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THE EFFECTS OF QUANTITATIVE EASING:
TAKING A CUE FROM TREASURY AUCTIONS

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The Effects of Quantitative Easing: Taking a Cue from Treasury Auctions
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ABSTRACT

To understand the effects of large-scale asset purchase programs recently implemented by central banks, we study how markets absorb large demand shocks for risk-free debt. Using high-frequency identification, we exploit the structure of the primary market for U.S. Treasuries to isolate demand shocks. These shocks are sizable, leading to large movements in Treasury yields and impacting corporate borrowing rates. Informed by a calibrated “preferred habitat” model of the term structure, we test for “local” demand effects and find evidence consistent with theoretical predictions. Crucially, this local effect is strongest when the risk-bearing capacity of arbitrageurs is low. Our estimates are consistent with the view that quantitative easing worked mainly via market segmentation, with a potentially limited role for other channels.

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1 Introduction

Demand for safe assets, and U.S. Treasuries in particular, plays a central role in the macro-financial landscape. To offset the negative effects of the recent financial crisis, central banks have implemented various large scale asset purchases, representing a sharp increase in demand for these assets. The most salient of these is the quantitative easing (QE) programs carried out by the Federal Reserve, which involved two trillion dollars of Treasury security purchases. Apart from the massive scale of these purchases, the Federal Reserve disproportionately bought long-term government debt, thus departing from the practice of having the distribution of its portfolio close to the distribution of outstanding debt (Figure 1).

While evaluating the program, Ben Bernanke, the chair of the Fed at the time, 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 mechanism behind this reaction is still not well understood. For example, standard macro-financial models imply that the demand for assets such as Treasuries is determined solely by economic agents’ intertemporal consumption decisions, which does not capture the sources of demand shifts initiated by the Fed. Although the workhorse macroeconomic models cannot readily explain the workings of the QE, several explanations have been put forth. Specifically, QE could be effective because it signaled to the markets that the Fed is serious about keeping short-term interest rates low for a long time (forward guidance). Or, perhaps the Fed exploited frictions (limited arbitrage) in the financial markets by purchasing securities in a particular segment. Finally, by buying assets on a massive scale, the Fed could signal a poor state of the economy which pushed interest rates down (“Delphic” effect; see [Campbell et al. \(2012\)](#) for more details). A central question for policymaking and academic research is which of these theories is the key channel. Given the paucity of QE events, it has proven remarkably hard to provide clear empirical evidence for each theory, as well as to assess the relative contributions of the proposed channels.

To address this challenge, we utilize the structure and timing of the primary market for Treasury securities. Similar to the empirical monetary policy literature (e.g., [Bernanke and Kuttner \(2005\)](#), [Gürkaynak et al. \(2007\)](#), [Gorodnichenko and Weber \(2016\)](#)), we look at high-frequency (intraday) changes in prices of Treasury futures in small windows around the close of Treasury auctions to identify unexpected shocks to demand for Treasuries. The key for identification is that all of the “supply” information (e.g. security characteristics such as the maturity, as well as the amount of newly offered and outstanding securities) is known and priced in by the market. For small enough windows around the close and release of the auction results, any price changes are reactions to information regarding the demand for the Treasury securities from the given auction. We interpret these price changes as demand shocks. Utilizing high-frequency changes in asset prices along with

the timing of Treasury auctions in this manner allows us to rule out confounding factors and identify unexpected shifts in demand in a model-free way.

Treasury auctions have a number of properties that can help us understand the workings of QE. First, although the auctions are not as large as the QE rounds, the Treasury sells about \$150 billion in notes and bonds per month in recent years. Because the primary market for Treasuries is the best venue for investors who wish to purchase large amounts of government securities, the release of Treasury auction results can reveal potentially large shifts in demand for Treasuries. The surprise movements in the yields are reasonably large: a typical (one standard deviation) shock is equivalent to a yield change of roughly 2 basis points, which is much larger than similar changes on non-auction dates. For comparison, [Chodorow-Reich \(2014\)](#) estimates that the first round of the QE program in the U.S. cut Treasury rates (five-year maturity) by 9 basis points following the announcement from Chairman Bernanke on December 1, 2008.

Second, because Treasury auctions for specific maturities are spread in time, we can identify changes in demand for government debt of specific maturities. As a result, we can trace how a shock in one part of the yield curve propagates to other parts of the yield curve. In this sense, we have natural experiments which can mimic targeted purchases of the Fed during QE programs.

Third, we document that demand shocks are driven by institutional investors such as foreign monetary authorities, investment funds, insurance companies and the like. This aspect is important as it rules out the inflation expectation channel, forward guidance, and signaling about the state of the economy as possible explanations of how QE influenced interest rates. Indeed, it is highly unlikely that e.g. insurance companies can influence inflation, future short-term interest rates, or aggregate output to the extent the Fed can. In a similar spirit, these agents are unlikely to have an informational advantage over the Fed. Therefore, variation during Treasury auctions can help us to isolate the effect of purchases in specific asset segments on the level and shape of the yield curve.

Finally, in sharp contrast to QE events, Treasury auctions are frequent and information is available back to 1979. This gives us an opportunity for crisper inference and to study state-dependence in the effect of targeted purchases of assets (e.g., crisis vs. non-crisis states). Because QE events were both infrequent and confounded with a massive financial crisis, having a long time series is instrumental for understanding how QE-like programs can work in normal times.

We use high-frequency data on prices of Treasury futures contracts (traded on the Chicago Mercantile Exchange) around announcements of results of Treasury auctions to construct surprise movements in demand for government debt. To interpret these movements, we present narrative evidence as well as regression results. We document that surprise movements likely stem from changes in demand of institutional investors. We show that, although the surprises quickly propagate across markets, one should not inter-

pret these shocks as structural. Specifically, there is time variation in how the surprises move markets, thus underscoring that multiple forces can determine demand for Treasuries.

Although we do not have a structural interpretation of unexpected changes in demand, we can still use shocks in demand for specific maturities of government debt to investigate how these shocks spread to other maturities. Specifically, we examine reactions across maturities through the lens of *preferred habitat* theory, which posits that certain investors have preferences for specific maturities. Building on [Vayanos and Vila \(2009\)](#), we present a series of numerical simulations to provide qualitative predictions about how the location of the shock in maturity space affects the relative change in the term structure and how the reaction depends on the risk-bearing capacity of marginal investors. Informed by theory, we test these predictions using daily changes in spot rates for government debt in response to our measures of surprise movements in private demand at particular maturities. We find evidence consistent with our theoretical predictions.

Why should we expect that the impact of private demand shocks is informative about the effects of shifts in demand arising from the Fed? As made clear in [Vayanos and Vila \(2009\)](#), the key mechanism through which market segmentation/preferred habitat forces operate is not the source of demand shifts, but rather how private agents in the market for Treasury debt absorb these demand shocks. Therefore, the best way to isolate and study the preferred habitat channel of QE is to identify unexpected demand shifts that are unrelated to other channels of QE. Despite the apparent distance between QE programs and unexpected movements in private demand during regular Treasury auctions, our empirical strategy provides clean identification of demand shifts and allows us to map out the impact of these shocks.

Our results suggest that QE programs can be effective in influencing interest rates for debt at specific maturities when financial markets are disrupted. On the other hand, QE programs are less likely to be effective at this task in normal times when risk-bearing capacity of arbitrageurs is greater. In this case, demand shocks at a specific maturity likely move the whole yield curve rather than a specific segment, and the response may peak at a maturity other than the targeted maturity. Furthermore, if the Fed attempts to use purchases of debt with specific maturities to shift down the whole yield curve during a crisis, this exercise may be ineffective and the Fed should intervene at multiple maturities.

Furthermore, our results provide a quantitative sense of *how much* QE programs could influence interest rates through the preferred habitat channel. Specifically, using our regression estimates, we show that the amount of government debt purchases during the QE1 program should generate declines in yields similar to what was observed in the data. In other words, given the reaction of yields to surprise movements in *private* demand during Treasury auctions, we can account for most of the market reaction to QE1 announcements. This result is consistent with the view that QE worked mainly via

market segmentation/preferred habit rather than other channels.

Our study contributes to several strands of previous research. First, we provide new evidence to the literature examining theoretically (e.g., [Vayanos and Vila \(2009\)](#)) and empirically (e.g., [Greenwood and Vayanos \(2014\)](#), [Krishnamurthy and Vissing-Jorgensen \(2012\)](#)) determinants of demand for government debt. In particular, we add to the literature departing from the “expectations hypothesis” (e.g., [Kuttner \(2006\)](#)) of the term structure of interest rates, and provide evidence for alternative explanations such as limited arbitrage and market segmentation. Our findings are complementary to [Lou et al. \(2013\)](#) and [Fleming and Liu \(2016\)](#) who also utilize Treasury auctions to explore how *supply* shocks interact with these forces. Second, we contribute to the rapidly growing literature studying the effects of QE programs in the U.S. and other countries (see [Martin and Milas \(2012\)](#) for a survey) and in particular the literature studying how market segmentation interacts with QE programs (e.g., [D’Amico and King \(2013\)](#)). While most of these studies focus on market movements around QE announcements (e.g., [Krishnamurthy and Vissing-Jorgensen \(2012\)](#), [Chodorow-Reich \(2014\)](#)), we instead focus on market movements around Treasury auctions that can also give us an opportunity to investigate market reactions to unexpected changes in demand for government debt not only in crisis but also in normal times. Third, our paper is methodologically related to earlier studies (e.g., [Kuttner \(2001\)](#), [Bernanke and Kuttner \(2005\)](#)) utilizing high-frequency data to construct surprise movements in policy. Although we do not measure unexpected movements in policy, we construct shocks in private demand that inform us about how markets can react to changes in policy.

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 futures contracts for these Treasury securities.

2.1 Primary Market for Treasury Securities

The Treasury sells newly issued securities to the public on a regular basis through auctions. Currently, 2-, 3-, 5- and 7-year notes are auctioned monthly. 10- and 30-year notes and bonds are auctioned in February, May, August and November with reopenings in the other 8 months. The frequency of auctions evolved 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.

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 and the price (the interest rate) at which they would like to make the purchase. For each competitive bidder, the submitted amount cannot be greater than 35% of the amount offered at the auction.

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), and individuals. These participants are classified into three groups. The first group is Primary Dealers (brokers and banks) that trade on their accounts with the Federal Reserve Bank of New York. This group typically buys the largest share of auctioned debt and is required to participate in every Treasury auction. The second group is Direct Bidders: non-primary dealers submitting bids for their own proprietary accounts. The third group is Indirect Bidders who submit competitive bids via a direct submitter, including Foreign and International Monetary Authorities placing bids through the Federal Reserve Bank of New York.¹

Additionally, the Treasury divides investors into the following classes: Investment Funds (mutual funds, money market funds, hedge funds, money managers, and investment advisors); Pension and Retirement Funds and Insurance Companies (pension and retirement funds, state and local pension funds, life insurance companies, casualty and liability insurance companies, and other insurance companies); Depository Institutions (banks, savings and loan associations, credit unions, and commercial bank investment accounts); Individuals (individuals, partnerships, personal trusts, estates, non-profit and tax-exempt organizations, and foundations); Dealers and Brokers (primary dealers, other commercial bank dealer departments, and other non-bank dealers and brokers); Foreign and International (private foreign entities, non-private foreign entities placing tenders external of the Federal Reserve Bank of New York (FRBNY), and official foreign entities placing tenders through FRBNY); Federal Reserve System (the Federal Reserve Banks System Open Market Account (SOMA)); Other (represents the residual from categories not specified in investor class descriptions above). [Fleming \(2007\)](#) describes in greater detail the breakdown by types and class of bidders.

As detailed in [Figure 2](#), there are four stages of a Treasury auction:²

1. *Announcement*: A few days before an auction, the Treasury releases all the pertinent

¹Additionally the Federal Reserve System purchases securities for its System Open Market Account (SOMA). Starting in 1997, the SOMA amount was changed from being listed within the announced offering amount to being additions to the announced offering amount. That is, if the Treasury auctions \$15 billion in bonds and the Federal Reserve would like to purchase \$1 billion in the auction, the Treasury issues \$16 billion in bonds. This change was made so that the Treasury would be able to provide better information to the market about the amount of securities actually available for sale to the public.

²See [Driessen \(2016\)](#) for details on the design of Treasury auctions. [Garbade \(2007\)](#) provides historical details regarding the manner in which the Treasury has conducted auctions.

information regarding the upcoming auction. An announcement includes security information (maturity, CUSIP identifier, schedule of coupon payments, etc.) as well as the amount offered, the bidding closing times, which class of bidders can participate, and other information describing the rules of the auction.

Figure 3 presents a typical announcement. At this auction, the Treasury offers \$16 billion in 30-year bonds. This is a new auction (that is, the Treasury does not reopen a previous auction) with the maximum award (that is, maximum allocation to a bidder) of \$5.6 billion.

2. *Bidding*: After the announcement, individuals and institutions may submit bids up until the closing times of the auction. The announcement in Figure 3 stipulated that non-competitive bids should be submitted by 12:00 p.m., while the deadline for competitive bids is 1:00 p.m.
3. *Results*: Most Treasury note and bond auctions close at 1:00 p.m. Competitive bids are accepted in ascending order (in terms of yields) after the auction closes until the quantity meets the amount offered minus the amount of non-competitive bids. All bidders receive the same yield as the highest accepted bid.³ Once the auction closes and the winning bids are determined, the information regarding the results is released immediately. Besides the winning yield, the Treasury announces various aggregate statistics regarding the bidding. Beginning in the early 2000s, auction results are released within minutes of the close of the auction (see Garbade and Ingber (2005)).

Figure 4 presents a typical announcement about auction results, which corresponds to the auction announcement presented in Figure 3. The demand (tendered) for the security was \$33.3 billion, most of the bids came from primary dealers (\$23.7 billion), \$489.9 million was bought by the Federal Reserve (SOMA), and a relatively low amount was bought via non-competitive bids (\$14.8 million). The “bid-to-cover”, the ratio of all bids received to all bids accepted, was $\$33.3/\$16.0=2.08$. The interest rate was set at 3.75 percent per year.

4. *Issuance*: A few days after the close of an auction, the Treasury delivers the securities and charges the winning bidders for payment of the security. At this point the winning bidders can hold the security to maturity and receive coupon payments, or sell the security on the secondary market.

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. Additionally, the

³Between 1970 and 1992, Treasury did not charge a uniform price. Instead, allocation of bonds was made at the individual yields stipulated by the bidders.

Treasury provides information regarding allotment by investor class (Investment Funds, Individuals, etc) starting in 2000.

2.2 Treasury Futures

We use Treasury futures prices to capture market-based expectations for outcomes of Treasury auctions. Treasury futures are standardized contracts that obligate the seller to deliver a valid Treasury security to the buyer at a later date. Futures contracts for 30-year Treasury bonds were introduced in 1977, followed later by 10-year, 5-year, and 2-year Treasury note futures. Treasury futures currently trade on the Chicago Mercantile Exchange (CME), and intraday tick-level data are available starting in 1995. The market for Treasury futures is deep: the average daily volume of trade in 2012 was more than 2 million contracts with more than \$100 billion of notional value.

The futures contracts close in March, June, September, and December. We focus on the “closest” contract, i.e. the contract that closes within 1-3 months as these are by far the most traded. For example, in February we use the March expiry, while in March we use the June expiry. Although contracts that close in a given month can still be traded, the volume of trades is substantially lower.

Note that futures are not tied to any specific bond issue (CUSIP). Each futures contract allows for a range of deliverable Treasury securities. 2-year futures contracts allow for delivery of Treasury notes with remaining maturity between 1-year 9-months to 2 years; 5-year futures allow for remaining maturity between 4-year 2-months to 5-year 3-months; 10-year futures allow for remaining maturity between 6-year 6-months to 10-years; and 30-year futures allow for delivery of Treasury bonds with remaining maturity of at least 15 years.⁴ In principle any permissible Treasury security can be delivered into a futures contract, but as explained in [Lauszweski et al. \(2014\)](#) in practice a so-called “cheapest to deliver” (CTD) security emerges for a given futures contract. Although which Treasury security is used for payment can vary over time, this variation happens at relatively low frequencies (weekly or monthly) and therefore our analysis at high frequencies should not be materially affected by this peculiarity of Treasury futures contracts.

Because futures cannot be matched to a specific CUSIP, we link a given auction to Treasury futures using the maturity offered in the auction. For example, if the Treasury auctions 7-year notes, we use the 10-year futures contract which allows delivery of securities maturing in at least 6.5 years and no more than 10 years. While this

⁴The 30-year futures contract is also known as the “classic T-Bond” future. This contract originally allowed for delivery of bonds with remaining maturity between 15 years and 30 years. In 2009, the CME Group introduced “Ultra T-Bond Futures” which uses Treasury bonds with remaining maturity of at least 25 years but no more than 30 years, and changed the range of deliverable maturities to the classic contract to bonds with remaining maturity between 15 years and 25 years. While the “Ultra” futures contract provides a better match for long maturities, the time series for the contract is relatively short and the volume of trades is small relative to the other longer-running futures. For these reasons we use the “Classic T-Bond Futures” to ensure consistency over time.

linking introduces a mismatch in terms of maturities, the difference between the maturity of matched futures contracts and the maturity of the auctioned government debt is relatively small.

We use Treasury futures prices for a number of reasons. First and foremost, Treasury futures provide a natural market-based measure of unexpected shifts in Treasury prices. Further, Treasury futures trade on a standardized exchange rather than over the counter. Another option would be to use “when-issued” prices of the Treasury securities being auctioned. While this has the benefit of matching perfectly the security being auctioned, the downside is the when-issued market has some strange pricing behavior. The biggest problem for our analysis is the when-issued market exhibits significant underpricing: the winning yield at the auction is significantly higher than the final yield observed in the when-issued market before the close of the auction (see e.g. [Fleming and Liu \(2016\)](#)).

2.3 Summary Statistics

In our analysis we focus on Treasury note and bond auctions. We exclude inflation protected securities (TIPS), floating rate notes (FRNs), cash management bills (CMBs), and callable bonds (the last of which was issued in 1984), 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-term nominal U.S. government debt.⁵ Further, Treasury futures contracts exist for 2-year, 5-year, 10-year, and 30-year nominal Treasury notes and bonds, but not for shorter term bills.

Figure 5 plots the number of note and bond auctions per year in our sample, broken up by term length. The number of auctions is relatively stable throughout the 1980s to mid 1990s. In the face of declining government debt, the number of auctions temporarily fell in the late 1990s and early 2000s, which also coincides with the termination of new issuances of 30-year bonds. After the Great Recession, the number of auctions increased significantly.

Table 1 presents summary statistics for note and bond auctions between 1979 and 2015, and the subsample 1995-2015 for which we have intraday Treasury futures prices. Since 1995, a typical offering is about \$20 billion which generates more than \$50 billion in demand so that the bid-to-cover ratio is approximately 2.6. The largest source of demand for Treasuries is primary dealers (their bid-to-cover ratio is ≈ 2) but other types of bidders also account a large fraction of auction offerings. Primary dealers purchase approximately 60 percent of auctioned Treasuries with the rest split equally between investment funds and foreign buyers.

⁵For example, between November 3, 2010 and June 29, 2011 (QE2), the Fed bought \$750 billion in Treasury securities, of which TIPS purchases were only approximately \$26 billion.

There is considerable variation in the offered amounts (standard deviation is $\approx \$9$ billion) as well as the level and composition of demand (standard deviation for the bid-to-cover ratio is ≈ 0.5 and the standard deviation of bid-to-cover ratio for primary dealers is 0.35). In our sample of Treasury note and bond auctions, the median maturity is 5 years. The winning yield (“high yield”) is on average close to 3.2 percent per year with standard deviation of 1.9 percentage points. The distribution of submitted bids tends to be fairly compressed: the high-median yield spread is approximately 3 basis points with standard deviation of 2 basis points. However, on some occasions the spread can be as high as 10 basis points.⁶

3 Quantifying Demand Shocks

In this section, we describe how we measure the surprise movements in prices of Treasury futures around Treasury auctions and document properties of these surprises. Our key assumption is that within small enough windows around the close and release of Treasury auction results, shifts in the prices of Treasury futures reflect unexpected changes in market beliefs about the demand for Treasuries with a specific maturity. Indeed, since the Treasury announces an offered amount well before an auction happens thus fixing supply, between the announcement and close of the auction futures prices should move only in response to changes in demand conditions. By focusing our analysis on a narrow window around the close time of an auction, we likely isolate variation only due to unexpected shifts in demand for this specific auction. As a result, we can identify a demand shock for a specific maturity and then use this shock to trace the reaction of Treasury futures prices for the given maturity and for other maturities as well as reactions for other parts of the financial market.

3.1 Shock Construction

Let $P_{t,pre}^{(m)}, P_{t,post}^{(m)}$ be the futures prices before and after the close of the auction on date t with maturity $m = 2, 5, 10, 30$. We measure the surprise movements in the futures prices as:

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

These surprises are computed for all maturities at date t irrespective of what maturity is being auctioned on date t . In other words, we compute $D_t^{(2Y)}$ (surprise movement in the 2-year Treasury futures) not only for auctions that offer 2-year government notes but also for auctions that offer Treasuries with other maturities.

⁶Between 1999-2015 when the data is available, the Fed purchased Treasuries through SOMA in approximately two thirds of auctions; when doing so they purchased an average of \$2.3 billion (standard deviation of \$2 billion).

For all auctions, $P_{t,pre}$ is the last price observed 30 minutes before the close of the auction. For auctions taking place between 1995 and 1999, $P_{t,post}$ is the first price observed 1.5 hours after the close of the auction; after 2000, we use the first price observed 30 minutes after the close of the auction. The Treasury began releasing results much faster in the early 2000s, but in the 1990s auction results frequently took over an hour after the close of the auction to be released. Unlike the close of the auction, the time at which the results are released is not reported by the Treasury. However, wire reports from Bloomberg allow for an upper bound on the release time. Note that we use symmetric windows around the events to eliminate predictable movements in prices identified in [Lou et al. \(2013\)](#) and [Fleming and Liu \(2016\)](#).

Panel A of Table 2 presents summary statistics for $D_t^{(m)}$ shocks. The mean values of the shocks are close to zero suggesting that surprises are not systematic. The standard deviation of $D_t^{(m)}$ increases in maturity m . To verify that these shocks are not spurious we also report (Panel B of Table 2) movements in futures prices on non-auction days (for days without auctions, the same “pre” and “post” windows are used as auctions in the same year). In all cases, the variance of the shocks on auction dates is larger than on non-auction dates. This pattern is consistent with auction results indeed influencing futures prices.

The table also reports moments for the zero lower bound (ZLB) and pre-ZLB periods. The variability of surprises for short maturities is considerably smaller during the ZLB period (December 2008 to present) than outside the ZLB period (1995 to December 2008). For longer maturities, the volatility is similar for ZLB and pre-ZLB periods. However, these statistics mask important heterogeneity. During the Great Recession, the volatility of surprises was elevated but then we observe strong compression for short maturities since the economy enters recovery (Figure 7). This finding is consistent with [Swanson and Williams \(2014\)](#) documenting that while the Fed’s policies during the Great Recession compressed fluctuations of short-term rates, the behavior of long-term rates is still relatively normal.

Note that the shocks are in terms of futures (log) prices. Although futures contracts do not have a natural definition of yield, an approximate yield can be computed using the Treasury securities delivered at the end of the contract. Using this approximation, a one standard deviation change in the log price of each contract is equivalent to a 2.0 to 2.5 basis point change in yield for each contract.⁷

Additionally, Table 2 documents that price changes of Treasury futures strongly co-move across maturities, with the strongest correlations between adjacent maturities. For example, on auction dates the correlation between $D_t^{(10Y)}$ and $D_t^{(30Y)}$ is 0.922 while the correlation between $D_t^{(2Y)}$ and $D_t^{(30Y)}$ is 0.672. Note that the correlations are generally

⁷For details on how to convert between Treasury futures prices and the yield on the corresponding “cheapest-to-deliver” Treasury security, see [Lauszweski et al. \(2014\)](#).

stronger between short ($D_t^{(2Y)}$) and longer maturities during the non-ZLB period than during the ZLB period. At the same time, the comovement of $D_t^{(5Y)}$, $D_t^{(10Y)}$ and $D_t^{(30Y)}$ does not appear to be materially influenced by the binding ZLB. These correlations suggest that shocks to a given segment of the maturity spectrum generally affect not only prices of that particular segment but also prices in other parts of the spectrum, but there is heterogeneity across time in the strength of the correlation. We return to this topic in Section 4.

3.2 Narrative Evidence

To provide a better understanding of what forces are behind these surprise movements, we plot the 30-year Treasury futures price during two 30-year Treasury bond auctions (Figure 6). The first is from an auction on August 11, 2011. Futures prices were relatively stable in the lead up to the close of the auction, but after the close and release of the auction results prices dropped sharply and immediately. The Financial Times wrote:

“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.’”

The second is from December 12, 2010. This auction was a reopening of previously issued 30-year bonds from the month prior. Once again, the futures prices are relatively stable in the lead up to the close of the auction. After the auction closes and results are released, prices immediately spike up. 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.’”

We interpret the two example auctions as follows. Before the auction closes, the market information set consists of all the supply information, both for outstanding securities as well as the amount on offer for the current 30-year auction. The 30-year futures prices reflect beliefs about the expected path of short-term interest rates, inflation expectations, and demand for long-term Treasury securities. After the auction closes and the results are 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 futures price reflects this unexpected shift in beliefs about Treasury demand. The contemporaneous articles in the financial press further suggest that the important driver of the demand shifts arise from foreign and domestic institutional investors. The last example also highlights why auctions can have important elements of price discovery: when investors have to purchase large amounts of Treasuries to meet their needs, they

may prefer to use auctions rather than attempting to make substantial transactions on the secondary market. As a result, auctions reveal new information about demand.⁸

3.3 Demand Determinants

Our assumption is that $D_t^{(m)}$ captures unexpected shifts in the demand for Treasuries. We further hypothesize that these shocks are particularly driven by demand shifts arising from institutional investors. Figure 6 and the corresponding reporting in the financial press provided some narrative evidence in this direction. Using other information released at the end of the auction provides more justification of this assumption.

One of the most commonly reported statistics in the financial press is the “bid-to-cover” ratio, the ratio of the dollar value of all bids received to all bids accepted. It is a natural measure of the demand at a given auction (the higher is the bid-to-cover ratio, the higher is demand). The bin scatter plot in Figure 8 shows that the bid-to-cover ratio (after controlling for its four own lags) is a strong predictor of our measure of demand shocks.

Table 3 presents more formal evidence by regressing our shocks on measures of demand reported at the auction:

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

This specification is estimated for each maturity separately in columns (1)-(4). Column (5) reports results when we pool across maturities and impose that $\beta^{(m)}$ is the same across maturities m . In all specifications we include the current bid-to-cover ratio as well as four lags of the bid-to-cover ratio (winsorized at the 1% level) but report estimated coefficients only for the current bid-to-cover ratio. These coefficients may be interpreted as the reaction of $D_t^{(m)}$ surprises to an innovation in the bid-to-cover ratio. To facilitate the comparison of the results, we standardize $D_t^{(m)}$ in these regressions to have zero mean and unit variance.

Panel A of Table 3 shows that bid-to-cover ratio is positively associated with $D_t^{(m)}$ and the effect of an increase in the bid-to-cover ratio is statistically and economically significant. For example, a one standard deviation (0.3) increase in the bid-to-cover ratio (after controlling for its own four lags) in a Treasury auction for 30-year bonds raises the price of the 30-year Treasury futures by $2.108 \times 0.3 = 0.63$ standard deviation (this corresponds to 0.16 log percentage point increase in the price of the Treasury futures or an approximate change of 1.5 basis points in the yield).

Panel B of the table reports sensitivity of futures prices to changes in demand by bidder type. The sensitivity of surprises to unexpected demand of indirect bidders increases with

⁸We could not find any reference in the press about monetary policy (or leaked information about future monetary policy) being a source of unexpected movements. Consistent with this observation, we do not find any statistical power of surprise movements in Treasury futures around Treasury auctions to predict future monetary policy.

maturity. For example, a unit increase in the bid-to-cover ratio for indirect bidders raises the price of 2-year Treasury futures by 2.7 standard deviations and the price of 30-year Treasury futures by 8.5 standard deviations. For direct bidders, the sensitivity is highest for short maturities. The sensitivity to changes in the bid-to-cover ratio coming from primary dealers for 2- and 5-year Treasury futures is smaller than the sensitivity for 10-year Treasury futures and greater than the sensitivity for 30-year Treasury futures. When we pool across maturities, demand of direct and especially indirect bidders generates *ceteris paribus* more variation in futures prices than demand of primary dealers.

Panel C uses additional investor allotment data from the Treasury to break down the amount accepted by types of bidders: Investment Funds, Foreign, Dealers, and Miscellaneous. Since the fractions by group add up to one, we set Dealers as the leave-out category. The estimated coefficients suggest that as the fraction accepted for investment funds and foreign buyers increases, $D_t^{(m)}$ increases too. The coefficients for the Miscellaneous category are generally smaller and less robust.

These results indicated that, indeed, a key determinant of $D_t^{(m)}$ surprises is movements in demand conditions as proxied by the bid-to-cover ratio.⁹ Furthermore, we observe that the demand from institutional investors is important in accounting for variation in $D_t^{(m)}$.

3.4 Comovement Across Markets

We now turn to analyzing how our demand shocks for Treasuries propagate across other financial markets. Given the relatively high degree of correlation across our demand shocks, in the following analysis we will find it useful to compress $D_t^{(m)}$ into a single summary statistics: the first principal component of $D_t^{(m)}$. This time series captures the general movement of the yield curve in response to demand shocks for government debt with various maturities. One can interpret this series as shifts in the yield curve. The first principal component explains 88 percent of variation in our shock measures. We denote the first principal component by D_t , which has zero mean and unit variance.

We measure the impact of demand shocks on other asset prices by running simple bivariate regressions:

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

where y_t is the change in some asset prices on auction date t . Where available, we use intraday changes within the same time window as our shocks D_t . However we also examine changes at the daily frequency, partly due to data limitations but also because daily changes may pick up responses in other asset markets that don't occur immediately.

As expected, yields in the secondary market react strongly to the demand shock. More

⁹Our identification strategy is effective at measuring *unexpected* shifts in demand for Treasury debt (D_t). On the other hand, D_t has little to say about reactions (if any) to *expected* demand shifts. When we regress our shocks D_t on a predicted ("expected") bid-to-cover ratio at each auction (defined as the fitted value from an AR(4) model), we find a coefficient very close to zero.

interestingly, this reaction is persistent in spite of the fact that our shocks are constructed from intraday movements. Appendix Figure B1 plots the contemporaneous reaction of 10-year spot rates to our shocks D_t , as well as the reactions up to 3 months in the future. The contemporaneous response is around 2-3 basis points, which implies a one-to-one reaction. The reaction remains strongly statistically significant nearly 1 month later, while the point estimate is remarkably stable even 3 months later.

Panel A of Table 4 reports results for corporate debt markets. The dependent variable in the first row of the panel is the intraday change in the Exchange Traded Fund (ETF) “LQD”, which tracks the iBoxx Liquid Investment Grade Index. The coefficient should be interpreted as the impact in percentage points of a one standard deviation change in D_t . We observe a strong reaction of LQD prices to the Treasury demand shock which account for more than 50 percent of variation in LQD during the time windows.

Rows 2 through 4 of the panel report the results for the daily change in yields for corporate AAA yields, the corporate B-AAA spread, and the 1-month P1 commercial paper rate. The negative coefficient for the AAA regression suggests that an increase in the price of Treasury futures (which means that the yield on Treasuries falls) is associated with a decrease in the AAA bond yields. Specifically, a one standard deviation shock to D_t decreases the AAA bond rate by 2.7 basis points. The same shock tends to increase the B-AAA spread by 2.3 basis points. We find no significant effect of the shock on the 1-month commercial paper rate (P1(M1)). Note that when we use daily rather than intraday changes as dependent variables, R^2 s decline considerably, which could underscore the benefits of using intraday data. In short, we find strong immediate reactions for relatively safe, liquid medium to long-term corporate debt and there is no movement in very short term rates or rates for risky corporate debt.

Panel B of Table 4 reports results for equities. 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 negative, the quantitative significance of shocks on equities is small: these shocks account for a tiny share of variation in equities.

Panel C of Table 4 presents results for inflation expectations and commodities. Rows 1 and 2 report the results for the daily change in inflation expectations implied by inflation swaps at the 10-year and 2-year horizon. We observe that demand shocks for Treasuries do not generate significant movements in inflation expectations. To explore the robustness of this finding, we examine price reactions of two additional assets which are often used to hedge against inflation. The dependent variable in row 3 is the intraday change in the ETF “GLD”, which tracks the price of Gold Bullion. Row 4 reports results for the daily change in the S&P Total Commodity Index. For neither of these variables do we find a significant correlation with D_t .

To further explore sensitivity of inflation expectations to demand shocks D_t , we plot

reactions of inflation swap rates at all available maturities in Appendix Figure B2. We find that the change in the inflation expectation “yield” curve exhibits little reaction to D_t . We find a similar lack of sensitivity of inflation expectations when we use specific $D_t^{(m)}$ instead of summary series D_t . Thus, although the inflation expectations channel may be at work during rounds of quantitative easing, our demand shocks do not have such an effect. This result is intuitive: changes in demand of institutional investors or foreign monetary authorities are unlikely to generate future fluctuations in the rate of U.S. inflation.

Table 4 reports “average” sensitivity of various asset prices to demand shocks D_t . These estimated sensitivities, however, should not be interpreted as structural. Indeed, a spectrum of forces can be behind D_t and the composition of the forces may vary over time thus making structural interpretation tentative at best. To highlight this caveat, we plot sensitivities for select asset prices estimated over rolling windows in Figure 9. The sensitivity of LQD prices, AAA interest rates, and B-AAA spread is relatively stable over time. On the other hand, the sensitivity of S&P500 flips sign from positive in the late 1990s to generally negative since the early 2000s. Although we do not have long-time series of inflation expectations (or assets used for hedging against inflation), we observe that during the Great Recession in the U.S., inflation expectations and D_t moved in opposite directions while in normal time these two series are approximately uncorrelated. In summary, a variety of factors can generate movements in D_t and one should not interpret D_t as structural shocks. Despite this limitation, we can still use $D_t^{(m)}$ shocks to study how unexpected demand interventions at specific maturities propagate to other maturities.

4 Channels of Treasury Demand Shocks

Although demand shocks $D_t^{(m)}$ strongly comove with one another, the responses are not uniform across maturities. To see the heterogeneity in reactions, we use daily changes in zero-coupon spot rates as constructed in [Gürkaynak et al. \(2007\)](#), which provide more granularity to the analysis (recall that we have only four maturities in Treasury futures contracts while the yield curve utilizes information for many more maturities but is available only at the daily frequency). Figure 10 plots “responses” of changes in the yield curve for auctions on two dates. On the first date (August 11, 2011), there was unexpectedly weak demand (as measured by changes in futures prices) during an auction of 30-year Treasuries. We observe that, although the whole yield curve shifted up, the strongest reaction was at long maturities. On the second date (February 6, 2007), there was an auction of 3-year government notes, and demand during this auction was unexpectedly strong. The whole yield curve shifted down, but the strongest reaction was at the 8-year maturity. These two cases illustrate that the “propagation” of demand shocks across

maturities does not amount to simple upward or downward shifts.

This raises the question: to what extent do Treasury demand shocks have local effects? In other words, does the location of the demand shock in maturity space matter? The two auctions in Figure 10 provide suggestive evidence that the location can in fact matter. In order to better characterize the impact of these demand shocks, we now examine the impact on the term structure of Treasury rates through the lens of the *preferred habitat* model of investor demand. The key idea is the existence of “clientèle” investors who have idiosyncratic demand for Treasuries of specific maturities. The other side of the market are risk-averse arbitrageurs, who smooth out these demand shocks. Using the model from Vayanos and Vila (2009), we create numerical predictions of what happens to the term structure when hit with demand shocks to various parts of the maturity space.

4.1 Preferred Habitat – Numerical Exercise

Our numerical exercises are as follows: consider a “three-factor” version of the Vayanos and Vila (2009) model consisting of the instantaneous rate, and two demand factors that are otherwise equivalent, but are located in the “short” and “long” ends of the maturity space. We then solve the model and study the impact of each demand shock as risk aversion increases from very low to very high. We consider the case where the “short” shock is concentrated at the 3-year maturity, while the “long” shock is at 20 years (corresponding to the average length of short-term and long-term auctions in our empirical section). See Appendix A for details regarding the model and calibration.

Figure 11 shows the change of the term structure in response to the short (top panel) and long (bottom panel) demand factors, as the risk aversion of arbitrageurs increases from low (lighter lines) to high (darker lines). In the case of low risk aversion, the impact is very similar: rates fall across the entire term structure, but the impact peaks at the short end of the yield curve, then drops off as the maturity increases. The only difference between the impacts of the short and long shocks is that the long shock has a larger impact; but the shape of the response is nearly identical.

However, as risk aversion increases, the responses become quite different depending on the location of the demand shock. A shock to the short demand factor sharply decreases short-term rates; but this impact dies off quickly and even turns slightly positive at the long end of the term structure. On the other hand, the long demand factor decreases both short and longer term rates, but the impact is much stronger in the long end of the term structure.

These results confirm that some of the findings of Vayanos and Vila (2009) for the limiting cases of no risk aversion and infinite risk aversion also hold for intermediate cases of risk aversion. As they explain, the intuition for these results is as follows: when arbitrageurs are perfectly risk-neutral, demand shocks have no impact as the expected path

of the instantaneous rate is the only determinant of the term structure. As arbitrageurs become somewhat risk averse, shocks to the instantaneous rate continue to be much more influential than demand shocks. But now arbitrageurs are concerned about instantaneous rate (duration) risk, and demand shocks cause changes to the exposure of their portfolio to this source of risk. Hence, even in cases of very low risk aversion, demand shocks do affect the term structure by altering the price of instantaneous rate risk.

Because short and long demand shocks cause arbitrageurs to take positions in bonds of different maturities, the location of the shock matters for determining the magnitude of the impact of demand shocks. But notice that instantaneous rate risk is common to all bonds; which bonds are most sensitive to this risk depends only on the stochastic properties of the instantaneous rate and demand factors (i.e. the mean reversion rate). In particular, the relative impact across the term structure is independent of the location of the demand shocks. In other words, when arbitrageurs have low risk aversion, the relative impact of short and long demand shocks to the term structure is roughly the same; only the overall size of the impact is affected by the location of the demand shock. In our calibration, for low values of risk aversion this leads to the peak impact occurring around $m \approx 4$. This could be lower or higher with different parameterizations, but remains independent of the shock's location in maturity space.

As arbitrageur risk aversion increases, demand shocks become more salient, which causes the term structure response to become more localized to each demand shock. For example, following a short demand shock which causes arbitrageurs to sell short-term securities, all else equal arbitrageurs would like to buy longer term securities to hedge the risk arising from the short demand shock, leading to upward pressure on prices (and downward pressure on spot rates). But this changes their exposure to the long demand shock as well, and this countervailing force leads arbitrageurs to sell sufficiently long-term securities. As seen in the top panel of Figure 11, when risk aversion is sufficiently high this countervailing force can become strong enough to lead to an increase in rates for very long-term securities.

To summarize the qualitative predictions: When risk aversion is low, the impact of an increase in demand for either short-term or long-term debt causes a decrease in rates everywhere. Moreover, while the magnitude may differ, the response to both demand factors are similarly shaped, peaking at intermediate maturities and declining for very long-term maturities. Conversely, when risk aversion is high, demand factors have a stronger local component: increases in demand for short-term debt will have a maximal impact on shorter-term maturities, while long-term shocks will peak at long-term maturities. Additionally, the response of long-term (short-term) rates to long (short) demand shock increases as risk aversion increases, respectively. Finally, although the magnitude of responses is more ambiguous, when risk aversion is high we expect the response of short-term rates to short demand shocks will be larger than to long demand shocks; and

vice versa for responses of long-term rates.

4.2 Empirical Results

Comparing the theoretical results from Figure 11 with Figure 10 suggest that, at least during the auction in Panel A, the preferred habitat model with relatively high risk aversion does a good job explaining the response of the term structure; Panel B is more ambiguous. We now take a more rigorous approach to testing the predictions of our numerical exercise.

A key variable is a measure of risk aversion of arbitrageurs. We proxy this using the measure of financial crises in the United States from [Romer and Romer \(2017\)](#). The crisis index is a continuous measure derived from narrative sources to identify periods of financial distress (higher values correspond to periods of more extreme financial crisis). Besides identifying financial distress during the recent financial crisis, the measure also identifies periods of distress in 1986, the early 1990s, and 1998 (Figure B3 in the Appendix).

In order to measure the impact of demand shocks on the entire term structure, we estimate the following regression equations

$$\Delta R_t^{(m)} = C_t \left(\alpha^{(m,H)} + \beta^{(m,H)} D_t^{(m')} \right) + (1 - C_t) \left(\alpha^{(m,L)} + \beta^{(m,L)} D_t^{(m')} \right) + \varepsilon_t^{(m)} \quad (4)$$

for each maturity $m = 1, \dots, 30$. $\Delta R_t^{(m)}$ is the daily change in the spot rate for the given maturity. C_t is an indicator variable that is equal to 1 when the [Romer and Romer \(2017\)](#) measure of financial crisis is non-zero. The coefficients $\beta^{(m,L)}$ capture the impact of demand factor $D_t^{(m')}$ at maturity m' (our normalized intraday futures price shocks) during periods of low risk aversion; similarly $\beta^{(m,H)}$ capture the impact during periods of high risk aversion. While our shock measure is constructed at a higher intraday frequency, in order to capture the full extent of how markets absorb these shocks we prefer to use these daily estimates of the yield curve. To the extent that shocks are absorbed completely within smaller windows than a day, using daily changes as an outcome variable simply adds noise to our estimates, but shouldn't result in any bias.

A straightforward way in which to test the predictions of the preferred habitat model is to estimate equation (4) in two separate subsamples: *i*) days with short auctions; *ii*) days with long auctions. In our baseline regression we break up auctions into 2-7 years and 10-30 years.¹⁰ We choose the 10-year cutoff for long vs. short rather than 30-year in order to have a more balanced sample; the results are robust to choosing different cutoffs. Breaking up the auctions in this manner allows us to more closely pinpoint the location

¹⁰Consistent with our exercise in Section 4.1, the average maturities of “short” and “long” auctions are 3 and 20 years respectively. Additionally, rather than using a narrative measure of financial distress, we used a market-based proxy for arbitrageur risk aversion. We define high risk aversion periods as those in which the “intermediary capital ratio” described in [He et al. \(2016\)](#) is low (Appendix Figure B4), and find similar results.

of the demand shock in the maturity space, and ties closely with the numerical exercise above.

For our measure of demand shocks $D_t^{(m')}$ on the right-hand-side of equation (4), in our baseline results we take the same approach above and match each auction with the (normalized) futures surprises of closest maturity (e.g. for 5-year auctions, use the 5-year futures surprise). The β coefficients should be interpreted as the response of spot rates for maturity m to a one standard deviation demand shock at maturity m' on the day when maturity m' is auctioned.

Figure 12 plots the low and high coefficients from the two subsamples.¹¹ During periods of low risk aversion, the impact of short and long demand shocks on the term structure closely mirror one another. Both shocks decrease spot rates across the entire term structure, and are hump-shaped. But when risk aversion is high, the short and long demand shocks have differential impacts. Both shocks exhibit stronger local effects. For the long shock, the impact is no longer hump-shaped as the impact continues to remain large as the maturity increases. The magnitude is also considerably larger than the corresponding responses during periods of low risk aversion. The impact of the short demand shock peaks at intermediate rates and then begins declining; further, the magnitude is larger than the corresponding response in periods of low risk aversion. Finally, when risk aversion is high, the response of short-term rates to short demand shocks is larger than their response to long demand shocks; and vice versa for the response of long-term rates.

These results confirm the key predictions of our numerical exercise: during periods of low risk aversion, short and long demand shocks have relatively similar impacts; and these impacts peak at short to intermediate maturities. During periods of high risk aversion, the impacts are more localized: the impact of short demand shocks peak at short maturities, while the impact of long demand shocks peaks at the long end of the term structure. This local effect is particularly strong for long-term demand shocks. We also find that the peak responses for both short and long demand shocks are larger during periods of high risk aversion than during periods of low risk aversion.

As a robustness check, rather than use demand shocks as identified by intraday Treasury futures changes, we can also use proxies of demand shocks from the auctions themselves. As found above, the bid-to-cover ratio is an effective proxy for demand shocks during auctions. We re-estimate equation (4) using the bid-to-cover ratio in place of our demand shocks (additionally including interactions with lags of the bid-to-cover as controls). Although we suspect the bid-to-cover ratio is not as clean a measure of demand shocks, this allows us to check the robustness of our results, as well as to expand the sample period to 1979-2015. Appendix Figure B8 plots the results using the same sample 1995-2015 as in Figure 12, while Appendix Figure B10 uses the entire sample 1979-2015 (p-values are in Appendix Figures B9 and B11, respectively). As expected, the standard

¹¹Appendix Figure B5 plots p-values testing for equality of the coefficients.

errors are a bit wider, but the qualitative responses are generally similar.

We also tried a number of additional empirical exercises, and find our results are robust to a variety of different specifications, including different cutoffs for short-term and long-term auctions and using different subsamples.¹²

5 Implications for QE

The responses of the yield curve to unexpected movements in demand during Treasury auctions offer several lessons for how one should understand the workings of quantitative easing (QE) programs implemented by the Fed and other central banks. For example, if the Fed is trying to decrease long-term Treasury rates relative to shorter-term rates, our results suggest that QE policies that directly purchase long-term Treasuries should be highly effective during financial crises. But if the Fed is trying to move the entire term structure of interest rates, during periods of high financial distress the Fed will have to be active in purchasing Treasuries throughout the yield curve. Thus, programs in spirit of “Operation Twist” may be effective because a central bank actively intervenes in multiple segments of the yield curve during a crisis.

As we move away from the most recent crisis, there have been discussions (see [Blinder et al. \(2016\)](#)) about whether central banks will continue to use unconventional policies in the future. Our results suggest that the impact of QE-style policies during non-crisis periods will likely differ greatly from those observed during the crisis. To the extent risk aversion is low and debt markets are more integrated, QE-type programs that attempt to move long-term rates relative to short-term rates may fail. During “normal” times of low risk aversion, the overall response of interest rates is less tied to the location of the shifts in demand. While we still expect targeted purchases of long-term Treasury debt from the Fed to reduce long-term rates, the largest declines may be for shorter term maturities that are not directly purchased by the Fed. Interestingly, our results suggest that the Fed may have a menu of options in terms of where it can intervene in the maturity space to hit the yield at a target maturity. Suppose the Fed wishes to decrease the long end of the yield curve. During a crisis, long-term debt purchases will lower the 30-year rate much more effectively than short-term debt purchases. However, during normal times, the Fed should be approximately indifferent between purchasing short-term or long-term debt.

We can also use our results to assess what fraction of the market response to QE1

¹²We additionally highlight one more robustness specification which more closely matches our numerical exercise. We take the first two principal components of our intraday shocks, D_t^ℓ and D_t^s , rotated such that D_t^s is uncorrelated with $D_t^{(30Y)}$ and normalized to have zero mean and unit variance. The first two principal components explain 97 percent of variation in our shocks. For long-term auctions the shock is D_t^ℓ ; similarly short-term auctions use D_t^s . In this way we have two distinct “short” and “long” demand factors, which more closely matches our numerical exercise. Appendix Figure B6 plots these results (p-values in Appendix Figure B7), and finds very similar results as the baseline specification. The only difference is the response of long-term rates to short demand shocks falls more closely to zero.

can be explained directly by shifts in demand for Treasury debt arising from the Fed.¹³ To summarize the timeline of the Fed’s actions, there were five announcements during QE1, four of which mentioned purchasing long-term Treasury securities. November 25, 2008: the Fed announced purchases of \$100 billion in GSE debt and \$500 billion in MBS. December 1, 2008: Chairman Bernanke stated that the Fed could purchase long-term Treasuries. December 16: the FOMC announced possible purchases of long-term Treasuries. January 28, 2009: the FOMC announced it is ready to expand agency debt and MBS purchases, and to begin purchasing long-term Treasuries. March 18, 2009: the FOMC announced it will purchase \$300 billion in long-term Treasuries, along with an additional \$750 billion in agency MBS and \$100 billion in agency debt.

Using small intraday windows around the time of the four announcements which mentioned Treasury purchases, [Chodorow-Reich \(2014\)](#) estimates the 5-year Treasury rate reacted by -9.2, -16.8, 3.1, and -22.8 basis points, respectively. For the same dates but using larger 2-day windows to account for the possibility of slow responses due to liquidity effects, [Krishnamurthy and Vissing-Jorgensen \(2011\)](#) estimates the announcements moved the 5-year Treasury rate by -28, -15, 28, and -26 basis points respectively; additionally, they find the 5-year rate moved by -23 basis points after the initial November 25 announcement.¹⁴ This gives a range of cumulative decline of between 45 and 74 basis points. Note that, because QE1 set the stage for subsequent QE programs, this decline could combine the promise to purchase \$300 billion in Treasuries in QE1 with the possibility of additional rounds of quantitative easing that would entail buying more government debt. In other words, the 45-74 basis point decline could overstate the response of the markets relative to a response one could have observed in the case when the Fed credibly committed to spend only \$300 billion to purchase government bonds during the entirety of *all* its quantitative easing programs.

With this caveat in mind, we can carry out a back-of-the-envelope calculation to assess how much of the response of yields is due purely to the shift in demand for long-term Treasuries from the Fed. During this period, a typical 5-year auction offered roughly \$30 billion. The coefficient in column (2) of Table 3 implies that a unit increase in the bid-to-cover (i.e. an increase in demand of \$30 billion) leads to a 1.4 standard deviation increase in our 5-year intraday shock. When converted into yields, this response is equivalent to an approximate decline of 3.3 basis points (standard error is 0.5 b.p.). This magnitude is broadly consistent with the estimate response of daily changes in spot rates reported in Figure 12. Thus, an increase in demand of \$300 billion would decrease 5-year rates by approximately 33 basis points with the 90 percent confidence interval of 23 to 48 basis points. Our estimate is close to the estimates from [D’Amico and King \(2013\)](#), reporting

¹³We focus on QE1 since the surprise component of QE2 and QE3 was likely smaller than that of QE1.

¹⁴[Chodorow-Reich \(2014\)](#) drops the November 25, 2008, announcement because it occurred after trading hours. In addition, the positive response to the January 28, 2009, announcement seems to be because markets were expecting a concrete statement about purchases.

that Treasury purchases during QE1 reduced yields by about 30 basis points.

Although this exercise represents a very large out-of-sample forecast for our data, it shows that the actual market reaction to QE1 announcements is consistent with the predictions of a preferred habitat model and the behavior of the market in response to observed shifts in *private* demand for Treasuries. This finding implies that other channels of QE (e.g., inflation expectations, forward guidance, signaling) could play a role smaller than thought before. Indeed, consistent with this observation, [Krishnamurthy and Vissing-Jorgensen \(2012\)](#) document that there was little movement in 5-year inflation expectations in response to QE1 announcements.

6 Concluding Remarks

Our analysis shows that quantitative easing (QE) programs “work” but these targeted interventions work mainly via market segmentation. To establish this result, we utilize Treasury auctions of government debt to identify Treasury demand shocks arising from changes in institutional investor demand.

While these shocks do not have structural interpretation, they provide us with variation that is not related to some prominent theories of how QE works (inflation expectations, forward guidance, signaling) and instead allow us to focus attention on the role of preferred habitat mechanisms. Crucially, these mechanisms are dependent on how private agents in the market for Treasury debt absorb these demand shocks, regardless of the source of these shocks. Therefore, we can use this variation to examine whether preferred habitat theory can rationalize responses of interest rates to unexpected changes in demand for government debt with specific maturities during regular Treasury auctions and, by extension, QE rounds.

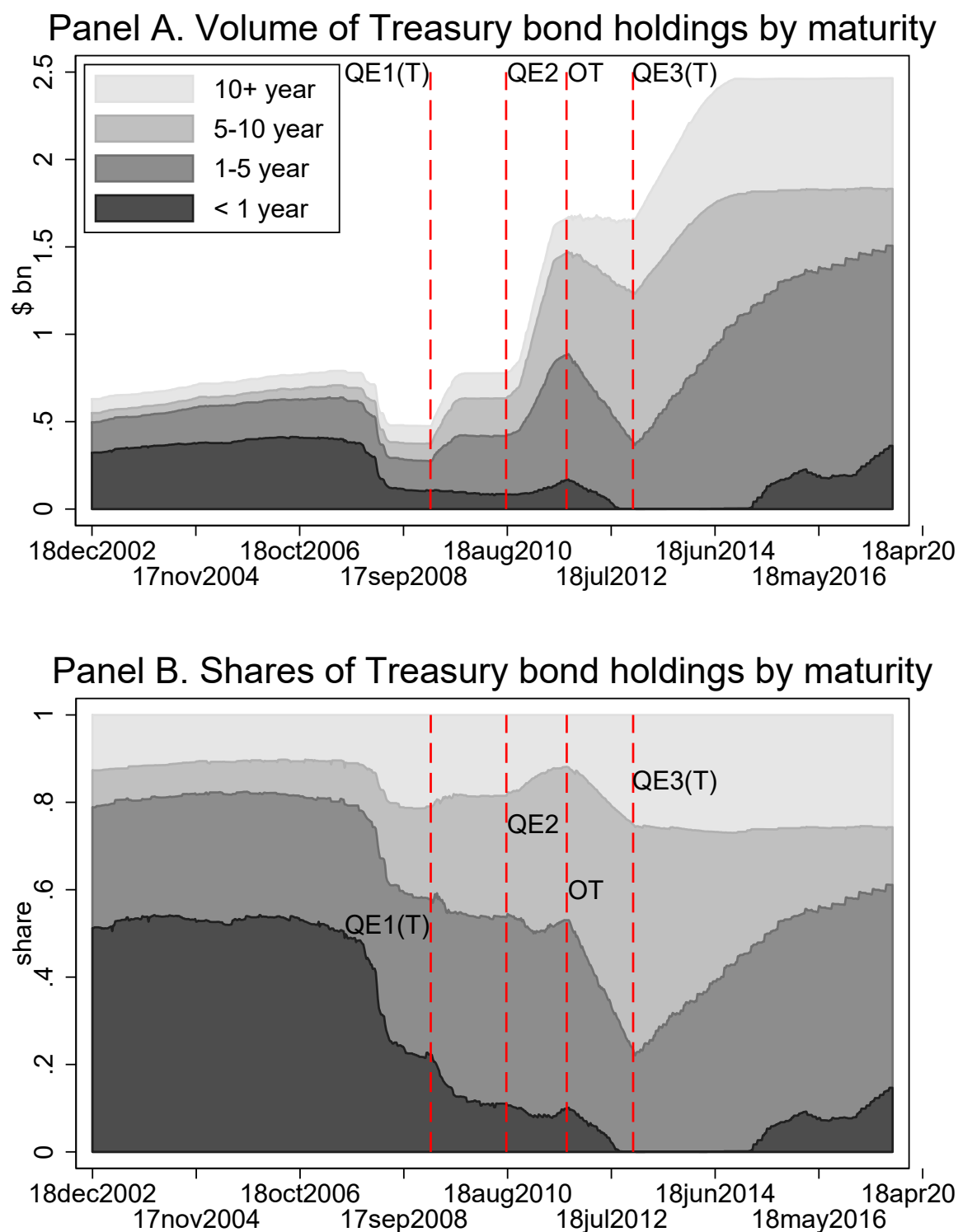
We find a strong local component of demand shocks (i.e., with some oversimplification, purchases of assets in a particular segment move prices more strongly in that segment), but the local concentration is decreasing in risk-bearing capacity. That is, local effects are stronger when markets are segmented (e.g. due to a crisis) than when markets are integrated. The magnitude of the responses during Treasury auctions is large enough to account for a large part of interest rate movements in response to QE announcements. Our analysis suggests that QE can be an effective policy tool in crises, but will be less powerful in moving specific segments of the debt market in normal times. Finally, some of the hypothesized channels of QE propagation may be quantitatively less important than thought before.

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Figure 1: Volume and composition of SOMA's holdings of U.S. Government Debt



Notes: QE1(T) denotes time when the Fed announced its decision to buy U.S. Treasuries as a part of the first round of quantitative easing. QE2 denotes the announcement of the second round of quantitative easing. QE3(T) denotes the time when the Fed announced its purchases of U.S. Treasuries as a part of the third round of quantitative easing. OT denotes the announcement of “Operation Twist”. Source: FRED database.

Figure 2: Auction Timing

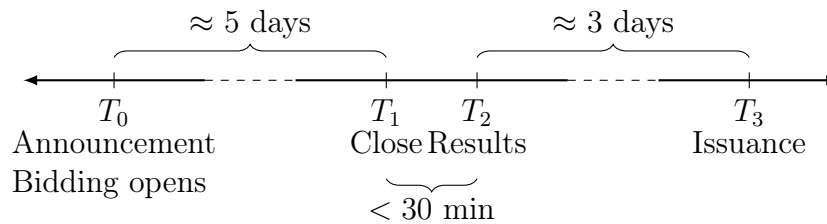


Figure 3: Example of an Auction Announcement

August 03, 2011

202-504-3550

TREASURY OFFERING ANNOUNCEMENT ¹

Term and Type of Security	30-Year Bond
Offering Amount	\$16,000,000,000
Currently Outstanding	\$0
CUSIP Number	912810QS0
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 CUSIP Number(s)	August 15, 2041 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 Increments ²	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
Maturing Date	August 15, 2011
SOMA Holdings Maturing	\$2,205,000,000
SOMA Amounts Included in Offering Amount	No
FIMA Amounts Included in Offering Amount ³	Yes
Noncompetitive Closing Time	12:00 Noon ET
Competitive Closing Time	1:00 p.m. ET

Figure 4: Example of an Auction Result Announcement

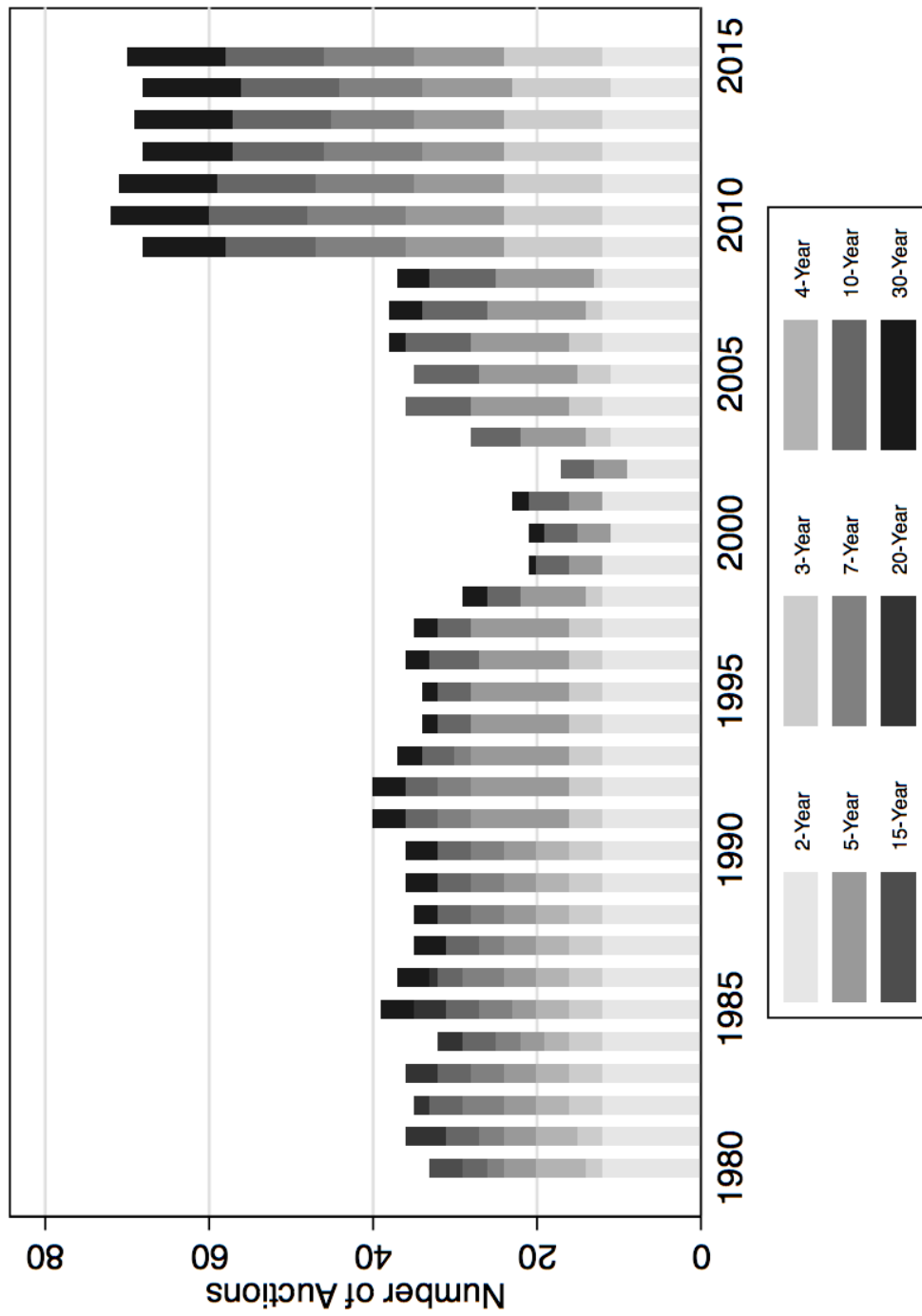
August 11, 2011

202-504-3550

TREASURY AUCTION RESULTS

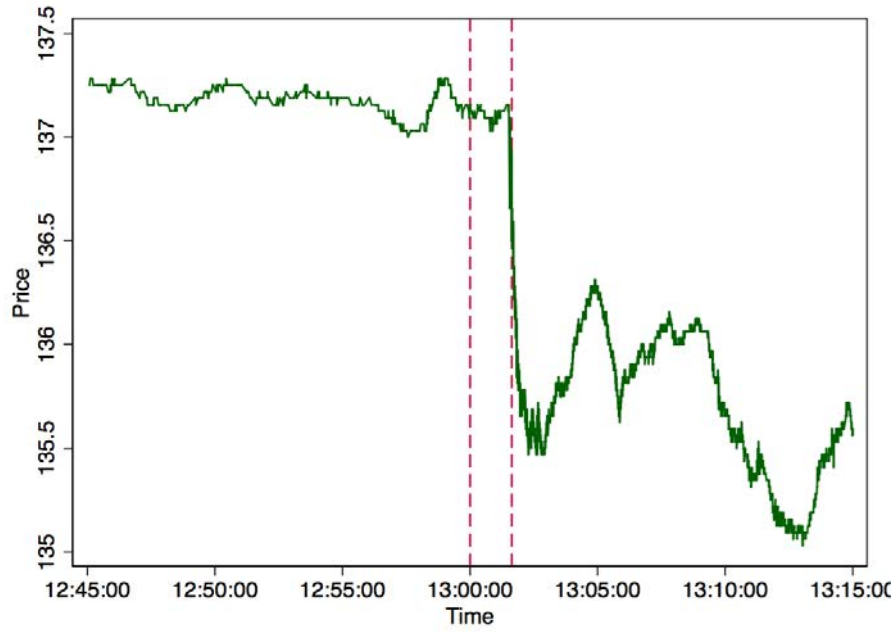
Term and Type of Security	30-Year Bond	
CUSIP Number	912810QS0	
Series	Bonds of August 2041	
Interest Rate	3-3/4%	
High Yield ¹	3.750%	
Allotted at High	41.74%	
Price	100.000000	
Accrued Interest per \$1,000	None	
Median Yield ²	3.629%	
Low Yield ³	3.537%	
Issue Date	August 15, 2011	
Maturity Date	August 15, 2041	
Original Issue Date	August 15, 2011	
Dated Date	August 15, 2011	
	Tendered	Accepted
Competitive	\$33,305,800,000	\$15,985,160,000
Noncompetitive	\$14,855,600	\$14,855,600
FIMA (Noncompetitive)	\$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
	Tendered	Accepted
Primary Dealer ⁶	\$23,734,000,000	\$10,921,532,000
Direct Bidder ⁷	\$6,567,000,000	\$3,119,654,000
Indirect Bidder ⁸	\$3,004,800,000	\$1,943,974,000
Total Competitive	\$33,305,800,000	\$15,985,160,000

Figure 5: Number of Auctions per Year

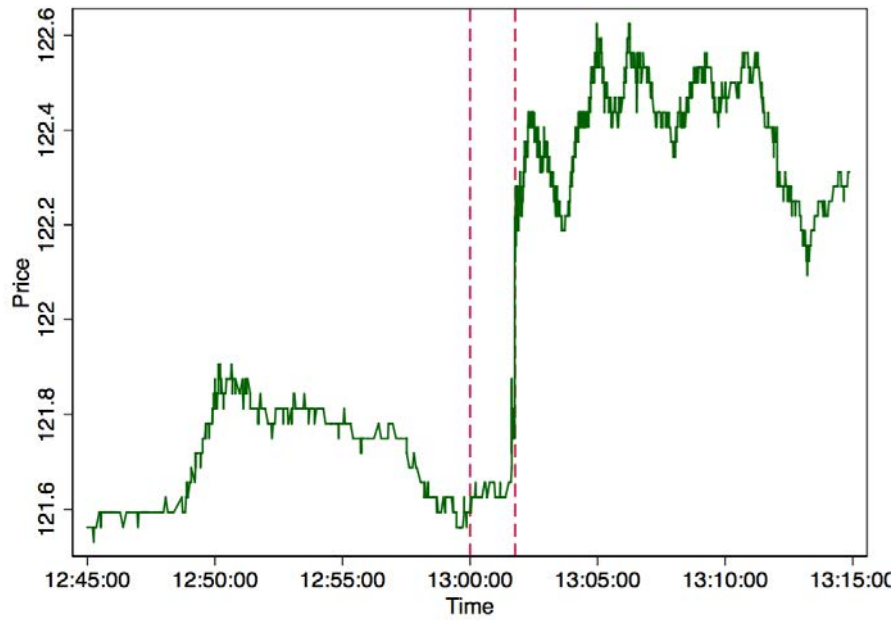


Notes: Number of note and bond Treasury auctions per year by term length in our dataset. The number of auctions temporarily fell in the late 1990s and early 2000s, before increasing sharply after the Great Recession.

Figure 6: 30-year Auctions

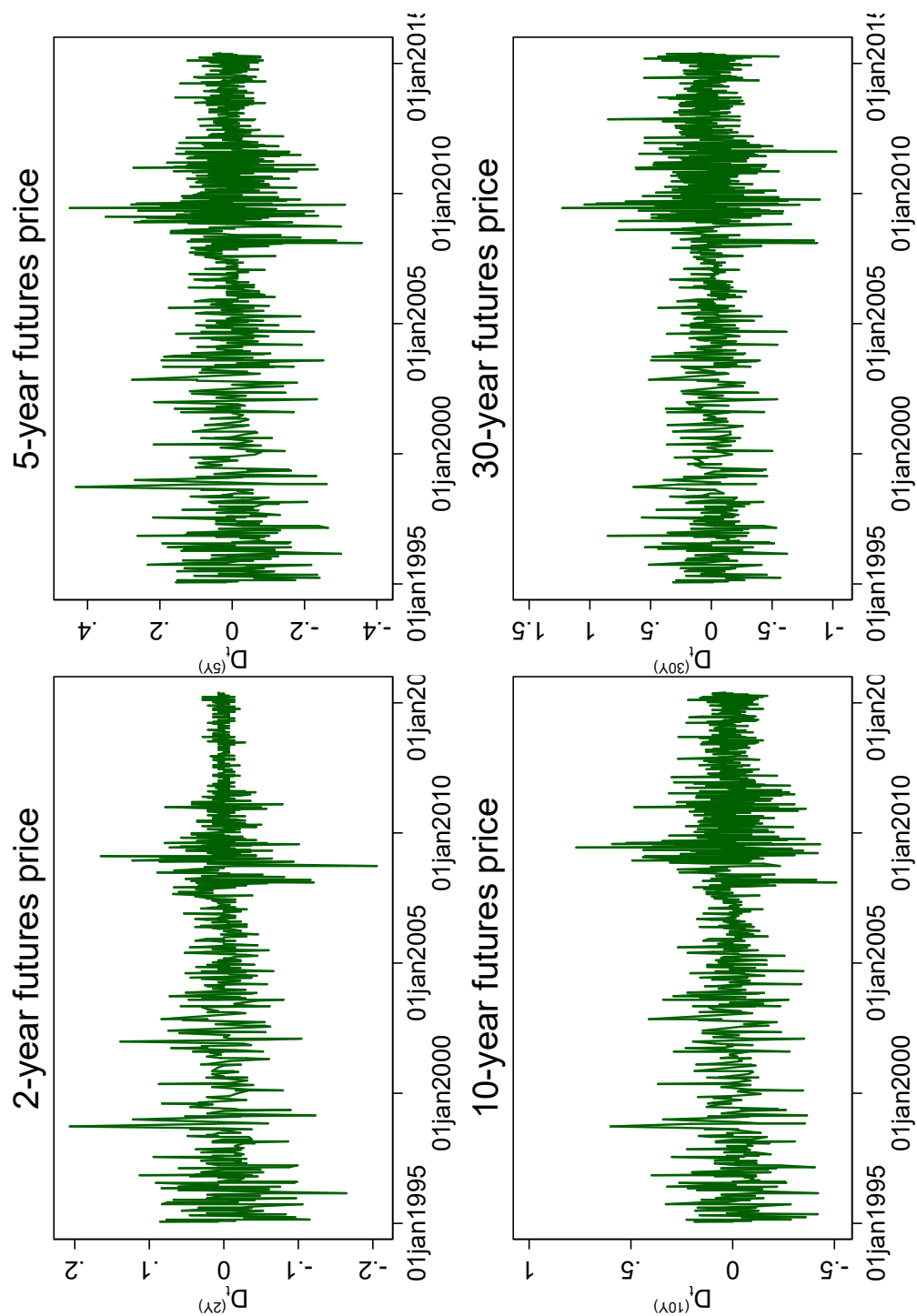


Notes: 30-year Treasury futures prices on August 11, 2011. An auction for 30-year Treasury bonds closed at 1:00pm (first vertical line), and results were released shortly after (second vertical line). Immediately following the release, Treasury futures prices dropped sharply.



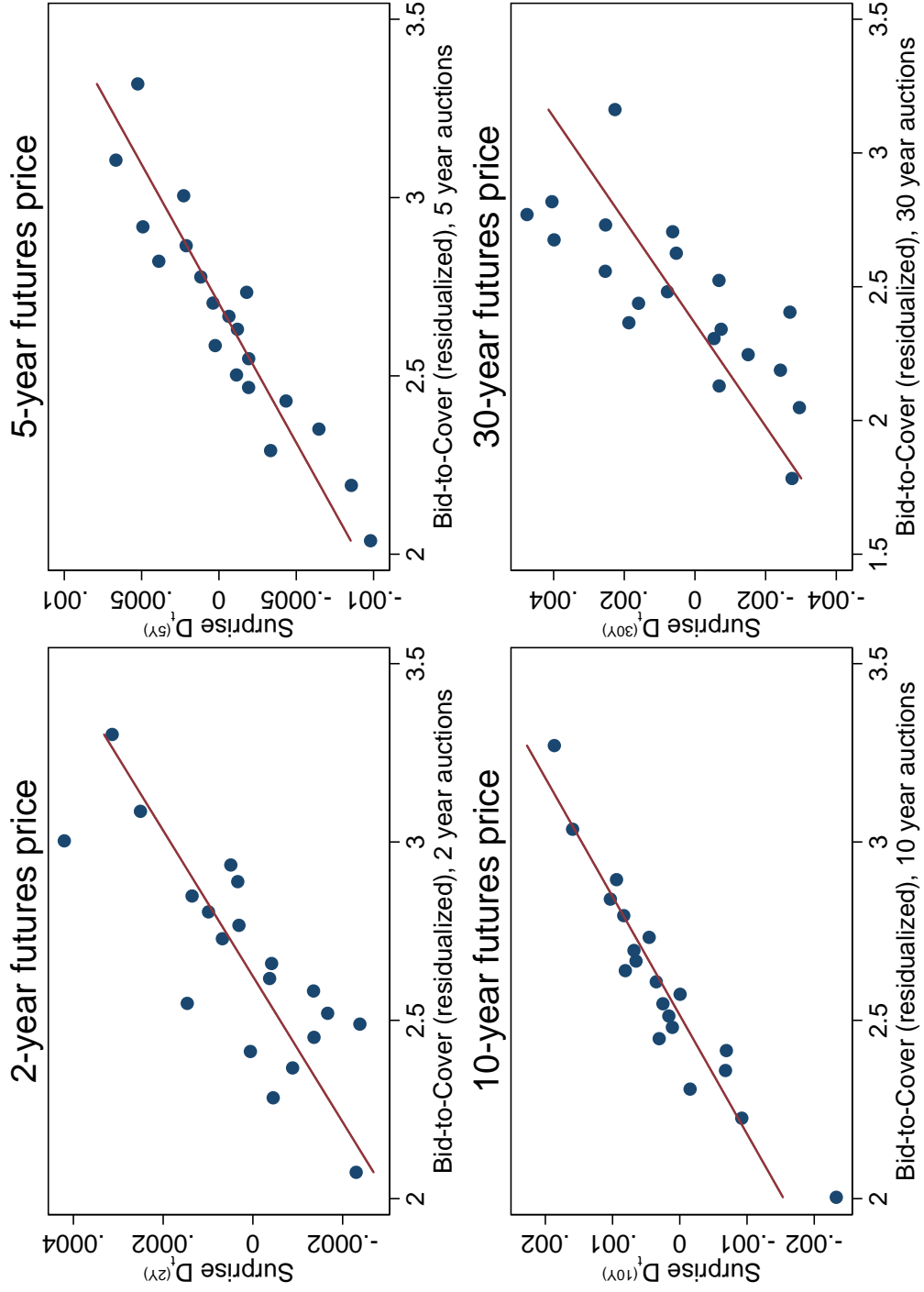
Notes: 30-year Treasury futures prices on December 12, 2010. An auction for 30-year Treasury bonds closed at 1:00pm (first vertical line), and results were released shortly after (second vertical line). Immediately following the release, Treasury futures prices rose sharply.

Figure 7: Time series of surprises in Treasury futures



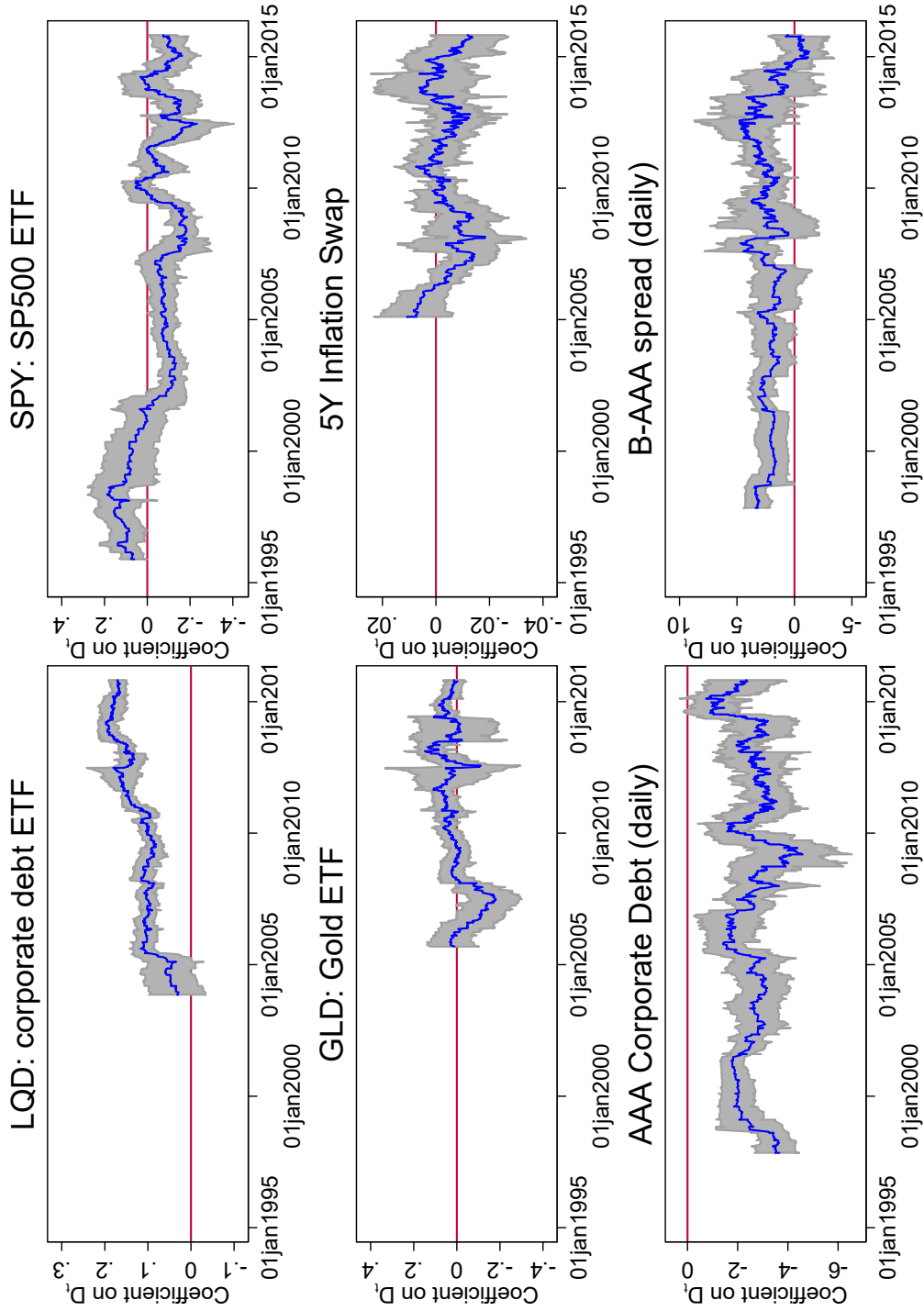
Notes: The figure plots time series of surprise movements in Treasury futures with maturities 2, 5, 10 and 30 years.

Figure 8: Demand Shocks and Bid-to-Cover



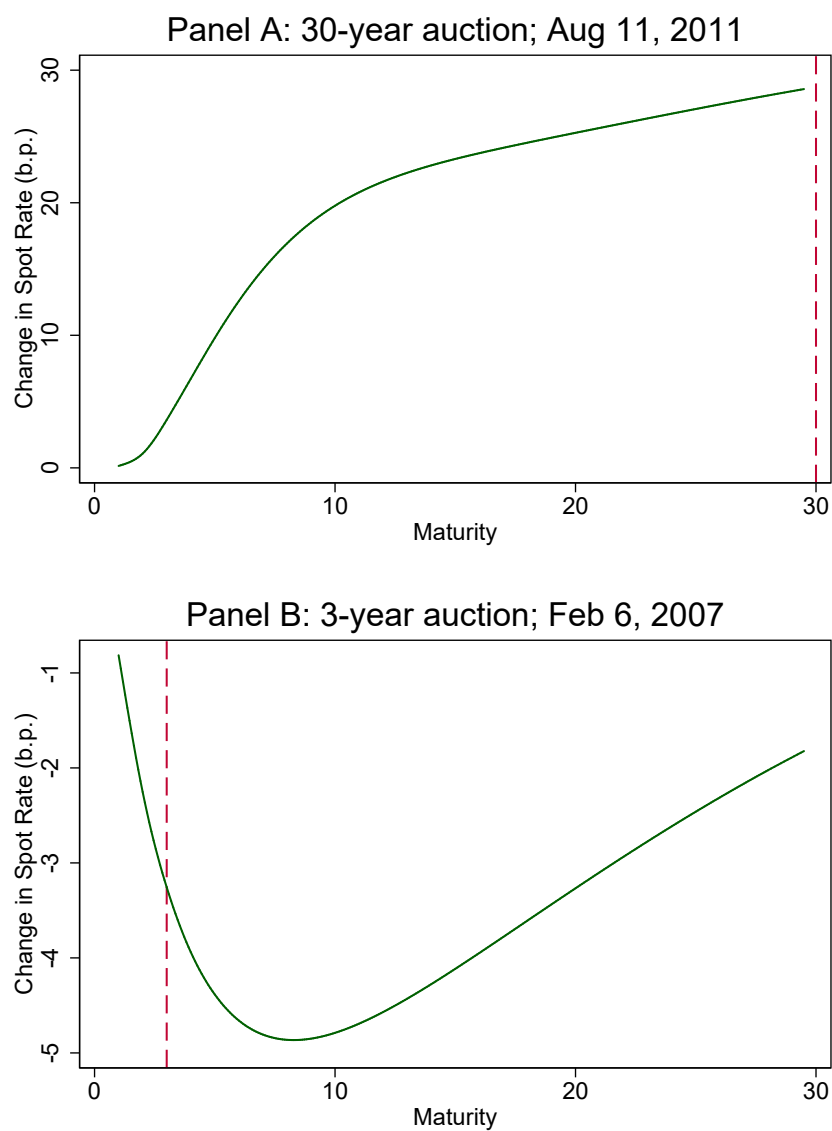
Notes: Bin scatter plot comparing demand shocks D_i and the bid-to-cover ratio from the auction (winsorized at 1% level). The bid-to-cover ratio is the fraction of dollar value of bids received to accepted at a given auction.

Figure 9: Rolling Regressions



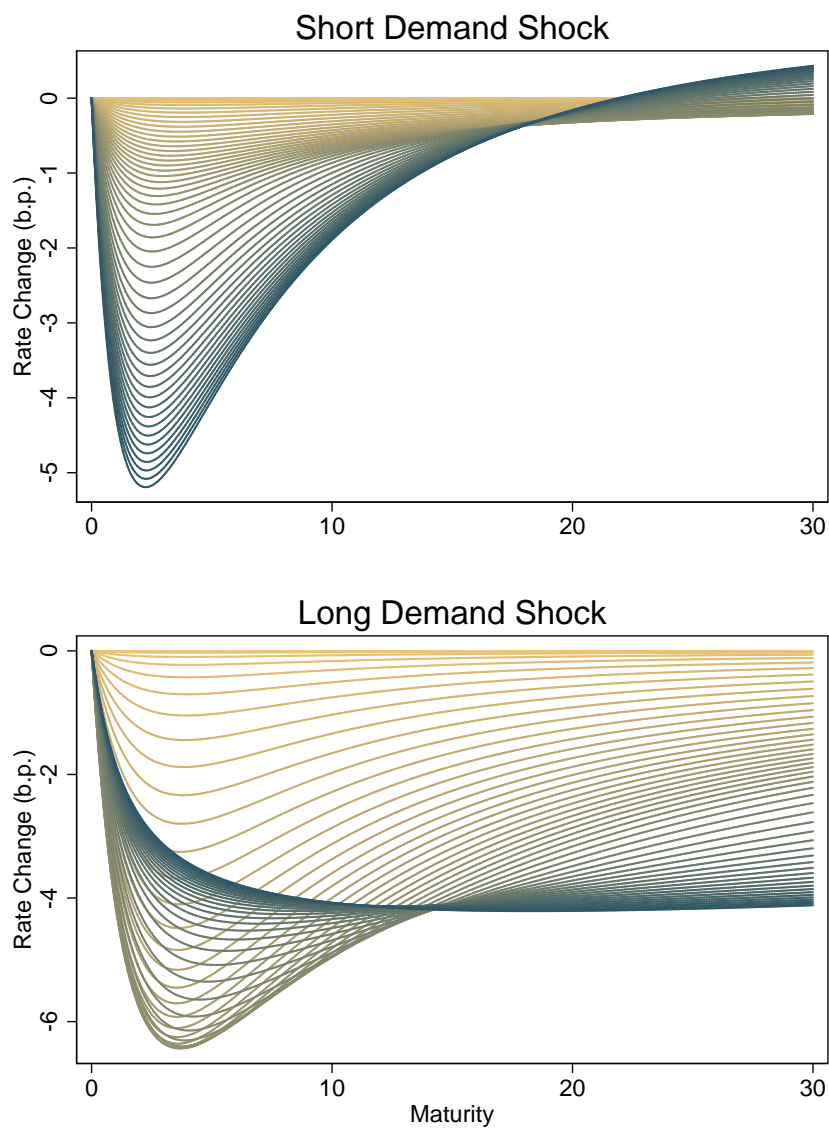
Notes: Coefficient estimates of rolling regressions; each data point is from estimating (3) for using the 60 most recent auctions. LQD, SPY, and GLD are intraday changes; 5-year inflation swap is daily change. AAA Corporate Debt is the daily change in the interest rate for AAA corporate bonds. B-AAA Spread is the daily change in the spread between B and AAA corporate bonds. The regressor is always intraday D_t , the first principal component in D_t^{2Y} , D_t^{5Y} , D_t^{10Y} , and D_t^{30Y} .

Figure 10: Changes in yield curves on select Treasury auction days



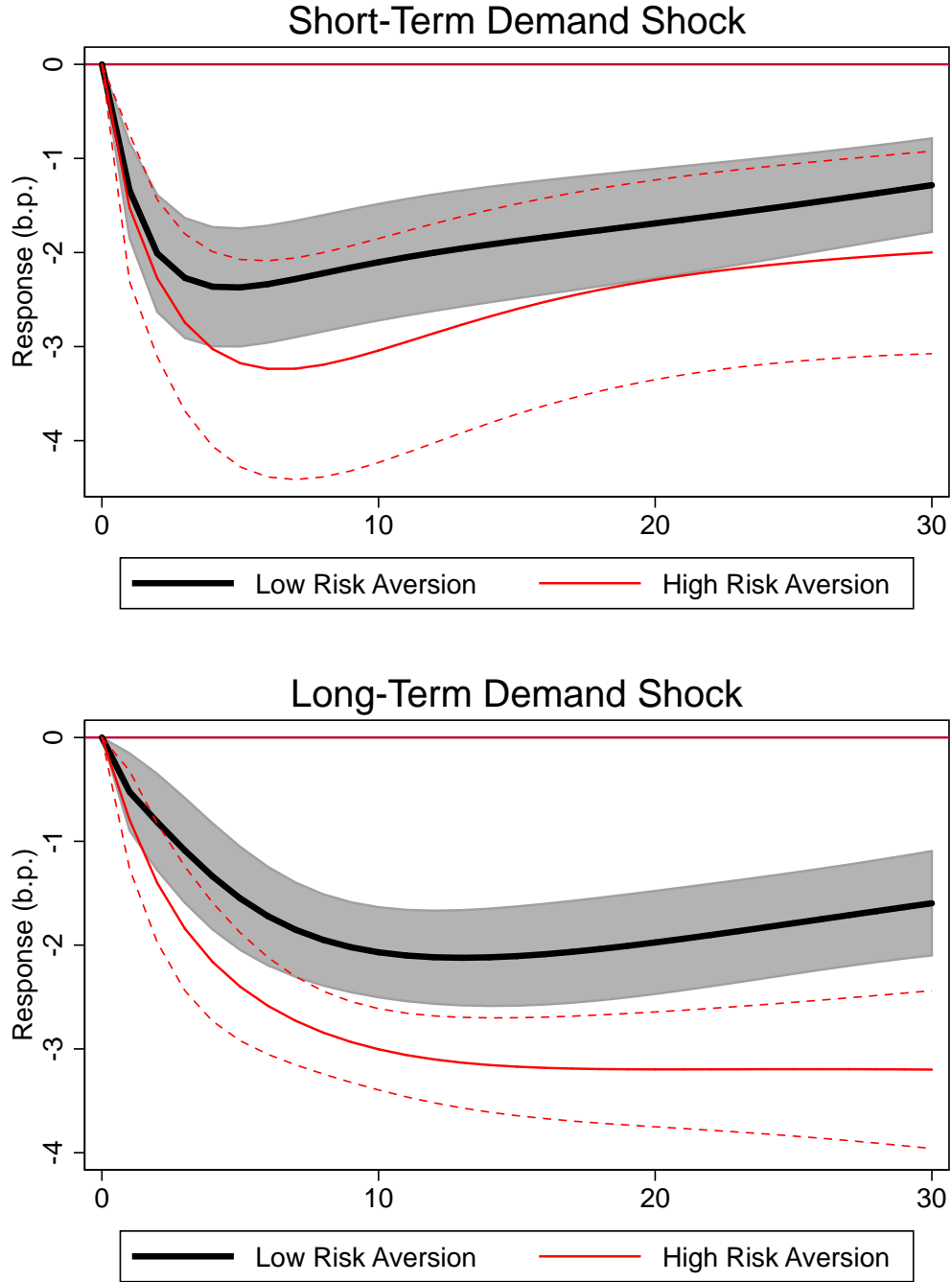
Notes: the figure plots changes in spot rates after 30-year auction on August 11, 2011 (top panel) and 3-year auction on February 6, 2007. The dashed vertical line shows the “location” of the auction in the maturity space.

Figure 11: Numerical Exercise



Notes: Numerical exercise studying the change in term structure of spot rates in response to one-standard deviation positive demand shocks, as risk aversion increase from low (lighter) to high (darker). The top panel is the impact of a short demand shock, and the bottom panel is the impact of a long demand shock.

Figure 12: Rate Responses (intraday Futures surprises)



Notes: Plots of the regression coefficients on the demand shocks $D_t^{(m')}$ from regression equation (4). For each auction the demand shock $D_t^{(m')}$ is the normalized futures surprise that most closely corresponds to the maturity of the auction (e.g. a 5-year auction corresponds to $D_t^{(5Y)}$). Each curve is from the subsample combinations: short-term and long-term auctions; and periods of high and low risk aversion. 2 standard error (Newey-West) confidence intervals are included.

Table 1: Auction Summary Statistics

Panel A: 1979-2015

	Mean	Median	Std. Dev.	Min	Max
Offering Amount (billions)	17.08	14.00	10.13	1.50	44.00
Total Tendered (billions)	47.44	36.38	31.97	2.37	160.96
Bid-to-Cover	2.60	2.57	0.52	1.22	5.88
Term (Years)	7.46	5.00	8.08	2.00	30.25
High Yield	5.39	4.77	3.66	0.22	16.28
High-Median Spread	0.03	0.03	0.02	0.00	0.14

Panel B: 1995-2015

	Mean	Median	Std. Dev.	Min	Max
Offering Amount (billions)	22.03	21.00	9.36	5.00	44.00
Total Tendered (billions)	61.46	52.98	32.04	11.35	160.96
Term (Years)	7.83	5.00	8.42	2.00	30.25
High Yield	3.26	3.20	1.91	0.22	7.79
High-Median Spread	0.03	0.03	0.02	0.00	0.13
Bid-to-Cover	2.62	2.60	0.49	1.22	4.07
Bid-to-Cover by type [#]					
Direct Bidders	0.24	0.25	0.18	0.00	0.84
Indirect Bidders	0.50	0.50	0.16	0.03	1.02
Primary Dealers	1.98	1.92	0.35	0.97	3.12
Fraction Accepted [†]					
Depository Institutions	0.01	0.00	0.02	0.00	0.32
Individuals	0.01	0.00	0.02	0.00	0.19
Dealers	0.58	0.58	0.14	0.20	0.98
Pensions	0.00	0.00	0.01	0.00	0.21
Investment Funds	0.20	0.18	0.13	0.00	0.64
Foreign	0.20	0.19	0.09	0.00	0.61
Other	0.00	0.00	0.00	0.00	0.03

Notes: Summary statistics for Treasury note and bond auctions. [†] indicates that the moments are computed for 2000-2015, the period for which these data are available. [#] indicates that the moments are computed for 2003-2015, the period for which these data are available.

Table 2: Treasury Futures Shocks Summary Statistics

Maturity	Mean	Std. Dev.	N	Correlations			
				$D_t^{(2Y)}$	$D_t^{(5Y)}$	$D_t^{(10Y)}$	$D_t^{(30Y)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A. Auction							
$D_t^{(2Y)}$	-0.000	0.034	871	1.000			
$D_t^{(5Y)}$	0.002	0.092	871	0.866	1.000		
$D_t^{(10Y)}$	0.007	0.143	871	0.782	0.958	1.000	
$D_t^{(30Y)}$	0.006	0.245	871	0.672	0.848	0.922	1.000
Panel B. No auction							
$D_t^{(2Y)}$	-0.000	0.031	4031	1.000			
$D_t^{(5Y)}$	-0.001	0.072	4096	0.861	1.000		
$D_t^{(10Y)}$	-0.002	0.107	4100	0.794	0.944	1.000	
$D_t^{(30Y)}$	-0.005	0.172	4099	0.674	0.830	0.905	1.000
Panel C. Auction, non-ZLB period							
$D_t^{(2Y)}$	-0.002	0.043	428	1.000			
$D_t^{(5Y)}$	-0.004	0.099	428	0.918	1.000		
$D_t^{(10Y)}$	-0.003	0.144	428	0.859	0.961	1.000	
$D_t^{(30Y)}$	-0.014	0.225	428	0.781	0.878	0.929	1.000
Panel D. Auction, ZLB period							
$D_t^{(2Y)}$	0.001	0.021	443	1.000			
$D_t^{(5Y)}$	0.008	0.083	443	0.823	1.000		
$D_t^{(10Y)}$	0.017	0.142	443	0.751	0.960	1.000	
$D_t^{(30Y)}$	0.026	0.261	443	0.640	0.839	0.921	1.000

Notes: On auction dates, shocks $D_t^{(m)} = \log P_{t,post}^{(m)} - \log P_{t,pre}^{(m)}$ are the log intraday change in Treasury futures prices before and after the close of an auction, for each contract $m = 2, 5, 10, 30$ years. For non-auction dates, the shocks are the log intraday changes in Treasury futures prices using the same window. Binding zero lower bound (ZLB) period covers 2008M12-2015M12. Non-ZLB period covers 1995M1-2008M11. Log changes are scaled up by a factor of 100.

Table 3: Demand Shocks and Measures of Demand

Panel A: Total bid-to-cover ratio					
	(1) $D_t^{(2Y)}$	(2) $D_t^{(5Y)}$	(3) $D_t^{(10Y)}$	(4) $D_t^{(30Y)}$	(5) Pool D_t
Bid-to-Cover	1.441*** (0.240)	1.399*** (0.230)	2.099*** (0.216)	2.119*** (0.565)	1.645*** (0.142)
Observations	238	306	227	100	871
R^2	0.156	0.201	0.302	0.270	0.215

Panel B: Total bid-to-cover ratio by bidder type					
Indirect Bidder	2.716*** (0.366)	3.664*** (0.667)	4.528*** (0.493)	8.532*** (1.235)	4.451*** (0.436)
Direct Bidder	2.236** (1.034)	1.026 (0.702)	0.295 (0.956)	1.145 (0.951)	1.173*** (0.448)
Primary Dealer	0.831** (0.387)	0.762** (0.316)	1.517*** (0.317)	0.057 (0.536)	0.887*** (0.178)
Observations	138	228	187	80	633
R^2	0.350	0.309	0.383	0.650	0.370

Panel C: Fraction accepted by bidder type					
Investment Funds	4.800*** (0.908)	3.401*** (0.854)	4.563*** (0.902)	6.436*** (1.462)	4.749*** (0.494)
Foreign	2.797** (1.162)	3.604*** (0.847)	5.173*** (1.220)	7.974*** (2.404)	4.393*** (0.676)
Misc	4.815* (2.614)	2.506** (1.203)	0.034 (3.713)	0.853 (5.119)	2.353** (1.193)
Observations	174	241	201	84	700
R^2	0.214	0.128	0.287	0.391	0.191

Regressions of demand shocks $D_t^{(m)}$ on the bid-to-cover ratio, total and broken up by bidder type (winsorized at 1% level). Four lags of bid-to-cover ratios (or fractions accepted) are included but not reported. Column (1) restricts the sample to include only auctions of 2-year notes. Column (2) restricts the sample to include only auctions of notes with (2,5] year maturity. Column (3) restricts the sample to include only auctions of notes with [7,10] year maturity. Column (4) restricts the sample to include only auctions of bonds with (10,30] year maturity. Newey-West standard errors are in parentheses.

Table 4: Reaction of market to surprises at Treasury auctions

Dep.variable: asset type	Estimate (s.e.)	N	R^2	Sample
	(1)	(2)	(3)	(4)
Panel A. Corporate debt				
LQD	0.110*** (0.008)	662	0.544	2002-2015
AAA [†]	-2.748*** (0.240)	801	0.243	1997-2015
B-AAA [†]	2.352*** (0.331)	801	0.065	1997-2015
P1 (1M) [†]	-0.044 (0.230)	801	0.000	1997-2015
Panel B. Equities				
SPY	-0.020 (0.018)	871	0.005	1995-2015
IWM	-0.081*** (0.024)	706	0.034	2000-2015
SP500 [†]	-0.072 (0.064)	871	0.004	1995-2015
Russell 2000 [†]	-0.169** (0.069)	871	0.013	1995-2015
Panel C. Inflation expectations and commodities				
10Y Inflation Swap [†]	-0.172 (0.131)	618	0.003	2004-2015
2Y Inflation Swap [†]	0.044 (0.229)	618	0.000	2004-2015
GOLD	0.021 (0.015)	595	0.004	2004-2015
GSCI [†]	0.008 (0.056)	871	0.000	1995-2015

Notes: The table reports regressions of changes in prices of various assets on D_t , the common surprise component in $D_t^{(2Y)}$, $D_t^{(5Y)}$, $D_t^{(10Y)}$, and $D_t^{(30Y)}$, coefficient ϕ in equation (3). The common component D_t is measured at the intraday frequency. Price changes for assets with [†] are measured at the daily frequency; other price changes are measured over the time window corresponding to what we use to construct surprises. LQD is intraday log change in corporate debt ETF price. AAA and B are daily change in Merrill Lynch corporate bond yields. P1 is daily change in 1-month commercial paper rate. SPY and IWM are intraday log changes in S&P 500 and Russell 2000 ETF prices. S&P 500 and Russell 2000 are daily log change in S&P 500 and Russell 2000 index. 10Y inflation swap and 2Y inflation swap are daily changes in inflation expectations implied by inflation swaps. GOLD is intraday log change in GLD ETF price. GSCI is daily log change in S&P Total Commodity Index. Newey-West standard errors (8 lags) in parentheses.

Appendix A Numerical Exercise Details

In this section we briefly describe the model and calibration of our numerical exercise. For more details regarding the model setup, see [Vayanos and Vila \(2009\)](#).

A.1 Numerical Exercise Model

There is a continuum of zero-coupon bonds with maturities $m \in (0, T]$ in zero net supply. A bond with maturity m has a time t price of $P_{t,m}$ and pays \$1 at time $t + m$. The spot rate is $R_{t,m}$ which is given by

$$R_{t,m} = -\frac{\log P_{t,m}}{m}$$

There are two types of investors: idiosyncratic/clientèle investors and arbitrageurs. By assumption idiosyncratic demand takes the following form:

$$y_{t,m} = \alpha(m)m(R_{t,m} - \beta_{t,m})$$

where $\beta_{t,m}$ is a demand shifter which responds to K demand factors:

$$\beta_{t,m} = \bar{\beta} + \sum_{k=1}^K \theta_k(m) \beta_{k,m}$$

Arbitrageurs choose how much of each bond to hold (denoted by $x_{t,m}$). Their budget constraint is:

$$dW_t = \left(W_t - \int_0^T x_{t,m} \right) r_t dt + \int_0^T x_{t,m} \frac{dP_{t,m}}{P_{t,m}}$$

where r_t is the instantaneous rate: $\lim_{m \rightarrow 0} R_{t,m} = r_t$. Arbitrageurs maximize an instantaneous mean-variance trade-off:

$$\max_x E_t dW_t - \frac{a}{2} \text{Var}_t dW_t$$

where the parameter a governs the level of risk aversion. In equilibrium, we have $y_{t,m} = -x_{t,m}$.

We assume the instantaneous rate and demand factors are stacked in a $K + 1$ vector \mathbf{Y} which follows an Ornstein-Uhlenbeck process:

$$d\mathbf{Y}_t = -\Gamma(\mathbf{Y}_t - \bar{\mathbf{Y}})dt + \mathbf{S}d\mathbf{B}_t$$

where \mathbf{B}_t is a vector of Brownian motions.

It turns out that the above is consistent with bond prices that are affine in the \mathbf{Y} factors. Denote the coefficients associated with variable $y_{j,t}$ (as a function of maturity m)

by $A_j(m)$. So

$$-\log P_{t,m} = \mathbf{Y}_t^T \mathbf{A}(m) + C(m)$$

We are interested in the response of the term structure to shocks to the demand factors, and hence need to solve the model for the coefficient functions $\mathbf{A}(m)$. Using the arbitrageur FOCs and taking into account the zero net supply condition, these functions must satisfy the system of differential equations

$$\mathbf{A}'(m) + \Gamma^T \mathbf{A}(m) - \mathbf{e}_1 = a\mathbf{M}\mathbf{A}(m)$$

where \mathbf{e}_1 is the first coordinate vector (assuming r_t is ordered first in \mathbf{Y}), and

$$\mathbf{M} = \left(\int_0^T \alpha(m)[m\Theta(m) - \mathbf{A}(m)]\mathbf{A}(m)^T \right) \mathbf{S}\mathbf{S}^T$$

Solving the above differential equation is made more difficult by the presence of the integral terms in \mathbf{M} . [Vayanos and Vila \(2009\)](#) solves the model for the limiting case when the risk aversion parameter $a \rightarrow 0$ or $a \rightarrow \infty$ (and the particular case when Γ and \mathbf{S} are diagonal), but for intermediate values a solution must be found numerically. For details regarding the solution algorithm, see [Ray \(2017\)](#).

A.2 Numerical Exercise Calibration

For our numerical exercise, we take the number of demand factors to be $K = 2$. We will interpret the first demand factor as a “short” demand factor denoted by $\beta_{t,s}$. The second factor is taken to be a “long” demand factor denoted by $\beta_{t,\ell}$. We assume

$$\Gamma = \begin{bmatrix} \kappa_r & 0 & 0 \\ 0 & \kappa_s & 0 \\ 0 & 0 & \kappa_\ell \end{bmatrix}$$

and set these mean reversion parameters to imply that shocks to the instantaneous rate have a half-life of approximately one year, while shocks to the demand factors have a half-life of 2.5 years.

For simplicity we also assume uncorrelated shocks, and that the size of the innovations for each factor is equal, i.e. $\mathbf{S} = \sigma\mathbf{I}$. We set $\sigma = .01$.

$\theta_s(m)$ and $\theta_\ell(m)$ govern where the demand shocks are located in maturity space. Although not realistic, we set these as Dirac delta functions, so that the short demand shock is entirely concentrated at idiosyncratic investors whose habitat is at $m = 3$ years; similarly for the long demand shock we choose $m = 20$ years. These maturities roughly correspond to the average maturity of the short-term and long-term auctions in the empirical counterpart. We could have instead assumed these functions have non-zero values

for a continuum of bonds. This complicates the numerical solution algorithm, and is part of ongoing work.

$\alpha(m)$ governs the sensitivity of idiosyncratic investors to changes in the price of bonds within their habitat. We don't have priors for this parameter, and for simplicity assume the function is constant. We set this value to match the following empirical counterpart: a standard deviation increase in our demand shock D_t is associated with an increase of 0.15 in the bid-to-cover ratio during short-term auctions. Given our parameterization above, a one-standard deviation positive short demand shock increases idiosyncratic demand by $3\alpha\sigma$. Equating these values implies $\alpha = 5$.

Finally, we let the risk aversion parameter vary from 0 to 500. The upper limit is ad-hoc; the value was chosen as the response of spot rates at this point begins to stabilize.

The spirit of the numerical exercise is not to match the data perfectly, but rather to gain some qualitative predictions for intermediate levels of risk aversion. Finally, it is important to note that the parameters a , α , and σ in this specification enter multiplicatively. Hence an appropriate rescaling of these values will give numerically identical responses.

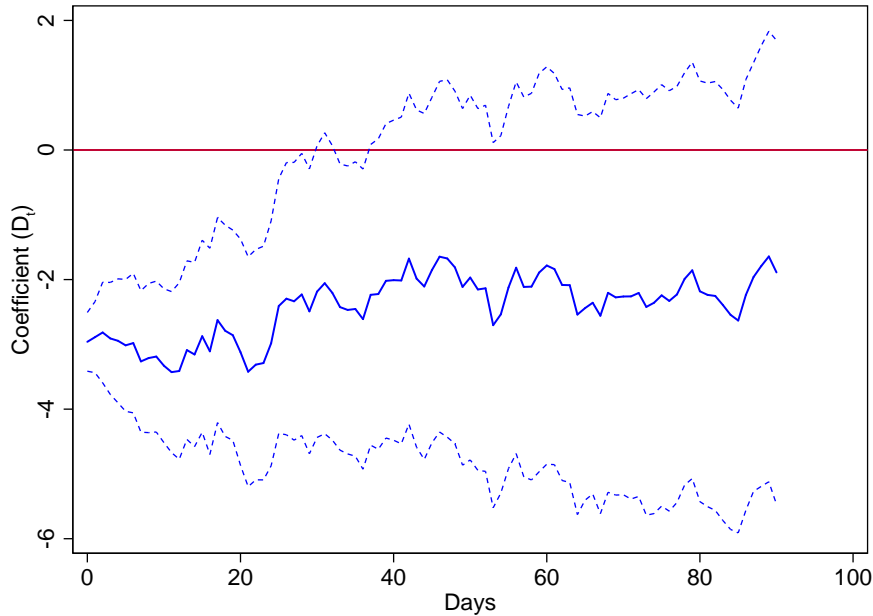
Table A1 summarizes the parameter calibration.

Table A1: Numerical Exercise Calibration

Parameter	Value
T	30
σ	.01
κ_r	0.7
κ_s	0.3
κ_ℓ	0.3
α	5
a	(0, 500)
$\theta_s(m)$	$\delta(3 - m)$
$\theta_\ell(m)$	$\delta(20 - m)$

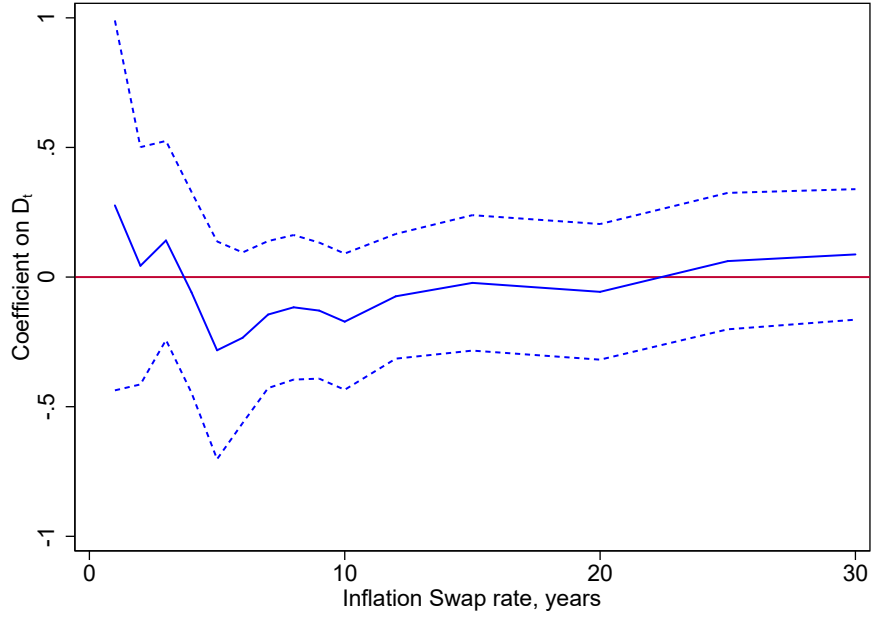
Appendix B Additional Figures and Tables

Figure B1: Response of 10-Year Spot Rates to Shock D_t



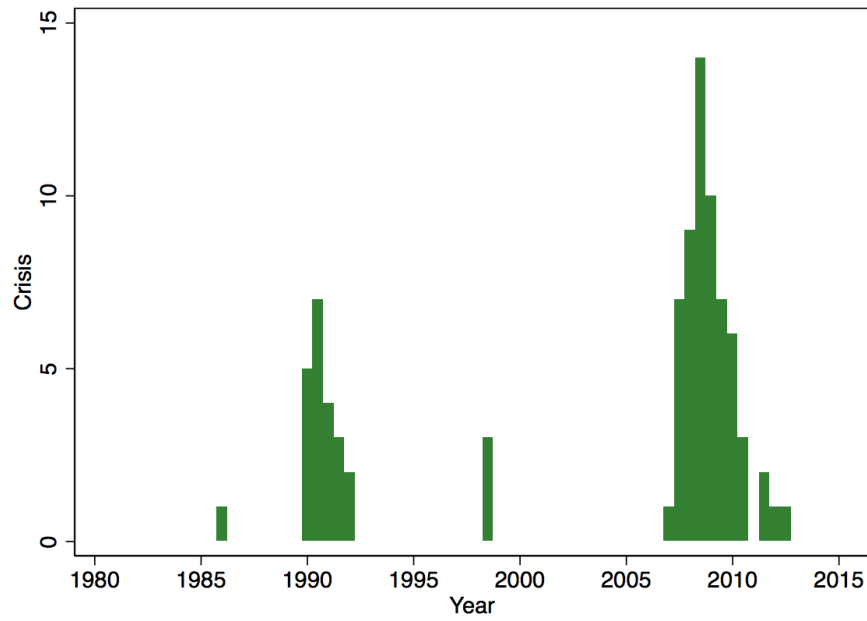
Notes: the figure plots responses of 10-year spot rates to a shock in the first principal component D_t . Spot rates come from [Gürkaynak et al. \(2007\)](#), estimated from daily prices from the secondary market for Treasuries. The regressions are “long-difference” regressions: on an auction date t , the dependent variable is $R_{t+h}^{(10Y)} - R_{t-1}^{(10Y)}$, i.e. the change in spot rates (in terms of basis points) h days after the auction relative to the day before the auction. We plot the coefficients from regressions for $h = 0, \dots, 90$. The solid line plots the point estimates, while dashed lines plot two-standard deviation (Newey-West) confidence bands.

Figure B2: Response of Inflation Swap Rates to Shock D_t



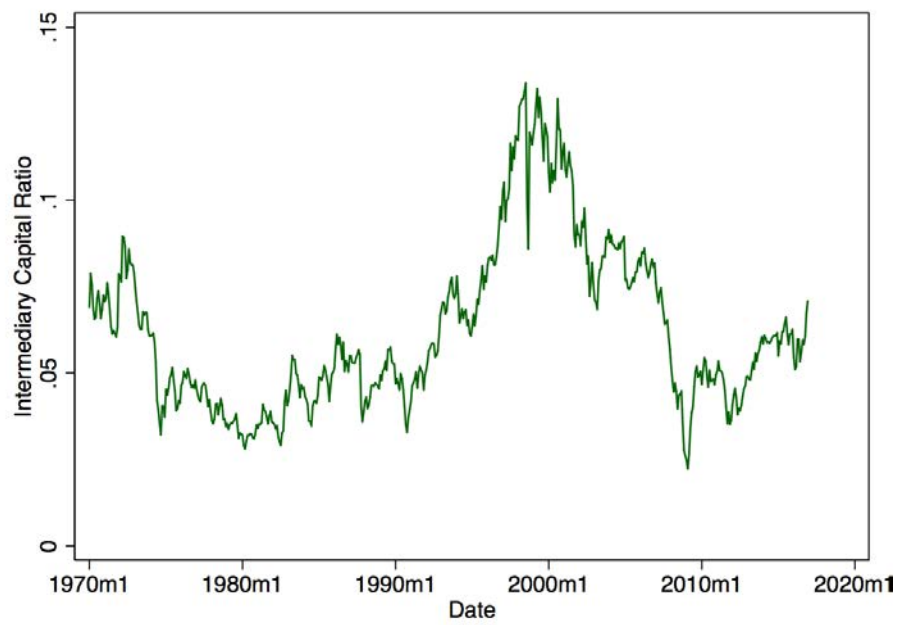
Notes: the figure plots responses of inflation swap rates across different maturities to a shock in the first principal component D_t . The solid line plots the point estimates, while dashed lines plot two-standard deviation (Newey-West) confidence bands.

Figure B3: U.S. Financial Crises



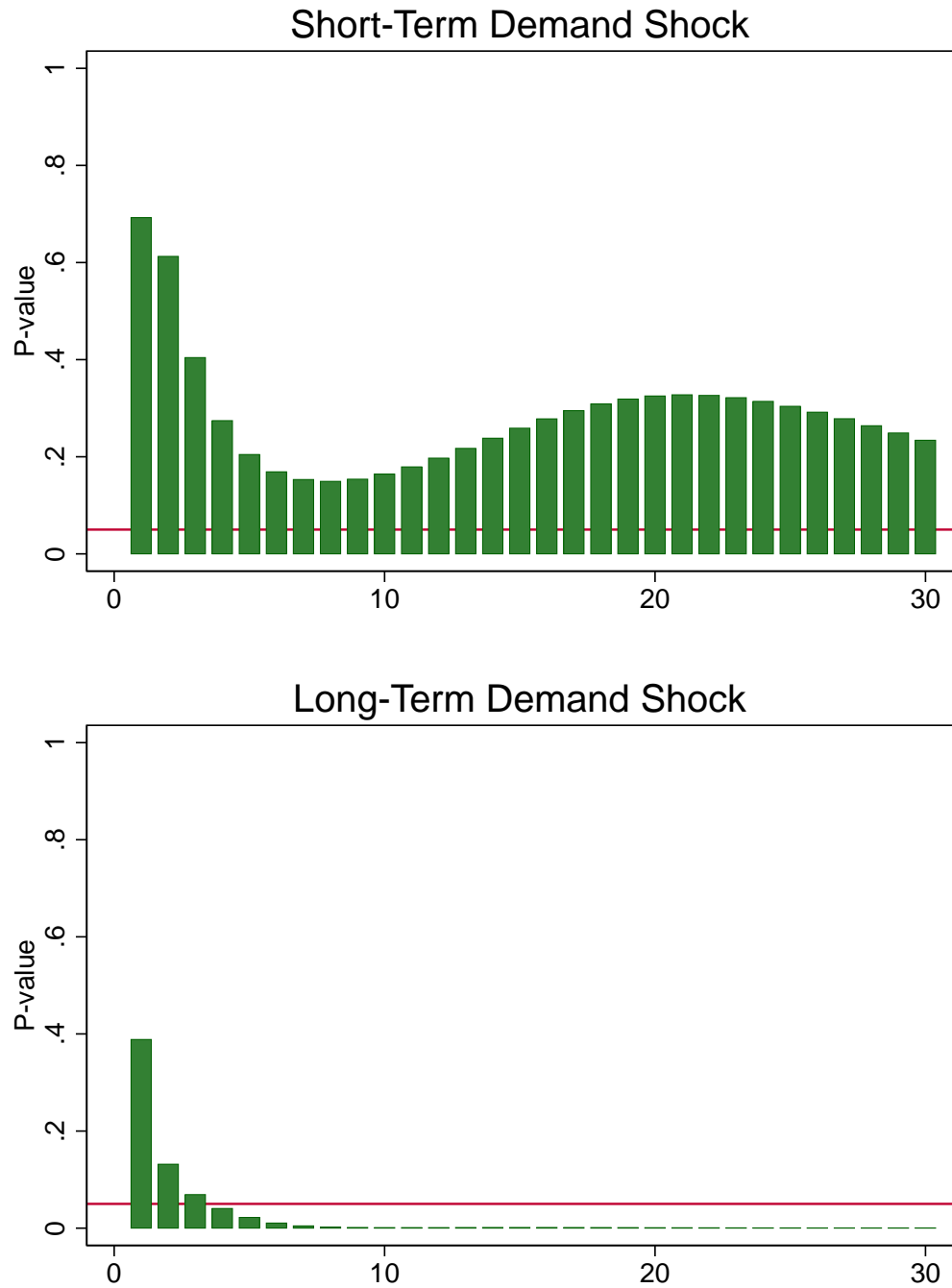
Notes: Financial Crisis indicator for the United States from [Romer and Romer \(2017\)](#).

Figure B4: Intermediary Capital Ratio



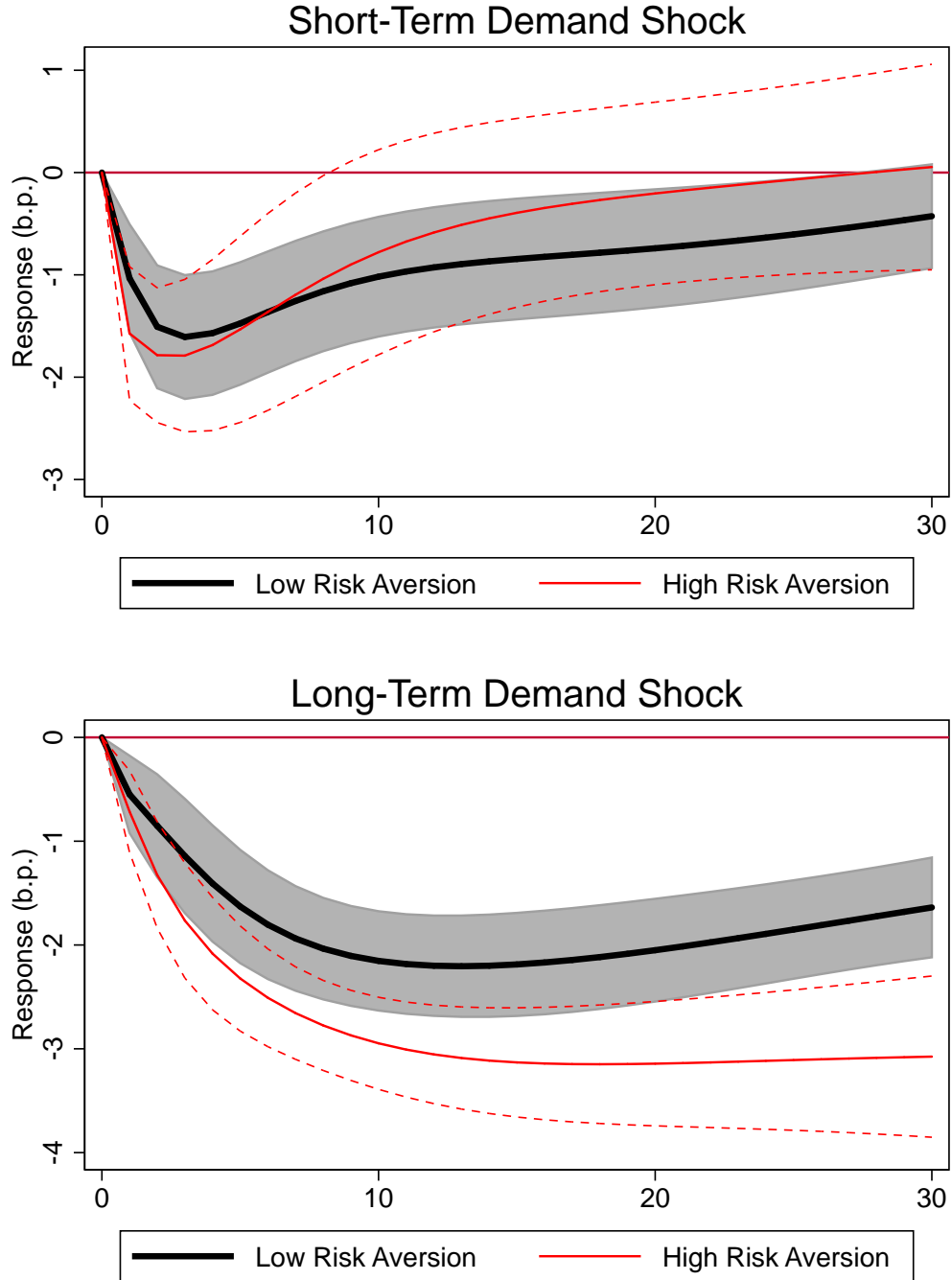
Notes: Intermediary capital ratio from [He et al. \(2016\)](#).

Figure B5: Rate Response P-Values



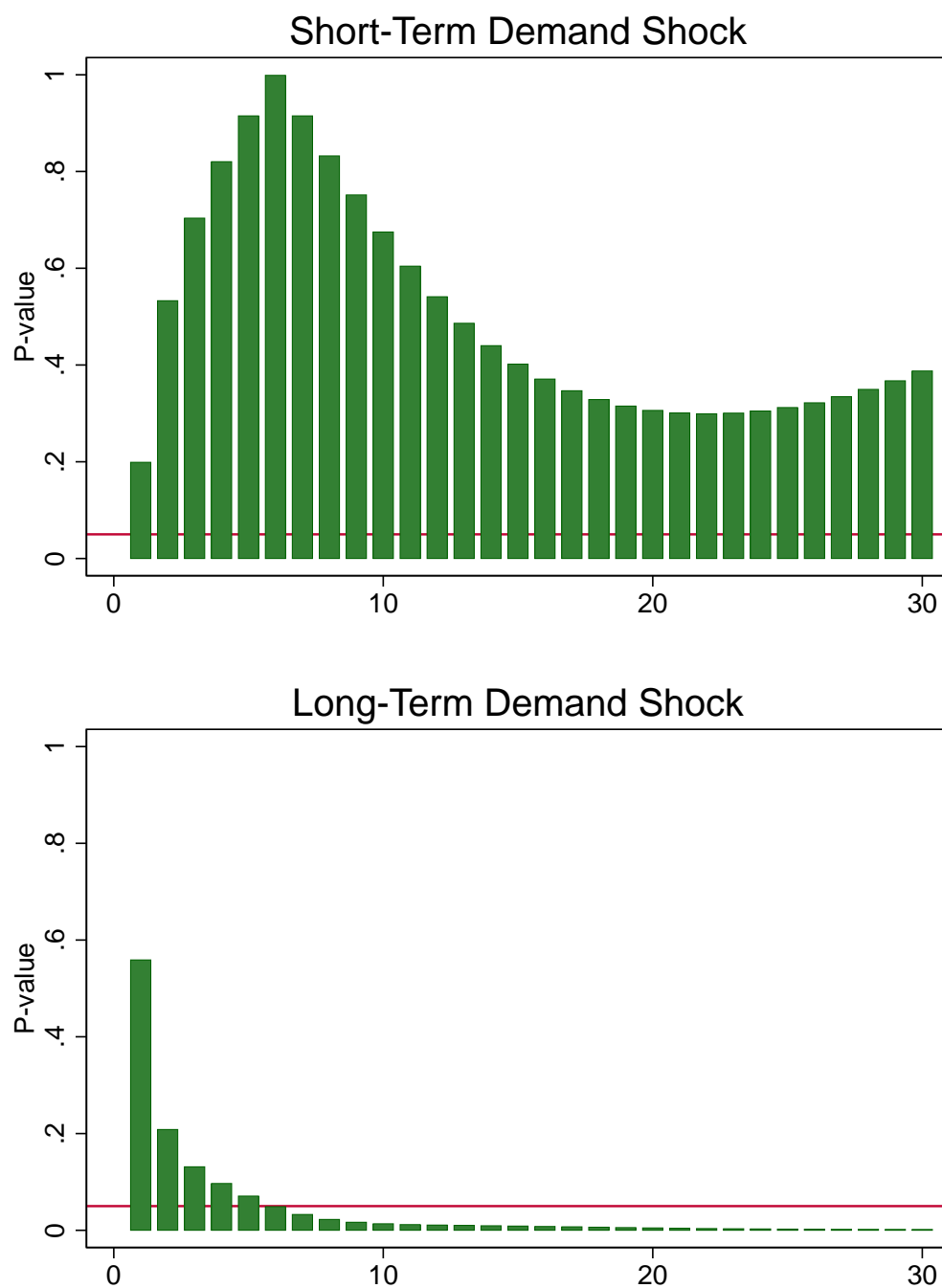
Notes: p-values testing equality of coefficients from Figure 12. Testing equality of all coefficients gives a p-value of 0.148 for the “short” sample, and $< .001$ for the “long” sample.

Figure B6: Rate Responses (rotated intraday Futures surprises)



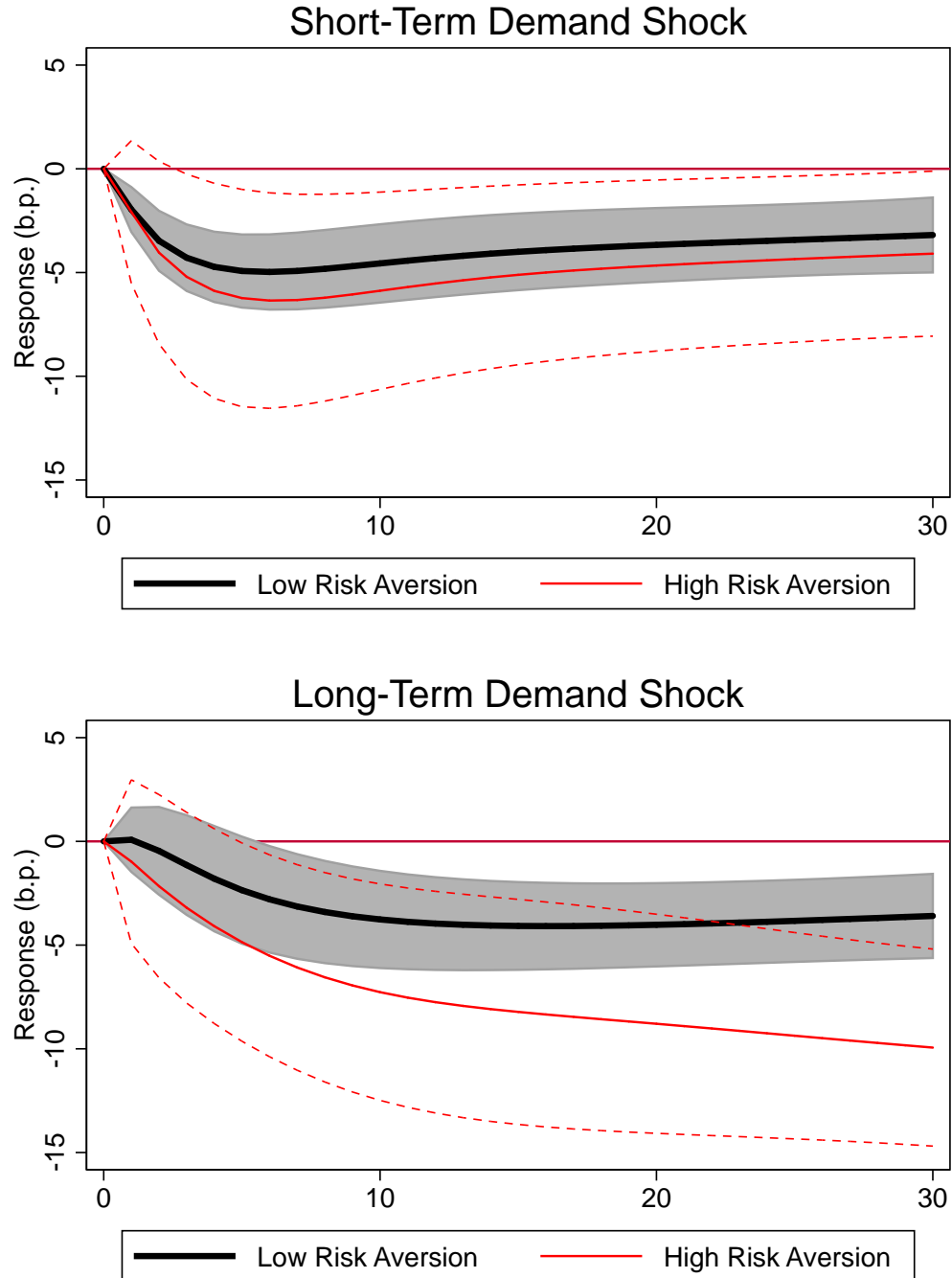
Notes: Plots of the regression coefficients on the demand shocks D_t^i from regression equation (4). The shocks are the first two principal components of our intraday shocks, D_t^ℓ and D_t^s , rotated such that D_t^s is uncorrelated with $D_t^{(30Y)}$. For long-term auctions the shock is D_t^ℓ ; similarly short-term auctions use D_t^s . Each curve is from the subsample combinations: short-term and long-term auctions; and periods of high and low risk aversion. 2 standard error (Newey-West) confidence intervals are included.

Figure B7: Rate Response P-Values (rotated intraday Futures surprises)



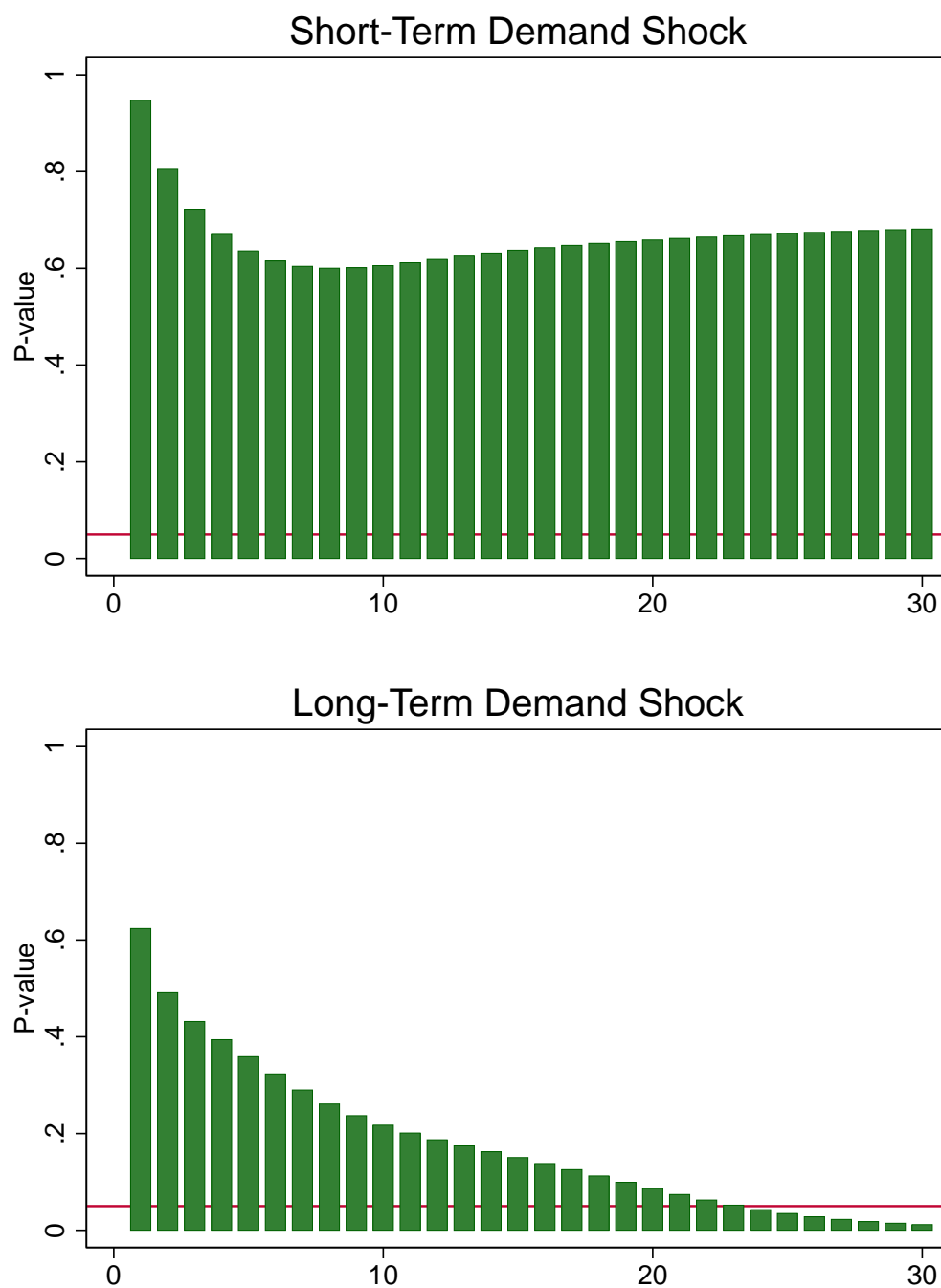
Notes: p-values testing equality of coefficients from Figure B6. Testing equality of all coefficients gives a p-value of 0.932 for the “short” sample, and $< .001$ for the “long” sample.

Figure B8: Rate Responses (Bid-to-Cover, 1995-2015)



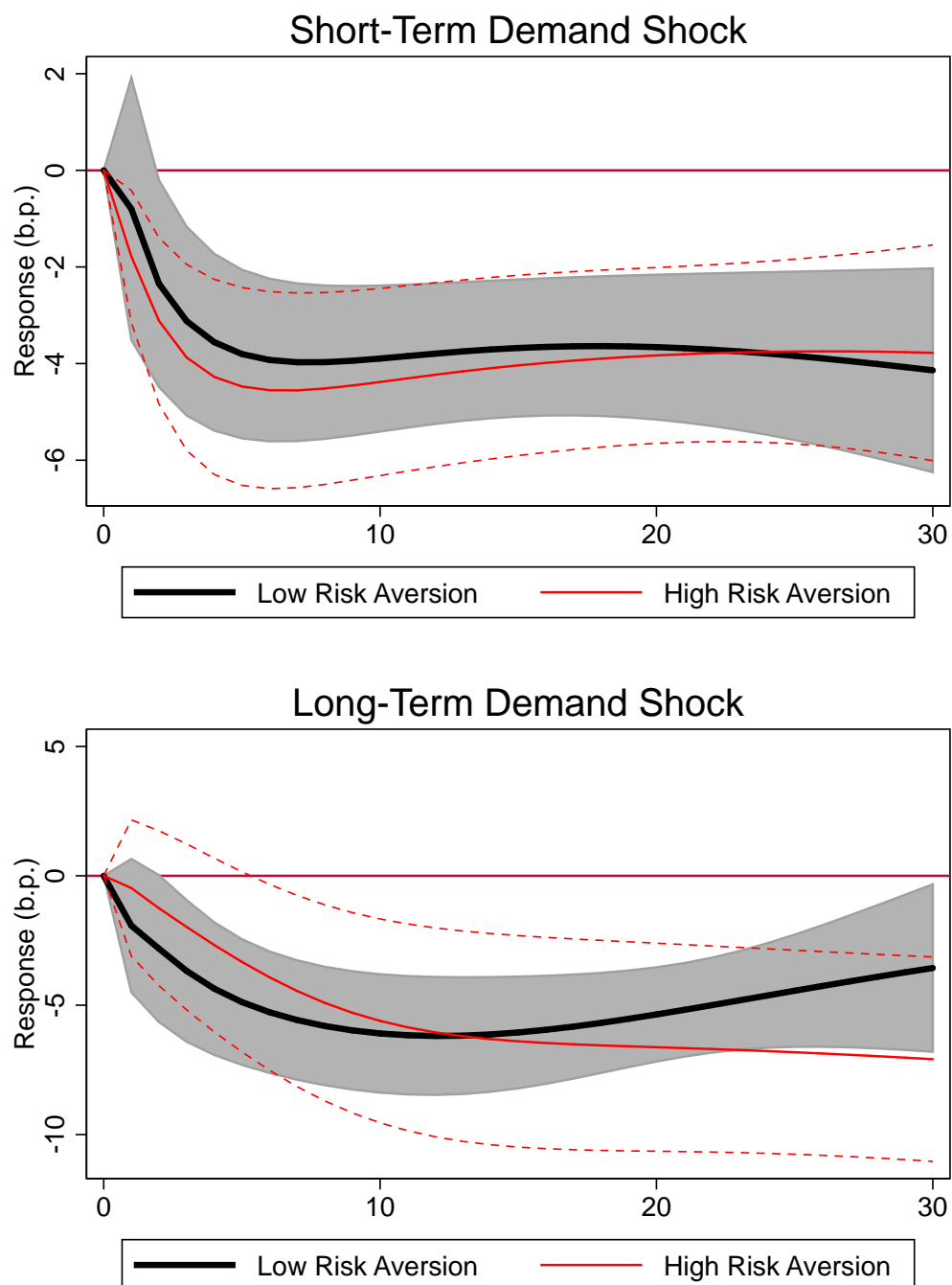
Notes: Plots of the regression coefficient on the contemporaneous bid-to-cover ratio b_t from regression equation (4) (winsorized at 1% level) for the sample 1995-2015. Note that both “long” and “short” curves use b_t , the bid-to-cover ratio (8 lags are included as controls). Each curve is from the subsample combinations: short-term and long-term auctions; and periods of high and low risk aversion as measured. 2 standard error (Newey-West) confidence intervals are included.

Figure B9: Rate Response P-Values (Bid-to-Cover, 1995-2015)



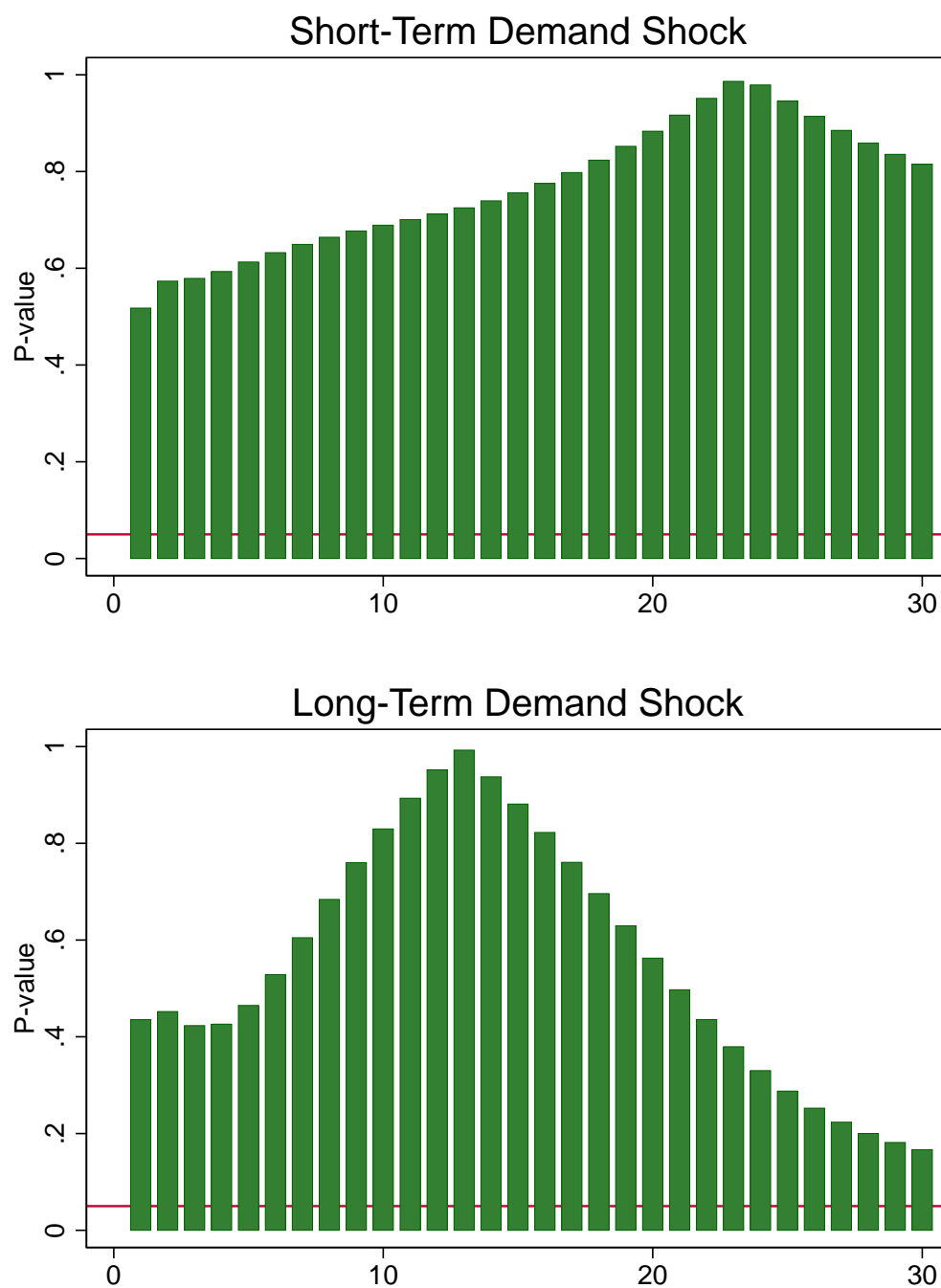
Notes: p-values testing equality of coefficients from Figure B8. Testing equality of all coefficients gives a p-value of 0.999 for the “short” sample, and $< .001$ for the “long” sample.

Figure B10: Rate Responses (Bid-to-Cover, 1979-2015)



Notes: Plots of the regression coefficient on the contemporaneous bid-to-cover ratio b_t from regression equation (4) (winsorized at 1% level) for the sample 1979-2015. Note that both “long” and “short” curves use b_t , the bid-to-cover ratio (8 lags are included as controls). Each curve is from the subsample combinations: short-term and long-term auctions; and periods of high and low risk aversion as measured. 2 standard error (Newey-West) confidence intervals are included.

Figure B11: Rate Response P-Values (Bid-to-Cover, 1979-2015)



Notes: p-values testing equality of coefficients from Figure B10. Testing equality of all coefficients gives a p-value of 0.999 for the “short” sample, and 0.973 for the “long” sample.