\tilde{\eta}_1^2 \tilde{\mathcal{A}}'(\tilde{\eta}_1) \\ \mathcal{V} &\equiv \eta_0 \mathcal{N} + (1 - \eta_0) \tilde{\mathcal{N}}\end{aligned}$$

All of these objects are implicitly determined by \mathbf{M} . Hence we can write the equation characterizing $\hat{\mathbf{A}}$ and \mathbf{M} (equations (21) and (22)), as the solution of a root-finding problem, as shown in the proof of Proposition 1:

$$f(\hat{\mathbf{A}}; \mathbf{M}; a) = \begin{bmatrix} \mathbf{e}_i + \left(\Gamma(\hat{\mathbf{A}})^\top - \mathbf{M} \right) \boldsymbol{\nu} - \hat{\mathbf{A}} \\ \text{vec} \left\{ \Gamma(\hat{\mathbf{A}})^\top - a \left\{ \mathcal{Y} - \mathcal{X} + \tilde{\mathcal{Y}} - \tilde{\mathcal{X}} \right\} \boldsymbol{\Sigma} - \mathbf{M} \right\} \end{bmatrix}$$

We utilize a continuation algorithm to solve the model numerically, which also serves as an equilibrium selection device. First, for $a_0 \equiv 0$ we have a known solution. Next, given a solution $\hat{\mathbf{A}}_s, \mathbf{M}_s$ for $a = a_s$, we compute the solution $\hat{\mathbf{A}}_{s+1}, \mathbf{M}_{s+1}$ for $a_{s+1} \equiv a_s + \varepsilon_s$ using $\hat{\mathbf{A}}_s, \mathbf{M}_s$ as an initial value for a numerical root-finding algorithm. Finally, we stop when $a_S \equiv \bar{a}$. When the step size ε_s is small, this allows for a stable numerical approach

to solving the model.²²

In order to compute second moments in the model, note that the long-run variance-covariance of the state $Var[\mathbf{y}_t] \equiv \Sigma^\infty$ solves the following matrix equation

$$\Gamma \Sigma^\infty + \Sigma^\infty \Gamma^\top = \Sigma \implies \text{vec } \Sigma^\infty = (\Gamma \oplus \Gamma)^{-1} \text{vec}(\Sigma)$$

where vec is the vectorization operator, and \oplus denotes the Kronecker sum, defined for any two square matrices A, B with respective dimensions $(a \times a), (b \times b)$ as $A \oplus B \equiv I_a \otimes B + A \otimes I_b$, and where \otimes is the Kronecker product. Then the auto-covariance of the state is given by

$$Cov[\mathbf{y}_{t+s}, \mathbf{y}_t] = \exp(-\Gamma s) \Sigma^\infty$$

and computing covariances of any model object is immediate due to the linearity in the model. For instance, the standard deviation of 10-year yields is given by

$$\sqrt{Var[y_t^{(10)}]} = \frac{1}{10} \sqrt{\mathbf{A}(10)^\top \Sigma^\infty \mathbf{A}(10)}$$

D.2 Localization Proofs

Definitions and terminology: To compare the effects of demand factors j and k , we compare their relative effects on bond prices. Suppose demand factor k is more concentrated on long-maturity bonds compared to demand factor j ($\theta_1^j > \theta_1^k$). Consider the effect of factor k on long-maturity bonds relative to its own effects on short-maturity bonds. If this relative movement is the same as factor j , then we say that demand factors have “global” effects on the yield curve. If instead the relative effect of factor k on long-maturity bonds is larger than that of factor j (and similarly, the relative effect of factor j on short-maturity bonds is larger than that of factor k), we say that demand factors have “local” effects on the yield curve.

We formalize this logic as follows. Let

$$\mathcal{B}_j(s, t) \equiv \frac{\mathcal{A}_j(s)}{\mathcal{A}_j(t)} \tag{D1}$$

This vector is the weighted average response of bond prices with Laplace frequency parameter s , relative to the weighted average response of bond prices with Laplace frequency parameter t . The weights in the Laplace transform are given by $e^{-s\tau}$, so $s > t$ implies that $\mathcal{A}_j(s)$ has more weight on short-maturity bonds than $\mathcal{A}_j(t)$. Hence, if $s > t$ and

²²There are numerous ways to improve the efficiency of our numerical approach, including common tools such as adaptive step sizes. However, in practice solving the model is efficient enough that setting fixed, small step sizes and using off-the-shelf root-finding numerical packages worked well for the purposes of stability of the solution algorithm.

$\mathcal{B}_j(s, t) > \mathcal{B}_k(s, t)$, then we have that the j -demand factor has a relatively larger impact on short-maturity yields, compared to the k -demand factor. If $s < t$ and $\mathcal{B}_j(s, t) > \mathcal{B}_k(s, t)$, then we have that the j -demand factor has a relatively larger impact on long-maturity yields, compared to the k -demand factor.

Hence, demand factors have “global” effects if $\mathcal{B}_j(s, t) = \mathcal{B}_k(s, t)$ for all demand factors j, k and frequency weights s, t . Demand factors have “local” effects if $\mathcal{B}_j(s, t) > \mathcal{B}_k(s, t)$ for demand factors j, k such that $\theta_1^j > \theta_1^k$ and frequency weights $s > t$.

Before stating and proving our results formally, we preview and discuss the results. Proposition 2 shows that demand shocks have global effects when arbitrageurs approach risk-neutrality ($a \rightarrow 0$) or when demand factors are risk-free ($\sigma_\beta = 0$). Proposition 2 further shows that the first-order effects of increasing risk aversion do not lead to a localization of demand shocks. That is, in a neighborhood around $a = 0$, increasing risk aversion does change the global nature of demand shocks.

Proposition 3 shows that the second-order effects of increasing risk aversion increase the localization of demand shocks. That is, for large enough values of risk aversion $a \gg 0$, demand shocks become localized. Proposition 3 also shows that with infinite risk aversion, demand shocks become fully localized. Note that this is a “discontinuous” result; the model is no longer arbitrage-free.

Assumptions:

1. The “general equilibrium” effects of imperfect arbitrage are not too large near $a = 0$: $\lim_{a \rightarrow 0} d^n / da^n (\mathbf{\Gamma}) \approx 0$.
2. The state dynamics and correlation matrices are diagonal: $\mathbf{\Gamma} = \text{diag} [\dots \ \gamma_{j,j} \ \dots]$ and $\mathbf{\Sigma} = \text{diag} [\dots \ \sigma_{j,j}^2 \ \dots]$.
3. Demand factors are identical besides the location of $\theta(\tau)^k$. That is, $\theta_0^j = \theta_0^k$, $\gamma_{j,j} = \gamma_{k,k}$, and $\sigma_{j,j}^2 = \sigma_{k,k}^2$ for $j, k > 1$.
4. There are no risky asset habitat demand traders: $\tilde{\alpha}(\tau) = 0$ and $\tilde{\theta}(\tau) = 0$.

Assumption 1 and 2 are for analytical tractability (and for instance hold trivially in partial equilibrium models such as Vayanos and Vila (2021)). Note that Assumption 1 does not imply that demand factors have no macroeconomic implications, but only assumes that changes in risk aversion in a neighborhood around risk-neutrality do not lead to changes in the dynamics of the model. Assumption 3 implies that besides the location in maturity space, demand factors are symmetric. Assumption 4 is also for tractability, and allows us to focus only on localization effects across maturities.

In order to simplify notation, define $\lim_{a=0} \frac{d^n}{da^n}(x) \equiv d_0^n x$ for any model object x .

Assumption 1 implies that as $a \rightarrow 0$,

$$\begin{aligned}\mathbf{M} &\rightarrow \mathbf{\Gamma}^\top \\ d_0\mathbf{M} &= \{\mathcal{X} - \mathcal{Y}\} \mathbf{\Sigma} \\ d_0^n\mathbf{M} &= n \{d_0^{n-1}\mathcal{X} - d_0^{n-1}\mathcal{Y}\} \mathbf{\Sigma}\end{aligned}$$

and hence we can recursively solve for all derivatives with respect to a at $a = 0$.

With these assumptions, we have that as $a \rightarrow 0$, \mathbf{M} is also diagonal and so is $s\mathbf{I} + \mathbf{M}$. To simplify notation, define the vector and matrix equations

$$[\mathbf{g}(s)]_i \equiv \frac{1}{s + \gamma_{i,i}}, \quad [\mathbf{G}(s)]_{i,j} \equiv \frac{1}{s + \gamma_{i,i} + \gamma_{j,j}} \quad (\text{D2})$$

and note that Assumption 3 implies that for all $j, k, m, n > 1$:

$$\mathbf{g}_j(s) = \mathbf{g}_k(s), \quad \mathbf{G}_{j,k}(s) = \mathbf{G}_{m,n}(s)$$

Using this notation, we have that

$$\lim_{a \rightarrow 0} \mathcal{A}(s) \equiv \mathcal{A}^0(s) = \frac{1}{s} \cdot \mathbf{g}(s) \circ \mathbf{e}_i = \left[\frac{1}{s(s+\gamma_{11})} \quad 0 \quad \dots \quad 0 \right]^\top \quad (\text{D3})$$

$$\lim_{a \rightarrow 0} \mathcal{A}'(s) \equiv \mathcal{A}'^0(s) = -\mathbf{g}(s) \circ \left[\frac{1}{s^2} \mathbf{e}_i + \mathcal{A}(s) \right] = \left[-\frac{2s+\gamma_{11}}{s^2(s+\gamma_{11})^2} \quad 0 \quad \dots \quad 0 \right]^\top \quad (\text{D4})$$

where \circ denotes the Hadamard (element-wise) product. Further,

$$d_0^n \mathcal{A}(s) = -\mathbf{g}(s) \circ \sum_{k=0}^{n-1} \binom{n}{k} d_0^{n-k} \mathbf{M} d_0^k \mathcal{A}(s) \quad (\text{D5})$$

$$d_0^n \mathcal{A}'(s) = -\mathbf{g}(s) \circ \left(d_0^n \mathcal{A}(s) + \sum_{k=0}^{n-1} \binom{n}{k} d_0^{n-k} \mathbf{M} d_0^k \mathcal{A}'(s) \right) \quad (\text{D6})$$

We also can characterize the limit of $\mathcal{X}(s)$:

$$\lim_{a \rightarrow 0} \mathcal{X}(s) \equiv \mathcal{X}^0(s) = \mathbf{G}(s) \circ (\mathbf{e}_i \mathcal{A}(s)^\top + \mathcal{A}(s) \mathbf{e}_i^\top) \quad (\text{D7})$$

and recursively the derivatives are found from:

$$d_0^n \mathcal{X}(s) = \mathbf{G}(s) \circ \left(\mathbf{e}_i d_0^n \mathcal{A}(s)^\top + d_0^n \mathcal{A}(s) \mathbf{e}_i^\top + \sum_{k=0}^{n-1} (d_0^{n-k} \mathbf{M} d_0^k \mathcal{X}(s) + d_0^k \mathcal{X}(s) d_0^{n-k} \mathbf{M}^\top) \right) \quad (\text{D8})$$

In particular, equations (D4) and (D7) imply:

$$\begin{aligned} \lim_{a \rightarrow 0} [\mathcal{X}]_{i,j} &= \begin{cases} 2\alpha_0 \mathcal{A}_1^0(\alpha_1) \mathbf{G}_{1,1}(\alpha_1) & \text{if } i = j = 1 \\ 0 & \text{otherwise} \end{cases} \\ \lim_{a \rightarrow 0} [\mathcal{Y}]_{i,j} &= \begin{cases} -\theta_0^j (\theta_1^j)^2 \mathcal{A}_1^{0'}(s) & \text{if } i > 1, j = 1 \\ 0 & \text{otherwise} \end{cases} \\ \implies [d_0 \mathbf{M}]_{i,j} &= \begin{cases} 2\sigma_{1,1}^2 \alpha_0 \mathcal{A}_1^0(\alpha_1) \mathbf{G}_{1,1}(\alpha_1) & \text{if } i = j = 1 \\ \sigma_{1,1}^2 \theta_0^j (\theta_1^j)^2 \mathcal{A}_1^{0'}(s) & \text{if } i > 1, j = 1 \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

So $d_0 \mathbf{M}$ is zero everywhere except the first column, which we denote $d_0 \mathbf{M}_1$. Then

$$d_0 \mathcal{A}(s) = -\mathbf{g}(s) \circ d_0 \mathbf{M}_1 \cdot \mathcal{A}_1^0(s) \quad (\text{D9})$$

$$d_0 \mathcal{A}'(s) = -\mathbf{g}(s) \circ d_0 \mathbf{M}_1 \circ (\mathcal{A}_1^{0'}(s) - \mathbf{g}(s) \cdot \mathcal{A}_1^0(s)) \quad (\text{D10})$$

and

$$d_0^2 \mathcal{A}(s) = -\mathbf{g}(s) \circ (d_0^2 \mathbf{M}_1 \cdot \mathcal{A}_1^0(s) + 2d_0 \mathbf{M}_1 \cdot d_0 \mathcal{A}_1^0(s)) \quad (\text{D11})$$

$$d_0^2 \mathcal{A}'(s) = -\mathbf{g}(s) \circ (d_0^2 \mathbf{M}_1 \cdot (\mathcal{A}_1^{0'}(s) - \mathbf{g}_1(s) \mathcal{A}_1^0(s)) + 2d_0 \mathbf{M}_1 \cdot (d_0 \mathcal{A}_1^{0'}(s) - \mathbf{g}_1(s) d_0 \mathcal{A}_1^0(s))) \quad (\text{D12})$$

The following Lemma derives some useful algebraic properties of the model.

Lemma 3. *For $n \geq 2$, the ratio*

$$\frac{d_0^n \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} = n \frac{d_0^{n-1} \mathcal{A}_1(s)}{\mathcal{A}_1^0(s)} + \frac{d_0^n \mathbf{M}_{j,1}}{d_0 \mathbf{M}_{j,1}} + \frac{\sum_{k=1}^{n-2} \binom{n}{k} [d_0^{n-k} \mathbf{M} d_0^k \mathcal{A}(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)} \quad (\text{D13})$$

Proof. We have that

$$\frac{d_0^n \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} = \frac{[\sum_{k=0}^{n-1} \binom{n}{k} d_0^{n-k} \mathbf{M} d_0^k \mathcal{A}(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)}$$

Since $d_0 \mathbf{M}$ is zero everywhere besides the first column, we have that $d_0 \mathbf{M} \mathbf{x}(s) = d_0 \mathbf{M}_1 \cdot \mathbf{x}_1(s)$ for any vector function $\mathbf{x}(s)$. Hence

$$\frac{[d_0 \mathbf{M} d_0^n \mathcal{A}(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)} = \frac{d_0^n \mathcal{A}_1(s)}{\mathcal{A}_1^0(s)}$$

which is independent of j .

Since $\mathcal{A}^0(s)$ is zero everywhere besides the first element, we have that $\mathbf{Q} \mathcal{A}^0(s) =$

$\mathbf{Q}_1 \cdot \mathcal{A}_1^0(s)$ for any matrix \mathbf{Q} , where \mathbf{Q}_1 is the first column of \mathbf{Q} . Hence

$$\frac{[d_0^n \mathbf{M} \mathcal{A}^0(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)} = \frac{d_0^n \mathbf{M}_{j,1}}{\mathbf{M}_{j,1}}$$

which is independent of s .

In particular, equation (D13) implies that for $n = 2$, the ratio is additively separable in the demand factor index j and the Laplace frequency weight s .

□

Proposition 2 (“Global” Demand Shocks). *Demand shocks have “global” effects under (near) risk-neutrality, or when demand is risk-free.*

(a) For any demand factors j, k and Laplace frequency parameters s, t :

$$\lim_{a \rightarrow 0} (\mathcal{B}_j(s, t) - \mathcal{B}_k(s, t)) = 0$$

(b) Assume $\Sigma_{j,j} = 0$ for all demand factors j (but $\sigma_i^2 > 0$ and $a > 0$). For any demand factors j, k and Laplace frequency parameters s, t , we have that:

$$\mathcal{B}_j(s, t) = \mathcal{B}_k(s, t)$$

(c) For any demand factors j, k and Laplace frequency parameters s, t , we have that:

$$\lim_{a \rightarrow 0} \frac{d}{da} (\mathcal{B}_j(s, t) - \mathcal{B}_k(s, t)) = 0$$

Proof. (a) For $j > 1$, $\mathcal{A}_j(s) = 0$ when $a = 0$, so apply L’Hopital’s rule to equation (D1):

$$\lim_{a \rightarrow 0} \mathcal{B}_j(s, t) = \frac{d_0 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(t)} \tag{D14}$$

Equation (D9) implies that the ratio:

$$\frac{d_0 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(t)} = \frac{\mathbf{g}_j(s) \mathcal{A}_1^0(s)}{\mathbf{g}_j(t) \mathcal{A}_1^0(t)}$$

and from Assumption 3, $\mathbf{g}_j(s) = \mathbf{g}_k(s)$ for any $j > 1, k > 1$. Hence:

$$\frac{d_0 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(t)} = \frac{d_0 \mathcal{A}_k(s)}{d_0 \mathcal{A}_k(t)}$$

and the result follows.

A useful corollary of this result is that $\lim_{a \rightarrow 0} \mathcal{B}_j(s, t) > 0$, since $\mathcal{A}_1(s) > 0$ and $\mathbf{g}(s) > 0$ (element-wise).

- (b) When demand is risk-free, Σ is zero everywhere except for the first element (equal to σ_i^2). Hence, we have that:

$$a \cdot \{\mathcal{X} - \mathcal{Y}\} \Sigma = a\sigma_i^2 \cdot \begin{bmatrix} \mathcal{X}_1 - \mathcal{Y}_1 & \mathbf{0} & \dots & \mathbf{0} \end{bmatrix}$$

where $\mathcal{X}_1, \mathcal{Y}_1$ are the first columns of \mathcal{X} and \mathcal{Y} . Since Γ is diagonal, for any $a > 0$, $\mathbf{M} \equiv \Gamma^\top + a \cdot \{\mathcal{X} - \mathcal{Y}\} \Sigma$ is zero everywhere except the first column and diagonal. Therefore, the $j > 1$ element of $\mathcal{A}(s)$ is given by

$$\begin{aligned} \mathcal{A}_j(s) &= \frac{1}{s} [(s\mathbf{I} + \mathbf{M})^{-1}]_{j,1} = \frac{a\sigma_i^2(\mathcal{Y}_{j,1} - \mathcal{X}_{j,1})}{s(s + \gamma_{j,j})(s + \gamma_{1,1} + a\sigma_i^2\mathcal{X}_{1,1})} \\ \implies \mathcal{B}_j(s, t) &= \frac{t(t + \gamma_{j,j})(t + \gamma_{1,1} + a\sigma_i^2\mathcal{X}_{1,1})}{s(s + \gamma_{j,j})(s + \gamma_{1,1} + a\sigma_i^2\mathcal{X}_{1,1})} \end{aligned}$$

Then the result follows since $\gamma_{j,j} = \gamma_{k,k}$ for $j, k > 1$ (by Assumption 3).

- (c) Differentiating equation (D1) (and applying L'Hopital's rule and removing terms equal to zero in the limit) gives

$$d_0\mathcal{B}_j(s, t) = \frac{d_0^2\mathcal{A}_j(s)d_0\mathcal{A}_j(t) - d_0^2\mathcal{A}_j(t)d_0\mathcal{A}_j(s)}{2d_0\mathcal{A}_j(t)^2}$$

Equation (D14) and the corollary from the proof of (a) implies

$$\lim_{a \rightarrow 0} \mathcal{B}_j(s, t) = \frac{d_0\mathcal{A}_j(t)}{d_0\mathcal{A}_j(s)} = \frac{d_0\mathcal{A}_k(t)}{d_0\mathcal{A}_k(s)} = \lim_{a \rightarrow 0} \mathcal{B}_k(s, t) > 0$$

Hence:

$$\begin{aligned} \frac{d_0\mathcal{A}_j(t)}{d_0\mathcal{A}_j(s)} d_0\mathcal{B}_j(s, t) &= \frac{1}{2} \left(\frac{d_0^2\mathcal{A}_j(s)}{d_0\mathcal{A}_j(s)} - \frac{d_0^2\mathcal{A}_j(t)}{d_0\mathcal{A}_j(t)} \right) \\ \frac{d_0\mathcal{A}_j(t)}{d_0\mathcal{A}_j(s)} d_0\mathcal{B}_k(s, t) &= \frac{1}{2} \left(\frac{d_0^2\mathcal{A}_k(s)}{d_0\mathcal{A}_k(s)} - \frac{d_0^2\mathcal{A}_k(t)}{d_0\mathcal{A}_k(t)} \right) \end{aligned}$$

From the Lemma 3, we have that

$$\frac{1}{2} \frac{d_0^2\mathcal{A}_j(s)}{d_0\mathcal{A}_j(s)} = \frac{1}{2} \frac{d_0^2\mathbf{M}_{j,1}}{d_0\mathbf{M}_{j,1}} + \frac{d_0\mathcal{A}_1(s)}{\mathcal{A}_1^0(s)}$$

which is additively separable in terms which are a function of j and s . The result follows. □

Proposition 3 (“Localized” Demand Shocks). *Demand shocks have “local” effects far from risk-neutrality, and are fully localized under infinite risk aversion.*

(a) Suppose $\Sigma_{j,j} > 0$. For any demand factors j, k and Laplace frequency parameters s, t :

$$\lim_{a \rightarrow 0} \operatorname{sgn} \frac{d^2}{da^2} (\mathcal{B}_j(s, t) - \mathcal{B}_k(s, t)) = \operatorname{sgn}(s - t)(\theta_1^j - \theta_1^k)$$

(b) When risk aversion $a = \infty$:

$$\frac{d \log P_t^{(\tau)}}{d\beta_t^k} = \frac{\theta^k(\tau)}{\alpha(\tau)}, \quad \frac{d \log P_t^{(\tau)}}{dr_t} = 0$$

Proof. (a) Differentiating equation (D1) (and applying L'Hopital's rule and removing terms equal to zero in the limit) gives

$$\begin{aligned} d_0^2 \mathcal{B}_j(s, t) = & \frac{1}{6d_0 \mathcal{A}_j(t)^3} (3d_0^2 \mathcal{A}_j(t)^2 d_0 \mathcal{A}_j(s) - 3d_0^2 \mathcal{A}_j(s) d_0^2 \mathcal{A}_j(t) d_0 \mathcal{A}_j(t) + \\ & 2d_0^3 \mathcal{A}_j(s) d_0 \mathcal{A}_j(t)^2 - 2d_0^3 \mathcal{A}_j(t) d_0 \mathcal{A}_j(t) d_0 \mathcal{A}_j(s)) \end{aligned}$$

Using the results from Prop 1, we can scale and rewrite as:

$$\begin{aligned} \frac{d_0 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(s)} d_0^2 \mathcal{B}_j(s, t) &= \frac{1}{3} \left(\frac{d_0^3 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} - \frac{d_0^3 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} \right) + \frac{1}{2} \left(\frac{d_0^2 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} \right) \left(\frac{d_0^2 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} - \frac{d_0^2 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} \right) \\ \frac{d_0 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(s)} d_0^2 \mathcal{B}_k(s, t) &= \frac{1}{3} \left(\frac{d_0^3 \mathcal{A}_k(s)}{d_0 \mathcal{A}_k(s)} - \frac{d_0^3 \mathcal{A}_k(t)}{d_0 \mathcal{A}_k(t)} \right) + \frac{1}{2} \left(\frac{d_0^2 \mathcal{A}_k(t)}{d_0 \mathcal{A}_k(t)} \right) \left(\frac{d_0^2 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} - \frac{d_0^2 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} \right) \end{aligned}$$

and note that the final parenthetical term in each expression is identical (Prop 3).

Focusing on the third-order terms, from Lemma 3 we have that

$$\frac{1}{3} \frac{d_0^3 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} = \frac{d_0^2 \mathcal{A}_1(s)}{\mathcal{A}_1^0(s)} + \frac{1}{3} \frac{d_0^3 \mathbf{M}_{j,1}}{\mathbf{M}_{j,1}} + \frac{[d_0^2 \mathbf{M} d_0 \mathcal{A}(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)}$$

The final term in the sum can be written

$$\frac{[d_0^2 \mathbf{M} d_0 \mathcal{A}(s)]_j}{d_0 \mathbf{M}_{j,1} \mathcal{A}_1^0(s)} = \sum_{m=1}^J \left[\frac{[d_0^2 \mathbf{M}]_{j,m}}{d_0 \mathbf{M}_{j,1}} \right] \cdot \left[\frac{d_0 \mathcal{A}_m(s)}{\mathcal{A}_1^0(s)} \right] \equiv \mathbf{u}_j^\top \mathbf{v}(s)$$

and hence

$$\frac{1}{3} \left(\frac{d_0^3 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} - \frac{d_0^3 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} \right) - \frac{1}{3} \left(\frac{d_0^3 \mathcal{A}_k(s)}{d_0 \mathcal{A}_k(s)} - \frac{d_0^3 \mathcal{A}_k(t)}{d_0 \mathcal{A}_k(t)} \right) = [\mathbf{u}_j - \mathbf{u}_k]^\top [\mathbf{v}(s) - \mathbf{v}(t)]$$

Further, from Lemma 3,

$$\begin{aligned} \left(\frac{d_0^2 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} - \frac{d_0^2 \mathcal{A}_k(t)}{d_0 \mathcal{A}_k(t)} \right) &= \frac{d_0^2 \mathbf{M}_{j,1}}{d_0 \mathbf{M}_{j,1}} - \frac{d_0^2 \mathbf{M}_{k,1}}{d_0 \mathbf{M}_{k,1}} \\ &\equiv [\mathbf{u}_j - \mathbf{u}_k]_1 \\ \frac{1}{2} \left(\frac{d_0^2 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(t)} - \frac{d_0^2 \mathcal{A}_j(s)}{d_0 \mathcal{A}_j(s)} \right) &= \frac{d_0 \mathcal{A}_1(t)}{\mathcal{A}_1^0(t)} - \frac{d_0 \mathcal{A}_1(s)}{\mathcal{A}_1^0(s)} \\ &\equiv -[\mathbf{v}(s) - \mathbf{v}(t)]_1 \end{aligned}$$

Therefore, we have that

$$\frac{d_0 \mathcal{A}_j(t)}{d_0 \mathcal{A}_j(s)} (d_0^2 \mathcal{B}_j(s, t) - d_0^2 \mathcal{B}_k(s, t)) = \sum_{m=2}^J [\mathbf{u}_j - \mathbf{u}_k]_m [\mathbf{v}(s) - \mathbf{v}(t)]_m$$

Dealing with each vector separately: first, we have that

$$\begin{aligned} \mathbf{v}(s) &= \frac{d_0 \mathcal{A}(s)}{\mathcal{A}_1^0(s)} = -\mathbf{g}(s) \circ d_0 \mathbf{M}_1 \\ \implies \mathbf{v}(s) - \mathbf{v}(t) &= -d_0 \mathbf{M}_1 \circ (\mathbf{g}(s) - \mathbf{g}(t)) \end{aligned}$$

Next, the j, m element of $d_0^2 \mathbf{M}$ is

$$[d_0^2 \mathbf{M}]_{j,m} = (\alpha_0 [d_0 \mathbf{X}]_{j,m} + \theta_0^j (\theta_1^j)^2 d_0 \mathcal{A}'_m(\theta_1^j)) \sigma_{m,m}^2$$

(and recall that $\theta_0^1 = 0$). We have that

$$\begin{aligned} \frac{[d_0 \mathbf{X}]_{j,m}}{d \mathbf{M}_{j,1}} &= \begin{cases} -(\mathbf{g}_j(\alpha_1) \mathcal{A}_1^0(\alpha_1) + \mathcal{X}_{1,1}^0(\alpha_1)) \mathbf{S}_{j,1}(\alpha_1) & \text{if } m = 1 \\ 0 & \text{otherwise} \end{cases} \\ &= \frac{[d_0 \mathbf{X}]_{k,m}}{d \mathbf{M}_{k,1}} \end{aligned}$$

where the second equality follows from Assumption 3.

Recall $d_0 \mathbf{M}_{j,1} = \sigma_i^2 \theta_0^j (\theta_1^j)^2 [d_0 \mathcal{A}'(\theta_1^j)]_1$, hence we can write

$$\begin{aligned} -\frac{\theta_0^j (\theta_1^j)^2}{d \mathbf{M}_{j,1}} d_0 \mathcal{A}'(\theta_1^j) &= -d_0 \mathbf{M}_1 \circ \mathbf{g}(\theta_1^j) \circ \left(1 + \mathbf{g}(\theta_1^j) \frac{\theta_1^j}{1 + \theta_1^j \mathbf{g}_1(\theta_1^j)} \right) \\ &\equiv -d_0 \mathbf{M}_1 \circ \mathbf{h}(\theta_1^j) \end{aligned}$$

Therefore,

$$[\mathbf{u}_j - \mathbf{u}_k] = -d_0 \mathbf{M}_1 \circ (\mathbf{h}(\theta_1^j) - \mathbf{h}(\theta_1^k))$$

which implies

$$[\mathbf{u}_j - \mathbf{u}_k] \circ [\mathbf{v}(s) - \mathbf{v}(t)] = (d_0 \mathbf{M}_1)^2 \circ (\mathbf{h}(\theta_1^j) - \mathbf{h}(\theta_1^k)) \circ (\mathbf{g}(s) - \mathbf{g}(t))$$

Hence, the sign of any element of the above vector is determined by the (element-wise) behavior of the functions \mathbf{g}, \mathbf{h} . From equation (D2), the function $\mathbf{g}_m(s)$ is decreasing in s for any element m . Further,

$$\begin{aligned} \mathbf{h}_m(x) &= \frac{3x^2 + 2(\gamma_{m,m} + \gamma_{1,1}) + \gamma_{m,m}\gamma_{1,1}}{(x + \gamma_{m,m})^2(2x + \gamma_{1,1})} \\ \implies \mathbf{h}'_m(x) &= -\frac{2x(x + \gamma_{1,1})(\gamma_{1,1} + \gamma_{m,m} + 3x)}{(x + \gamma_{m,m})^3(2x + \gamma_{1,1})^2} \end{aligned}$$

so $\mathbf{h}_m(x)$ is also decreasing in x for any element m . Thus, we have that

$$\text{sgn} [(\mathbf{h}_m(\theta_1^j) - \mathbf{h}_m(\theta_1^k)) \cdot (\mathbf{g}_m(s) - \mathbf{g}_m(t))] = \text{sgn}(\theta_1^j - \theta_1^k) \cdot (s - t)$$

and therefore the sum over the $m \geq 2$ elements has the same sign. The result follows.

- (b) If $a = \infty$, arbitrageurs invest their entire wealth in the risk-free rate and hence hold no long-maturity bonds: $X_t^{(\tau)} = 0$ for all τ and t . Thus market clearing implies that habitat investors also take zero positions: $Z_t^{(\tau)} = 0$. Thus, the results follow from differentiating the preferred habitat demand with respect to any demand factor β_t^k or short rate i_t and setting to zero.

□

Appendix E Data Appendix

This data appendix briefly describes the data sources and data series used in this paper. This is intended to a brief guide to researchers who aim to extend or replicate our work from raw data.

Treasury auctions

All of the information regarding the details of each treasury auction can be freely downloaded from treasurydirect.gov. Data on announcements and results are available starting in 1979. Data on amounts accepted and tendered by bidder are available since 2003. Data on allotment by investor class begins in 2000.

Intraday treasury data

We obtain intraday (tick-level) data on the secondary market for U.S. Treasuries through GovPX, which is currently maintained by the Chicago Mercantile Exchange (CME). These data are available for purchase directly from several vendors; for instance, CME or Wharton Research Data Services (WRDS). We rely on an institutional subscription to the GovPX database accessed through WRDS. We pull the WRDS databases titled `govpx_tick(year)` for years 1995-2017. Our GovPX data covers the period 1995 through 2017. These data are available to researchers whose affiliated institutions subscribe to the GovPX database via WRDS; otherwise, these data can be purchased from the CME's DataMine repository directly by creating an account on DataMine and contacting the CME Member Services Department (membership@cmegroup.com).

A previous version of this paper used intraday data on Treasury futures to construct auction demand shocks. This data is available for purchase directly from the Chicago Mercantile Exchange (CME) through their DataMine repository.

Zero-coupon Treasury yields are from [Gürkaynak et al. \(2007\)](#). Zero-coupon corporate bond yields are from the Treasury's "HQM" data series, available from FRED.

Federal funds futures

We make use of federal funds futures, which are traded on the Chicago Mercantile Exchange (CME). This data can be purchased directly through CME on their website, or as part of a subscription to a data repository that provides it. Refinitiv Datastream provides data on federal funds futures traded on the Chicago Mercantile Exchange since 1994.

Asset prices and other financial indicators

Daily historical data on inflation swaps, commodity prices, spreads, and credit default swaps are obtained through an institutional subscription to Refinitiv Datastream. Individual researchers may also purchase access to Datastream. Intraday historical data on equities (LQD, SPY, IWM, GLD in Table 4) are derived from the NYSE Trades and Quotes (TAQ) database, which is available to individual or institutional subscribers in WRDS. The coverage of these series varies, and is shown in the right-most column of Table 4.

Macroeconomic aggregates

This paper also relies on data on U.S. industrial production and PCE inflation. We download these series from the Federal Reserve Economic Database (FRED).

Debt volume data

Our discussion of the weighting function η relies on trading volume for Treasury securities sourced from the Federal Reserve and the Securities Industry and Financial Markets Association (SIFMA). The statistics on trading volume that we cite are freely available online at the following URLs:

<https://www.federalreserve.gov/releases/cp/volumestats.htm>

<https://www.sifma.org/resources/research/us-fixed-income-securities-statistics/>