Abstract: The financial crisis saw a large premium paid for Treasury notes over bonds, reaching six percent of face value. We relate this premium to the underlying sources of liquidity supply and demand. On the supply side, we find that arbitrageurs faced low direct costs but high frictions, and that the largest premium coincided with a high price charged by market makers to carry new positions. On the demand side, we find that those investors in more distress or with more active trading strategies demanded the notes relatively more as the premium grew.
Abstract: The financial crisis saw a large premium paid for Treasury notes over bonds, reaching six percent of face value. We relate this premium to the underlying sources of liquidity supply and demand. On the supply side, we find that arbitrageurs faced low direct costs but high frictions, and that the largest premium coincided with a high price charged by market makers to carry new positions. On the demand side, we find that those investors in more distress or with more active trading strategies demanded the notes relatively more as the premium grew.
I. Introduction

The rapid contraction of the financial industry in 2007 - 2009 pulled many prices out of their usual orbits. Of the many resulting anomalies, perhaps none was as stark as the divergence in the Treasury market between bonds, i.e. Treasuries issued with 30 years to maturity, and notes, i.e. all other coupon-paying Treasuries. Bonds traded at a relative discount that reached six percent of face value, even with cash flows matched exactly. So extreme a violation of the law of one price, in so big a market, indicates the powerful attraction of a force other than future cash flows, and the logical suspect would be liquidity. In this paper we assess the role of liquidity in this episode, and by extension, the role of liquidity in general during times of market stress. We do this by relating Treasury prices to, on the one hand, the supply of liquidity from arbitrageurs and market makers, and on the other hand, to the demand for liquidity, as revealed by the circumstances of institutions taking the rich or cheap side of the trade.

Figure 1 shows the evolution of this anomaly. Each line represents the price of a note minus the price of a replicating portfolio, comprised of a bond and the bond’s principal STRIP. So for example, the red line represents three securities that mature on 2/15/15: a 4% note issued in 2005, an 11.25% bond issued in 1985, and the principal STRIP from this bond. The line shows the price of the note minus the sum of \((4/11.25)\) times the price of the bond and \((1-4/11.25)\) times the price of the STRIP. We form this comparison because the cash flows from the bond plus the STRIP exactly match the cash flows from the note. Figure 1 plots all nine bond/note pairs that were outstanding in September 2008, when Lehman went bankrupt, and it shows that their relative prices trace the familiar contour of the crisis, widening first during the August 2007 quant meltdown, and then hitting local peaks with the March 2008 Bear Stearns collapse and global peaks after Lehman. This correspondence to the crisis, which is often

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1 STRIPS stands for Separate Trading of Registered Interest and Principal of Securities. These are single cash flow securities formed from the individual coupon and principal components of Treasury coupon securities.
characterized as (among other things) a flight to liquidity, also points to relative liquidity as the underlying cause of the price differences.²

What could make notes so much more liquid than bonds, as to command these premia? The immediate difference between the securities is age, which Fontaine and Garcia (2012) and others connect to bond pricing through liquidity. When a Treasury bond and note share a maturity date, the bond is at least 20 years older; in the case of the securities we focus on, the bonds were issued in the 1980s, and the matched notes in the 2000s. Thus, the bonds have had much longer to settle into buy-and-hold portfolios. Bonds from the 1980s are also much smaller, in principal outstanding, than notes from the 1980s, because the initial issuances were smaller, and because some of the issuance has been repurchased. Also, much of the issuance remaining has disintegrated over time through stripping. So while the time since issuance might seem like water under the bridge, the consequences could be relevant to a security’s liquidity, and thus to liquidity premia in crisis times.

We analyze the bond/note divergence (which is what we will call it from here on) in several stages, the first of which is to document that it affected every maturity-matched pair. There are nine such pairs, and Figure 1 shows strong evidence of commonality in their divergences. Throughout our analysis, we focus on prices of securities outside of the most recently issued of a particular maturity sector, so as to mitigate the influence of any “on-the-run premium” in our findings. We look beyond the often-used inter-dealer Treasury-price databases, which capture little of the “off-the-run” market, to an internet-based request-for-quote platform that hosts much of this market.

We next address the resilience of the bond/note divergence to the forces of arbitrage. The divergence is an obvious potential arbitrage opportunity, so its size and persistence indicate some

² A short animation of the time series evolution of the cross-section of actual Treasury yields illustrates the magnitude and systematic nature of the price divergences: [http://finance.wharton.upenn.edu/~kschwarz/movie.html](http://finance.wharton.upenn.edu/~kschwarz/movie.html).
combination of inability and/or unwillingness to trade against it in sufficient size. We focus attention on the necessary elements of such a trade, which include the repo to finance a long position in the bond and the reverse repo to sell the note short. Using a database of interdealer transactions, we gauge the frequency and pricing of such repos. We find that the net funding costs are insufficient to offset much of the arbitrage profit, but we also find that the incidence of repos is particularly low when the divergence is greatest. This suggests a low demand either to put on the trade or to use the repo market, where the latter could reflect the possibility of delivery fails. In particular, prospective security-borrowers may prefer to fail rather than to agree to a negative rate to “reverse in” a security (e.g. Evans et al 2009). On the other side, security-lenders may be discouraged from “repoing out” specific securities by the prospect of not getting their securities back. Accordingly, we track the incidence of fails over this period, and we find that they surged as the declining Fed Funds rate pushed general collateral repo rates near zero, and as repo market participants de-levered following Lehman’s bankruptcy. So the widest divergence corresponds less to an explicit repo expense and more to a repo-market breakdown.

Next we consider the role of liquidity in determining prices. We extend our analysis to the full set of Treasury securities and form a measure of relative mispricing, which varies by security and over time, by subtracting from each security’s price the price implied by a yield curve fit to all coupon securities. We then relate this price difference to potential sources of liquidity difference, including issue size, age, and quantities stripped, and also to market-based measures of liquidity, including the bid/ask spread and trading volume. We find a strong relation to relative prices, particularly when market-wide liquidity is low. Older securities and smaller-size securities, in particular, have relatively lower prices, as do those with lower trading volume and higher bid-ask spreads. These are distinguishing features of the Treasury bonds relative to the same-maturity notes, so this indicates that they account for a significant portion of the divergence.
A question related to the role of liquidity in prices is how liquidity is priced in the first place. That is, why does a liquidity provider charge the bid/ask spread we observe? Spreads are often associated with asymmetric information about true value (e.g. Glosten and Milgrom, 1985), and the adverse selection cost it imparts, but this is unlikely to explain much of the spread charged for Treasury securities, let alone the variation of spreads across Treasury securities. This focuses attention on the other costs borne by a liquidity provider, in particular on the expected cost of carrying the position until the next trade in the other direction, and the expected cost of bearing the position’s risk over that time. These costs vary substantially across Treasury securities because they vary both in trading frequency and in duration. Thus, we can identify the prices charged to bear carry cost and price risk with pooled regressions of bid-ask spreads on proxies for these risks. We find that the prices charged for bearing them each rose substantially in the crisis, but it was the price charged to carry new positions that rose to extreme heights at the peak of the divergence.

Finally, we track liquidity-related price variation back to investor demand by relating the cross section of trades to the cross section of the traders’ circumstances. We do this using all Treasury security transactions for all U.S. insurance companies, which we combine with extensive information on the insurers’ financial conditions and trading histories. Insurers collectively hold about three percent of the stock of U.S. Treasuries, and their circumstances vary in ways that likely influence their relative demand for liquid securities. This means that we can measure the contribution of liquidity demand to the securities’ relative pricing by regressing the insurers’ trades on measures of their circumstances and the interaction of these circumstances with the securities’ relative prices. We find that both higher leverage and annuity exposure lead to higher demand for a Treasury security as its relative price increases, and

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3 The Federal Reserve’s Flow of Funds data, Table L.209, shows the combined holdings of Life, Property, and Casualty Insurers, as of 12/31/2008, to be $171 Billion, compared with the $6.1 Trillion of publicly held Treasury securities (other than savings bonds) then outstanding (see http://www.federalreserve.gov/releases/z1/current/z1r-4.pdf).
so does a trading history that indicates a higher value placed on liquidity. Furthermore, by interacting demand with the evolution of relative prices over time we show that this demand increases with the size of the mispricing. Thus we conclude that liquidity demand drives up the price of liquidity, particularly during times when arbitrage capital is scarce.

The rest of the paper is in five sections. Section II documents formally the arbitrage trade, measures the price divergence, and discusses related literature. Section III describes our data sources and our construction of variables. Section IV, addresses the costs of implementing the arbitrage trade and Section V examines the impact of liquidity on relative prices and trading activity. Section VI summarizes and concludes.

II. The Divergence and Related Literature

A. The Arbitrage Opportunity

A couple of months after Lehman’s bankruptcy, on 11/20/08, Treasury coupon securities closed the day at the yields displayed in Figure 2. Notes are represented by black dots and bonds by blue asterisks. In this particular snapshot of the yield curve, there are nine bonds that share a maturity date with an off-the-run note, and all nine of the matching notes are 10-years (we refer throughout to securities originally issued with $n$ years to maturity as $n$-years). The bond yields lie consistently and substantially above the note yields, despite the lower durations implied by their larger coupons. The bonds with more than ten years remaining to maturity follow a curve largely consistent with the nine highlighted bonds, but the absence of matching notes prevents measuring their relative pricing precisely. Thus, we focus on the bond/note contrast by limiting our analysis to bonds with less than ten years remaining to maturity.

For bonds with maturity-matching notes, we can precisely measure relative pricing through a simple replication. To match the cash flows of a note with coupon $C_N$, using a bond with coupon $C_B$
and a STRIP maturing on the same date, one simply buys \(C_N/C_B\) of the bond and \((1-C_N/C_B)\) of the STRIP.\(^4\) For each of the nine bond/note pairs we subtract the price of the replicating portfolio from that of the note (using the midpoint of bid and ask prices), yielding the time series plot in Figure 1. The price differences are generally positive and strongly correlated,\(^5\) and they track the intensity of the financial crisis. There is an initial rise at the quant meltdown of August 2007 (Khandani and Lo (2011)), a local peak at the Bear Stearns crisis in the spring of 2008, and then the big spike in the frantic months after the bankruptcy of Lehman Brothers (Gorton and Metrick (2012)). The arbitrage opportunity peaks at about $6 per $100 of face value and is significantly positive for several months in late 2008 and early 2009. The price differences subsequently move back down to nearly where they were before the crisis.

Figures 1 and 2 raise the questions this paper addresses: what drove Treasury prices so far out of line, and why was this force consistently in one direction, pushing the prices of notes above those of bonds? Because Treasury securities have the same, and apparently minimal, default risk, the literature on price discrepancies between Treasuries focuses on their relative liquidity, which can vary over time and across securities. Also, the behavior of securities markets during this time is often characterized as a flight to quality and to liquidity, which could differentially affect the more liquid Treasury securities. In the rest of the section we review the literature on Treasury-market price discrepancies that could shed some light on the pricing of notes relative to bonds.

B. Literature review

A comparison similar to notes vs. same-maturity bonds is between Treasury bills and Treasury notes within six months to maturity. Both at that point are pure discount Treasury securities, so a similar

\(^4\) We use bond principal strips throughout, as note principal strips are scarce (see Table I).

\(^5\) The most negative price differentials coincide with the Federal Reserve’s Quantitative Easing-related announcements and purchases of Treasury securities.
arbitrage relation exists. Amihud and Mendelson (1991) show that the notes’ bid/ask spreads are wider, and their yields are higher, relative to the more recently issued bills. The combination of yield and spread differences allows profits for traders who do not try to unwind their positions before maturity, so the authors conclude that this is an illiquidity premium available to patient capital.6

Another similar comparison is between bond and note principal STRIPS with the same maturity. These securities often command different prices, as Jordan, Jorgensen and Kuipers (2000) show, with bond principal STRIPS typically trading at a discount to note principal STRIPS. Jordan, Jorgensen and Kuipers (2000) also show that STRIP price differences largely reflect the relative pricing of the original securities, meaning that a principal STRIP is relatively cheap if the security from which it is stripped is relatively cheap. They also show that bonds are stripped much more than notes, which also holds true in our later sample period.

A third similar comparison is between on-the-run, i.e. “new” securities, and just-off-the-run, i.e. “old”, securities. New securities tend to trade at premium prices, and this is generally attributed to the their greater liquidity (e.g. Fleming (2003), Goldreich, Hanke and Nath (2005), Barclay, Hendershott and Kotz (2006), and Pasquariello and Vega (2009)), and as new securities become old at the next issuance, this appears to represent an arbitrage opportunity for capital patient enough to wait until the next issuance. However, Krishnamurthy (2002) finds that the cost of borrowing the new bond to short it tends to offset the premium. Fontaine and Garcia (2012) extend the analysis of how a security’s age affects its liquidity by examining other pairs of Treasury securities with the same maturity but different age. They assume that age-driven price differences reflect liquidity, and from these pairs construct an index that correlates with what they term “funding liquidity.” Hu, Pan and Wang (2013) also construct

6 Taxes also explained some of the variation in prices at that time (Kamara, 1994), but the tax code has been changed to remove this differential treatment of notes and bills.
an aggregate measure from the Treasury market, as the sum of the root mean square deviation of
individual Treasury yields from a smoothed curve, across all securities on any given day. They interpret
the measure as capturing liquidity crises, which among other things shows a local peak around Bear
Stearns and a global peak after Lehman.

Matched-maturity comparisons are also possible between Treasury securities and other securities
with the same creditworthiness, i.e. the full faith and credit of the federal government. One such group
of securities is Refcorp bonds, which arose from the Savings and Loan crisis. Longstaff (2004) shows
that Treasury securities often trade at a large premium over same-maturity Refcorp issues, and attributes
this premium to current and expected liquidity. In the euro-area, Schwarz (2014) shows that the yield
spread between comparable German federal government and KfW agency securities, which have an
identical German federal government guarantee, is a real-time, tradable proxy for market liquidity and
liquidity risk. This yield spread spiked above 80 basis points, first after Lehman’s bankruptcy, and then
again amid the Greek debt crisis in 2011. Also, inflation-protected Treasury securities economically
equate to regular Treasury securities paired with inflation swaps, but as Fleckenstein, Longstaff and
Lustig (2014) show, their prices moved far apart in the crisis.

In summary, the existing literature finds price differences among same-maturity Treasury
securities and Treasury equivalents, and generally attributes the differences to a premium for liquidity.

III. Data

In this section we introduce the data that we use for the bulk of our analysis. We first describe
our dataset of secondary market prices for Treasury securities. We complement these data with
additional security-level data that we use to form proxies for relative liquidity.
We also collect secondary market trading activity and portfolio holdings of Treasuries for U.S. insurance companies. With these data, we gain insight into the trading activity of a large end-buyer of Treasuries.

A. Treasury Transactions on the TradeWeb Platform

We construct a panel dataset of daily observations for all nominal Treasury securities outstanding, including STRIPS. We begin with bid and ask price quotes from TradeWeb, a large electronic trading platform that specializes in customer-to-dealer trades of fixed income securities, including U.S. Treasuries. We have this data from May 3, 2004 through December 31, 2011. An advantage of TradeWeb relative to inter-dealer trading platforms, such as eSpeed and BrokerTec, is broader coverage of the off-the-run securities on which we focus.

The TradeWeb data report quotes averaged across market makers, at four moments each day: 8:05AM, 3:00PM, 4:00PM and 4:45PM (U.S. Eastern time). From these times, we choose the 3:00PM snapshot, as it appears most representative of intraday liquidity since trading volume is lower overnight and late in the day (Fleming and Remolona (1997)). Our results are not sensitive to this choice. The TradeWeb data do not include trading volume per se but from June 2008 onward they do reveal the time of the last buy and the last sell of the indicated security, as of each of the four quote snapshots each day. From this we calculate the variable $TTT$, defined for each security on each day from June 2008 onward as the average, as of 3:00PM, of the time (in days) since its last buy and the time since its last sell.

We complement the Treasury market data from TradeWeb with the corresponding funding costs for each security in the specials repo market. Our repo data come from a large interdealer broker. Our

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7 An independent market research report from February 2014 cites TradeWeb as the leading electronic U.S. Treasury trading platform. Greenwich Associates (2014) estimates that 25 percent of total fixed income trading volume is executed electronically, and that 45 percent of institutional investors use electronic platforms for at least part of their fixed income transactions.
sample contains all repo transactions handled by the broker from April 1, 2004 through March 1, 2009. For each transaction we see the specific security that served as collateral for the repo, the rebate rate, the settlement date, and the term.

B. Liquidity Variables

We capture the cross section of Treasury securities’ liquidity using several measures. From the TradeWeb data, we calculate the Bid-Ask as \( \frac{\text{Ask} - \text{Bid}}{\text{Price}} \) as of 3:00PM. The proxy Volume for the overall daily trading volume in a security adds the buys and sells by insurance companies as reported in the database described below. Data on amounts outstanding come from the Treasury Department’s Monthly Statement of the Public Debt, which reports initial issuance, repurchases, re-openings, and also principal amount stripped. Data are all end-of-month, and from them we construct \( \log(\text{Out}) \), the log of the principal outstanding, \( \text{Share Stripped} \), the share of the principal amount outstanding that is held in stripped form, and \( \log(\text{Age}) \), the log of the time since issuance, which we compute at a daily frequency.

Table I reports summary statistics for the liquidity variables, along with some additional information about the securities, and shows that bonds are less liquid by several measures. The average quoted bid-ask spread is 3 basis points in general, but nearly 6 basis points for bonds alone, and bonds trade far less frequently than ten-years: almost three days elapses between trades of a given bond vs. three trades a day for a ten-year note. Bonds are also much smaller, older and more stripped, on average, than other securities, and they also have much higher coupons, consistent with the yield curves prevailing at their issuance.

Figure 3 shows the evolution of bid-ask spreads during the sample period. Prior to September 2008, average spreads were very low, on the order of 2 basis points. They widened sharply around the bankruptcy of Lehman and narrowed only slightly near the end of the year before spiking again in the spring of 2009. They subsequently drifted back down, but not all the way to where they started. This
pattern is stronger among bonds, which in the worst of the crisis traded at spreads that were often in excess of 20 basis points and triple those of notes.

C. Trading and Holdings Data for Insurance Companies

Our final dataset reports the transactions in, and holdings of, Treasury securities by U.S. insurance companies. U.S. insurance companies are required to report every purchase and sale of a Treasury security, indicating the date, size and direction of each transaction, and to report their quarter-end holdings by security. These data are packaged and resold by eMaxx. We limit our sample to insurers that show holdings and transactions in coupon Treasury securities, including STRIPS, in the period from the first quarter of 2006 through the fourth quarter of 2011, and that can be matched with accounting data from SNL Financial. This leaves transactions by 2,321 insurers.

For each insurer we calculate several statistics summarizing its trading activity. *Volume-Weighted Holding Horizon* is the volume-weighted average number of days between the purchase and sale of each Treasury security that the insurer trades. A larger holding horizon indicates that the insurer tends to hold a security for a longer time following a purchase. *Churn* is an insurer’s average trading volume per month in Treasury securities divided by its average holding of Treasury securities, and thus indicates a more active trader. Finally, *BuysToSells* is an insurer’s net Treasury security purchases divided by its

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8 The original data from eMaxx is at the level of insurer-date-CUSIP-investment advisor, and we aggregate the data to insurer-date-CUSIP by summing transactions that have identical insurer, date, and CUSIP. eMaxx is a Reuters subsidiary that obtains the source data from the statutory filings of regulated insurance companies.

9 Holding horizon measures the average number of days that an insurer *j* holds a security *i* in its portfolio.

\[ \text{Horizon}_j = \frac{\sum_{t=1}^{T} (Q_{i,j} \cdot \text{Days}_{i,j})}{\sum_{t=1}^{T} Q_{i,j}} \]

\( Q_{i,j} \) is the quantity that is both bought and subsequently sold of security *i* for insurer *j*. \( \text{Days}_{i,j} \) is the holding horizon in days for security *i* and insurer *j*. We drop observations for which there is not a matching purchase and sale in our sample.

10 Churn is an insurer’s average trading volume per month in Treasury securities divided by its average holding of Treasury securities, and thus indicates a more active trader. Finally, BuysToSells is an insurer’s net Treasury security purchases divided by its
total volume of Treasury security transactions,\(^{11}\) so it increases with an insurer’s propensity to hold a security to maturity, rather than to sell it.

From the SNL Financial accounting data we construct several measures of insurers’ financial strength and liquidity. *Capital/Assets* is a measure of the leverage of the insurer, where *Capital* is an accounting measure of policyholder surplus, and *Assets* is the book value of total assets.\(^{12}\) *Annuity* is an indicator variable equal to 1 if the insurer sells more annuities than life insurance or property/casualty insurance, and equal to 0 otherwise. As discussed in McMenamin et al. (2012), annuities provide customers with some ability to withdraw their savings, which creates liquidity risk for insurers. *RBC* is an indicator variable equal to 1 if the reported ratio of total adjusted capital relative to risk-based capital, measuring the insurer’s capital adequacy, is greater than the median for all insurers in our sample, and 0 otherwise.\(^{13}\) Finally, *Net Income* is an indicator variable equal to 1 if the insurer’s net income is positive, and 0 otherwise.

The insurance company data is our source for Treasury trading volume. The statistic *Trading Volume* in Table I represents trading by insurers, and the statistic *Volume\(_{i,t}\)* used in the regressions is the trading by insurers in security *i* on day *t*, divided by all trading by insurers on day *t*.

**IV. Exploiting the Arbitrage**

How would an investor have fared, betting on the divergence to subside? This depends on financing considerations that we have not yet addressed. The trade requires buying a bond and its STRIP and shorting the note, and then waiting for convergence. Such a trade also calls for borrowing funds to

\[ \text{BuysToSells}_i = \frac{\sum_{t=1}^{T} \sum_{j=1}^{J} (Buys\_{i,j,t} - Sells\_{i,j,t})}{\sum_{t=1}^{T} \sum_{j=1}^{J} (Buys\_{i,j,t} + Sells\_{i,j,t})} \] for CUSIP *i*, insurer *j*, and day *t*.

\(^{11}\) The vast majority of insurers are private, so it is impractical to use market values.

\(^{12}\) Merrill, Nadauld, Sherlund, and Stultz (2012) show that insurers with below-median levels of regulatory capital were more likely to sell securities at fire sale prices during the recent financial crisis.
take a long position in the relatively cheap bond and for borrowing the relatively expensive note in order to short it. We reference the concurrent repo rates in order to replicate the experience of trading at the divergent prices. This replication can go only so far, since the repo rate available to one market participant may not be available to another. But we can at least gauge whether, as in Krishnamurthy (2002), the estimated financing costs borne by well-positioned traders are in the neighborhood of the gross profit implied by the divergence.

Our data shed light on financing costs, but there are necessarily some limitations on what they can illuminate due to the short maturity of the typical repo transaction and the much longer term over which an investor might potentially wish to hold the trade. Most repos are overnight (both Duffie (1996) and Jordan and Jordan (1997) use exclusively overnight repo data). In our database, 82 percent of the transactions are overnight. Thus we estimate the realized financing costs of a hypothetical investor by stringing together a series of overnight rates. The investor might have preferred longer-term repos, maybe even as long as the securities’ maturity so as to avoid early termination or rate increases, but we cannot gauge the expense or availability of such arrangements from the data, so we focus on the overnight transactions.

An investor putting on the trade pays interest on the money borrowed for the bond and the STRIP, and receives interest on the money loaned to reverse in the note. The interest the investor pays is bounded above by the General Collateral (GC) rate, as by definition this rate applies when the collateral is not a specific security but rather any acceptable security (or a mix of different securities) within a certain type of collateral. To be conservative we assume that the long position is financed at this upper bound, the overnight Treasury GC rate, which we collect from Bloomberg. The interest received on the note is

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14 We include “over-the-weekend” repo transactions in our analysis as overnight trades.
15 Keane (1996) states that term repos longer than 90 days are in practice not available at all.
reduced by any scarcity value the note commands in the repo market. That is, the note could be “special.” As the notes are likely desirable to short in the cash market, they are correspondingly likely to be special in the repo market. We do not observe the rate for each note on each day; the average day sees transactions in 20 percent of the maturity-matched notes. So we estimate the cost of reversing in the notes in question as the average rate of the maturity-matched notes for which we see transactions, on each day. For the days when we see no transaction in the maturity-matched notes, we assume the note rate is zero (implying that the net funding cost is equal to the GC repo rate), which is the minimum we observe on any day.

The financing rates are plotted in Panel A of Figure 4, which shows the GC rate and the average specials rate on the notes throughout our sample period. The key quantity is the difference between these rates, as the trader would pay the GC rate and receive the specials note rate. This difference is generally small: it is between 0 and 23 basis points on 75 percent of the days in our sample period. It spikes on occasion, but not in late 2008, the period of greatest divergence between prices in the cash market. At that time, the GC rate declines along with the Fed Funds rate as it approaches zero. Since the note specials rate does not become negative, the difference between the GC and specials rate is close to zero as well. Panel B of Figure 4 summarizes the financing cost implied by the difference by plotting the cumulative cost from the beginning to the end of the period. The realized financing cost of the trade from well before the divergence emerged to after it subsided is just 0.72 percent, and the slope of the cumulative cost is about the same before the mid-2007 onset of the divergence as it is after. Thus, the realized cost of financing the trade is small relative to the divergence, and an order of magnitude smaller than the peak divergence.

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16 Our repo sample ends in March 2009.
The low cost of financing the arbitrage trade at the time of greatest apparent opportunity raises questions, most immediately whether this is really the cost that a hypothetical trader would have paid. Similar doubts arise from any data on the history of transactions, but the answer is less clear than in the case of stock or bond transaction prices, because a repo counterparty’s business is not open to all comers. This was a time of extreme market stress, so it stands to reason that some traders could not access financing at all. Thus, the costs in Figure 4 better represent the experience of a large and well-regarded hypothetical trader than that of just any trader.

Another question raised is why the specials note rates bottom out at zero. The answer likely lies in a trader’s alternative, at the time, to fail to deliver a shorted Treasury. As Evans et al. (2009) note, a delivery fail runs the same cost as a securities loan with a zero interest rebate, plus any expected cost of getting bought in. So if the buy-in risk is low enough, then a short-seller would rather fail to deliver a security than to borrow it at a negative repo rate. That this alternative was available and attractive is apparent in the incidence of both repos and fails. Figure 5 shows the number of repo transactions in our database each week, and reveals a steep drop in late 2008. The figure also shows the incidence of Treasury delivery fails as calculated by the Fed, and reveals an even steeper rise. Furthermore, looking across all overnight Treasury transactions in our repo database, there are 834 with a zero interest rate, and none with a negative rate. Thus it appears that the alternative of failing drew a line at zero under the note rate, and that this line bound tightly when monetary policy drove the GC rate near zero itself.

Our results indicate that a well-positioned trader could have traded against the divergence at a cost that proved much lower than the divergence itself. Traders could have expected costs to run higher,

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17 A new market convention adopted in May 2009 made it much more costly to fail to deliver a Treasury security.
and for the divergence to expand or persist more than it did, but to the extent that data can reveal, financing costs offset very little of the profit that the divergence implies.

V. Pricing and Provision of Liquidity

What role does liquidity play in the divergence? In the first part of this section we take this question to the entire cross section of Treasury securities by relating their relative prices to their fundamentals. We also take this question to the time series by gauging how the relation of prices to fundamentals varies with aggregate liquidity, as represented by the average bid-ask spread, and by gauging how and why the price charged for liquidity varies with the cross section of bid-ask spreads and the cross section of the securities’ financing and interest-rate risks.

In the second part of this section we take this question to the demand for liquidity, as captured by the transactions of insurers. The goal is to connect the current relative price of the security bought or sold with the current circumstances of the insurer, in particular the circumstances likely to affect the insurer’s demand for liquidity.

A. Explaining Prices

To generalize our results beyond only the set of securities with identical maturity dates, we now examine relative pricing for all Treasuries by calculating a “fitting error” for each security, defined as the difference between the price of each security and the price implied by a smoothed yield curve. For each date in our sample, we use the cross-section of Treasury prices for coupon securities from TradeWeb to parametrically estimate a fitted curve. We estimate the yield curve using the six-parameter model of instantaneous forward rates developed by Svensson (1994)\(^\text{18}\). By construction, the mean fitting

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error is close to zero (not precisely zero, since prices are not linear in yields), and the squared fitting error is close in value and in spirit to the noise measure in Hu, Pan and Wang (2013). However, our approach uses the fitting error of each security separately as a measure of relative mispricing, rather than aggregating the fitting errors over all Treasury securities, and we subsequently examine security-level determinants of the fitting errors.

The security’s fitting error corresponds to the price divergence of identical cash flow portfolios from the bond/note trade defined in Section II. As a check on the validity of this approach, we confirm that the fitting errors largely replicate the more limited cash-flow matching approach described in Section II; the average fitting error of 30-year bonds becomes significantly negative during the crisis, the average fitting error of 10-year notes becomes significantly positive, and the difference peaks at around 6 percent as in Figure 1.

Next, we run pooled cross-sectional, time-series regressions where the dependent variable is the fitting error. The independent variables are differences among the securities that could affect their liquidity. The most salient differences are age and size: the bonds are older, smaller and more stripped, and existing research associates both greater age (Amihud and Mendelson (1991), Fontaine and Garcia (2012)) and lower principal amount (Longstaff, Mithal and Neis (2005)) with lower liquidity. Accordingly, we include $\log(Age)$, $\log(Out)$, and $Share Stripped$ as explanatory variables. The bonds also have bigger coupons, and while existing research does not, to our knowledge, associate coupon with liquidity, there could be an association, and the difference between bonds and notes is quite large, so we include $Coupon$ as an explanatory variable. Panel B of Table I shows that age, coupon, share stripped, and amount outstanding are all highly correlated, which makes it difficult to distinguish their separate effects in the multiple regression. Accordingly, we also run simple regressions on each. We also include the security-specific $Bid-Ask$ and $Volume$, and an indicator for the matched bond/note pairs. This
indicator *Net Long Matched Pair* is set to 1 for the notes in the pairs and -1 for the bonds, so the estimated coefficient captures the average difference in prices between the matched pairs. The regression covers the period from January 2006 through December 2011, so a large portion of our sample is outside of the crisis period.

The regression models take the general form:

\[ FE_{i,t} = \alpha + \beta Liq_{i,t} + \epsilon_{i,t} \]  

(1)

where \( FE_{i,t} \) is the fitting error, in price terms, for security \( i \) on day \( t \), and \( Liq_{i,t} \) denotes the characteristic of security \( i \) on day \( t \).\(^{19}\) We report a simple regression for each independent variable and three multiple regressions with different sets of the independent variables. Results are in Panel A of Table II.

The regressions show that the fitting error relates significantly to liquidity. This is apparent in relation to fundamentals: a Treasury security is more expensive when it is more abundant, either because more was issued or less was stripped, and also when it is younger. It is also apparent in the relation to the standard metrics of liquidity: price is higher when trading volume is greater, and when the bid/ask spread is tighter. At the point estimates, a one basis point increase in a security’s bid-ask spread reduces its price by about three basis points, and doubling its amount outstanding increases its price by thirteen basis points (\( \log(2) \times 18.9 = 13.1 \)). In the multiple regression, bid-ask spreads, amount outstanding, and trading volume all still enter as before. In the multiple regressions, the point estimate of age moves more dramatically toward zero and becomes less significant. So price relates positively to supply, even controlling for the liquidity metrics, but the effect of age appears to be largely absorbed by these metrics. That the coupon relates negatively to price in the simple regressions is not surprising, given its close

\(^{19}\) We use the characteristic for the current month for liquidity indicators that are only observed at the monthly frequency.
relation to age. In the multiple regression including all regressors, the coefficient on coupon becomes significantly positive.\(^{20}\)

Regarding the bond/note pairs in particular, the liquidity variables explain some, but far from all, of the divergence. The coefficient on the indicator for the pairs is significant on its own and also in the multiple regression, shrinking somewhat from the former to the latter. So the liquidity differences captured by these variables are relevant to the divergence, but the static relation between price and liquidity fit by this regression model is an incomplete explanation.

To gauge the roles of the potential sources of illiquidity discounts in the ballooning of the divergence in the crisis, we estimate the variation over time of the cross-sectional relation between prices and general illiquidity. We do this by indexing the overall state of illiquidity over time, and then interacting it with the liquidity measures. The index, which we denote \(AggLiq\), is the daily average bid-ask spread across all Treasury securities in our sample. Figure 3 shows its evolution over our sample.

To allow the level of market-wide illiquidity to affect the slope and intercept estimate for each Treasury \(i\) on each day \(t\), we modify equation (1) as follows:

\[
FE_{i,t} = \alpha_i + \beta_iLiq_{i,t} + \epsilon_{i,t}
\]  

Then, assuming that the intercept and slope are linear functions of the aggregate liquidity, \(AggLiq\), we have:

\[
\alpha_i = a + b\ AggLiq, \quad \beta_i = c + d\ AggLiq
\]  

\(^{20}\) Conceivably, the higher price for higher-coupon securities reflects their higher current yield, in that agents investing on behalf of consumers who don’t understand the tradeoff between current yield and future capital losses (see, e.g., Donnelly (1988)) may find them attractive.
Substituting equation (3) into equation (2) gives us the interaction effect. The characteristics of each security affects that security’s sensitivity to changes in market-wide liquidity, shown as follows:

\[ FE_{i,t} = a + b \text{AggLiq}_{i,t} + c \text{Liq}_{i,t} + d \text{AggLiq}_{i,t} \text{Liq}_{i,t} + \epsilon_{i,t} \]  

(4)

We repeat each regression from Panel A with the aggregate liquidity interactions added. We do not include aggregate liquidity on its own since we include day fixed effects. The results are shown in Panel B of Table II.

In the time series we see in Panel B that the interaction effects have the same sign as the corresponding level effects in Panel A, which means that the cross-sectional relation of price to these variables grows with market-wide illiquidity, i.e. older, smaller, and more-striped securities all grow cheaper as liquidity dries up. For a sense of the magnitude of this effect, the average level of the bid-ask spread rose from 2 to 11 basis points at its widest, which implies that the effect of a one basis point increase in a security’s spread on its price goes from \(-0.79 + (-0.41) \times 2 = -1.6\) basis points to \(-0.79 + (-0.41) \times 11 = -5.3\) basis points. Thus, worsening aggregate liquidity significantly amplifies the effect of securities’ liquidity attributes on their prices.

B. Time Variation in the Price of Liquidity

A security’s bid-ask spread shows the price charged by liquidity providers. Figure 3 shows that the average price roughly quadrupled during the crisis. This raises two main questions. First, what is the role of quantity? That is, how much of the variation reflects variation in the quantity of risk borne by liquidity providers, and how much reflects variation in the price charged per unit of risk? And second, which risks are important? In particular, which risks borne by liquidity providers were particularly responsible for the high spreads during the crisis? We address these questions with a series of monthly
pooled regressions, where the independent variable is a security’s bid-ask spread, and the dependent variables are proxies for the risks the security poses to a liquidity provider.

A security poses two main risks to a liquidity provider: price risk and financing risk. Price risk is the risk that the security’s value changes while the liquidity provider positions it, and financing risk is the risk that the security is difficult or costly to finance over this same period. The liquidity provider’s bid-ask spread for a security reflects any prices he charges for the expected price and carrying risks he would bear. These expectations increase with how long the liquidity provider expects to wait until a trade arrives to take the position off his hands, and while we cannot observe what exactly he expected, we can proxy for it with the time elapsed since the previous trade. Specifically, we calculate time to trade, $TTT$, for a given security on a given day to be the average of the time since the last buy and the time since the last sell, and take this as the liquidity provider’s expected time to carry a new position.

Regarding the price risk borne by the liquidity provider while financing, the relative sensitivities of Treasury securities to changes in interest rates are roughly proportional to their durations, and the current level of overall interest risk is reflected in the implied volatilities of interest-rate options. The Merrill Lynch Option Volatility Estimate, i.e. the MOVE index, averages across options on different maturities, and is a popular reference for this purpose. So for each security on each day, we take its price risk per unit of time to be its duration times the MOVE index, which we notate $Duration \times Volatility$, the units of expected carrying risk to be $TTT$, and the units of expected price risk to be $Duration \times Volatility \times TTT$.\textsuperscript{21} We run one regression per month and plot the fitted coefficients. The time series of average $Duration \times Volatility$, $TTT$ and $Duration \times Volatility \times TTT$ are in Panel A of Figure 6, and the regression coefficients, along with confidence interval bands, are in Panel B.

\textsuperscript{21} Volatility is measured in 100ths of a basis point, Duration is measured in years, and TTT is measured in days.
The salient trend in Panel A of Figure 6 is a strong upward trend in the time since a Treasury last traded, from half a day in mid-2008 to over a full day by mid-2011. This could result from either a general drying up of liquidity, or a drying up on this particular platform, TradeWeb. The database does not reveal TradeWeb’s market share, but news reports point to a general trend, rather than a TradeWeb-specific trend. For example, Bloomberg reported on March 29, 2015, that average daily Treasury trading by primary dealers shrank from 13 percent of the amount outstanding in 2007 to just 4.1 percent in 2015, and also that “…electronic trading of Treasuries has proliferated over the past decade and now accounts for 44 percent of all transactions.” So the increasing time between the electronic trades at TradeWeb points more to the general downward liquidity trend than to a decline in market-share.

Since neither $Duration \times Volatility$ nor $TTT$ spiked substantially during the crisis, it stands to reason that the spike in spreads reflects spikes in the price per unit, rather than quantity, of risk. That is indeed borne out by the results in Panel B of Figure 6. The prices charged to bear both price and financing risk rise and fall in concert with the average spread, with the price to bear financing risk showing the most volatility, particularly at the late-2008 peak of both spreads and the divergence. The high price to bear financing risk accords with the breakdown of the repo market documented above. To put these numbers in perspective, note that the estimated coefficients on $TTT$ and $Duration \times Volatility \times TTT$ are around 2.5 and 0.6, respectively, in October and November of 2008. This means that a hypothetical security with the average $TTT$ of around 2 days and zero $Duration \times Volatility$ associates with $2.5 \times 2 = 5$ basis points of spread, and the same $TTT$ with the average $Duration \times Volatility$ of around 7 associates with $(2.5 \times 2) + (0.6 \times 2 \times 7) = 13.4$ basis points of spread.
Thus, aversion to leverage and aversion to risk separately played large roles in the high price of liquidity provision in the crisis.22

C. Propensity to Exploit or Exacerbate the Arbitrage

As difficult as it may have been to short the relatively expensive notes, it was always feasible for those who held the notes to sell them, use the proceeds to purchase bonds with similar duration (or bonds and a STRIP), and earn a profit on the difference in price. Similarly, investors considering buying a Treasury security among the matched pairs could purchase the relatively cheap bonds instead of the notes. The goal of this section is to understand the demand that, despite the opportunity presented by the bonds, supported the higher price of the notes. We do this by determining which investor circumstances associate with demanding the notes more when they are relatively more expensive. We follow each trade made by 2,321 insurers in 457 CUSIPs over a 6-year sample period that spans the crisis,23 and we also trace each trade back to the circumstances of the insurer that made it. This allows us to tease out the relationship between the circumstances that potentially relate to liquidity demand and the trader’s choice between securities.

We focus on two sets of circumstances, capturing on the one hand the insurer’s trading style, as indicated by its trading history, and on the other its financial stress, as measured by accounting data. The trading-style variables are Churn, which increases with an insurer’s trading and thus likely increases with its demand for liquidity, and Value-Weighted Holding Horizon and BuysToSells which represent an insurer’s propensity to hold a security for a while, and thus likely decrease with its demand for liquidity.

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22 Panels A and B of Figures 6 can explain why, in Figure 3, bond spreads end up higher in late 2011 than they started before Lehman. Since the prices charged to bear price and financing risk are no higher in late 2011, and since trading slowed down in between, it appears that liquidity providers charged more because they expected to carry the positions for longer.

23 The total number of CUSIPS outstanding varies over the sample period as some older securities mature and new ones are issued (on average, about half of the sample-total CUSIPS are outstanding at any given time). 89 percent of the insurers show Treasury holdings throughout the entire period.
The financial-stress variables include Capital/Assets, RBC and Net Earnings, which all increase with the health of the insurer and thus point to lower stress, and Annuity, which indicates that the insurer is a potential source of emergency liquidity. As in Coval and Stafford (2007) and Merrill, Nadauld, Sherlund, and Stultz (2012), the financial stress that variables such as these pick up likely increases the insurers’ demand for liquidity in their investments.

Table III shows summary statistics for our measures across insurers in aggregate and disaggregated by the main type of coverage the insurer offers.24 The Property and Casualty (PC) insurers are more numerous, but the life insurers are much bigger. Life insurers are the only group exposed to annuity risk, and within this class, 39 percent of insurers have a business focus in annuities. Due to the differences across different types of insurers, we include insurer-type fixed effects in our subsequent analysis.

For each insurance company \( j \) in month \( t \), we construct the net purchases of security \( i \) as \( \text{Buys}_{i,j,t} - \text{Sells}_{i,j,t} \), scaled by the amount outstanding of security \( i \), to control for variation in issue size. We then relate net purchases to the magnitude of security \( i \)’s fitting error at time \( t \) and the cross-sectional characteristics of each insurer \( j \) at time \( t \).25 We use the monthly-average value of the daily fitting errors to create a monthly fitting error.

First, to examine how insurers as a whole responded to the relative mispricing in bonds versus notes, we conduct regressions of the form:

\[
NP_{i,j,t} = \alpha + \beta FE_{i,t} + \epsilon_{i,j,t}
\]  

---

24 We follow SNL’s categorization of insurers to group them into life, health, and property and casualty.
25 The cross-sectional characteristics constructed from insurer transactions are constructed from the entire sample period for each insurer, while the cross-sectional accounting variables vary for each insurer by month. The accounting variables are available as quarterly data, which we then linearly interpolate to a monthly frequency.
where $NP_{i,j,t}$ is net purchases and $FE_{i,t}$ is the average fitting error, in price terms, for security $i$ in month $t$. We estimate the regression for the entire set of insurers and each of the three insurer types separately. Table IV shows the parameter estimates for equation (5). The first column shows that insurers as a whole demand a Treasury security more when its fitting error is larger, i.e. when its price is relatively high. The next three columns show that this result holds for each of the three classes of insurers, although the effect appears stronger for life insurers. A one percentage point increase in a security’s fitting error leads to a $703 increase in the average life insurer’s net purchases of the security, for every $1 billion outstanding of the issue. Aggregating to all of the life insurers in our sample (570), this implies a total of $400,710 of net purchases per $1 billion outstanding, or roughly 0.04 percent of the total issue. On balance, insurers are net sellers of relatively cheap Treasuries and/or net buyers of relatively expensive Treasuries at times when the pricing differential is larger.

To identify the circumstances of insurers driving their trades, we modify equation (5) by allowing the intercept and slope coefficients to vary by insurer, so that the equation becomes

$$NP_{i,j,t} = \alpha_{j,t} + \beta_{j,t} FE_{i,t} + \epsilon_{i,j,t}$$

(6)

We moreover assume that the intercept and slope are linear functions of the characteristics of the insurer, collected in a vector, $Risk_{j,t}$:

$$\alpha_{j,t} = a + b' Risk_{j,t}, \quad \beta_{j,t} = c + d' Risk_{j,t}$$

(7)

Substituting equation (7) into equation (6) yields

$$NP_{i,j,t} = a + b' Risk_{j,t} + c FE_{i,t} + d' Risk_{j,t} FE_{i,t} + \epsilon_{i,j,t}$$

(8)
which we then estimate in a pooled regression. The main object of interest is the coefficient on the interaction term, $d$, as it tells us whether a particular characteristic of an insurer makes it more or less likely to buy a Treasury security when the security’s relative price rises.

The results from estimating equation (6) are shown in Table V, with the characteristics entering individually in the first seven columns and together in the eighth. Among the individual results, the trading variables all associate liquidity demand with buying at higher prices. Investors with shorter average holding periods, more frequent portfolio turnover (Churn), and more sales relative to purchases all show net purchases increasing with the fitting error. The financial variables associate higher stress with demand for the more expensive securities: lower income and higher leverage both relate significantly to higher demand, and at reduced significance, higher annuity exposure and lower regulatory capital also relate to higher demand. In the multiple regression, two of the trading variables and two of the financial-stress variables are statistically significant, in the same directions. Among the variables, annuity exposure has a particularly strong effect, indicating three times the sensitivity of demand to higher price. 26

To summarize, we find that both trading history and a balance sheet profile indicating liquidity demand corresponds to higher demand for Treasury securities when they grow more expensive. This bears out the view that investor demand for liquid securities drove Treasury prices apart during the crisis, and likely contributed to the extended period during which prices remained apart.

VI. Conclusion

The relative prices of Treasury securities can usually be explained with high precision by their future cash flows, but external stress can bring other factors to bear on their pricing. The stress of the

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26 This calculation is based on comparing the coefficient estimate on interaction of Annuity and the fitting error, and the coefficient on the fitting error alone.
financial crisis moved the relative prices of bonds and notes far from the relation implied by their future cash flows, and both intuition and existing research on related episodes point to relative liquidity as the key factor. We analyze the price divergence from the perspective of arbitrageurs, market makers and end users of Treasury securities, identifying the separate and important roles of the demand for, and the supply of, liquidity in this episode.

The financial crisis is generally understood to have seen a flight to safety, where safety includes both quality and liquidity. Our analysis makes several contributions to this understanding. The first is simply the magnitude of the price effect among perfectly-matched securities with equal and nearly perfect quality. The next point is the low cost, to the extent the data can reveal, of executing the arbitrage through to convergence. This is not to say that the divergence presented a sure profit to anyone willing to trade, but rather that the transactions that did occur amounted to a low ultimate net cost to those who could access them.

We link the securities’ relative prices to their relative liquidity. One link is to the potential drivers of liquidity: the relative price of a security reflects its liquidity fundamentals, decreasing as it shrinks or ages, and it also reflects other indicia of liquidity, including bid-ask spread and trading volume. Another is that the price charged to provide liquidity – both the price charged to finance a security until it trades again, and the price to bear its risk over that period – varied substantially through the crisis, peaking in the days after Lehman when the divergence was large.

Finally, we ask what drives the demand bidding up the more-liquid securities. We do this by relating the trading decisions of insurance companies to circumstances that could drive their demand for liquidity. We find that both insurers with histories of demanding liquidity, and those in financial stress, demand the pricier Treasuries more at times that they are relatively more expensive.

Dependable price relationships break down in crises, and it is critical for investors, regulators and policymakers to understand why. This is true for a number of reasons. First, financial institutions
pursue leveraged strategies based on these relationships, and this tends to amplify the effects of their breakdown. Secondly, understanding the origins of mispricing helps identify the types of investors under stress, as well as the types likely to be more or less sensitive to liquidity crises. Thirdly, the transmission of monetary policy relies on arbitrage and tight pricing relationships between similar assets. For instance, in normal times, monetary policy works by influencing the overnight Fed Funds rate, but this then affects other interest rates, and hence the broader economy. In the recent period of quantitative easing, the Federal Reserve’s purchases of Treasuries were intended to lower interest rates on high-quality private instruments. If arbitrage mechanisms break down, then so do these transmission channels of monetary policy. For all of these purposes, looking at the benchmark Treasury market is a particularly clean and very precise way to investigate breakdowns in pricing relationships during periods of market turmoil, and the lessons learned should have applicability to other fixed income securities and perhaps even to different asset classes.
References


Figure 1. Price Difference between Maturity-Matched Treasury Securities

Each line shows the difference in price between two maturity-matched Treasury security portfolios with identical cash flows. Each price spread subtracts the price of a 10-year original issue note from that of a replicating portfolio that consists of a 30-year original-issue bond plus an interest STRIP that matures on the same date.
Figure 2. This figure shows the yield curve for 10-year and 30-year original-issue Treasury notes and bonds, respectively, on November 20, 2008. Each point represents the actual yield-to-maturity of a different security on this date. The blue stars represent Treasury bonds. The black dots represent Treasury notes. The yield is given in percentage points on the vertical axis and time-to-maturity is in years on the horizontal axis.
Figure 3. This figure shows the daily bid-ask spread (in price terms), for off-the-run securities in our sample. The thick yellow line is the average across all off-the-run Treasury notes and bonds. The solid black line shows the average for only the nine maturity-matched 10-year Treasury notes in our sample, and the blue dotted line shows the average for the maturity-matched 30-year Treasury bonds. The data are from the TradeWeb platform. The vertical axis is measured in percentage points.
Figure 4. Overnight Treasury Funding Costs

Panel A: GC and Specials Rates
Figure 4. The figure in Panel A shows overnight repo rates in percentage points, annualized. The solid black line is the average overnight special repo rate across the off-the-run Treasury notes comprising the nine matched portfolios in our sample. The special repo rates are from a large inter-dealer broker’s transactions. The dotted blue line is the overnight Treasury GC repo rate, obtained from Bloomberg. Panel B shows the running integral of the GC minus specials rate from Panel A, the cumulative net funding cost to the bond/note trade.
Figure 5. The dashed blue line shows the daily average number of overnight Treasury special repo transactions in our sample, at a weekly frequency, referencing the scale on the left vertical axis. The solid black line shows the daily average volume of Treasury fails in $ billions, at a weekly frequency, referencing the scale on the right vertical axis. This is the average of fails to deliver and fails to receive, as reported by primary dealers to the Federal Reserve Bank of New York.
Figure 6. Decomposing the Bid-Ask Spread

Panel A: Duration in Years, Time-to-Trade in Days, and their Interaction
Panel B: Monthly Regression Coefficient Estimates and Confidence Intervals (Dependent Variable: Bid-Ask Spread<sub>i</sub>)

Figure 6. Panel A shows the monthly average level of TTT, Duration×Volatility and Duration×Volatility×TTT for all coupon Treasury securities in our sample. The solid yellow line shows average TTT, which is measured in days, referencing the scale on the right vertical axis. The long-dashed blue line shows average Duration×Volatility, referencing the scale on the left vertical axis. Duration is measured in years. Volatility is measured in 100ths of a basis point. We use the Merrill Lynch Option Volatility Estimate (MOVE) index as our proxy for interest rate volatility. The short-dashed green line shows the interaction of Duration×Volatility with TTT.

Panel B shows the coefficient estimates and 95 percent confidence intervals for a series of monthly, pooled, multivariate regressions of the Bid – Ask Spread<sub>i</sub> onto TTT<sub>it</sub>, Duration<sub>it</sub>×Volatility<sub>i</sub> and Duration<sub>it</sub>×Volatility<sub>i</sub>×TTT<sub>it</sub> for each security i on each day t, where the Bid – Ask Spread<sub>i</sub> is measured in basis points. The thick, solid, yellow line shows the point estimate for TTT. The thick, long-dashed, blue line shows the point estimate for Duration×Volatility. The thick, short-dashed, green line shows the point estimate for Duration<sub>it</sub>×Volatility<sub>i</sub>×TTT<sub>it</sub>. The corresponding color/pattern thin lines show the confidence intervals for the respective coefficient estimate.
### Table I. Treasury Security Characteristics

#### Panel A: Means and Standard Deviations (entire sample)

<table>
<thead>
<tr>
<th></th>
<th>Bid-Ask Spread (basis points)</th>
<th>Amount Out ($bn)</th>
<th>Share Stripped</th>
<th>Age (years)</th>
<th>Trading Volume ($mn)</th>
<th>Coupon (percentage pts)</th>
<th>Time-to-Trade (Days)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>St Dev</td>
<td>Mean</td>
<td>St Dev</td>
<td>Mean</td>
<td>St Dev</td>
<td>Mean</td>
</tr>
<tr>
<td>All Coupons</td>
<td>3.25</td>
<td>3.03</td>
<td>23.32</td>
<td>11.03</td>
<td>0.06</td>
<td>0.12</td>
<td>5.32</td>
</tr>
<tr>
<td>2-Year</td>
<td>1.61</td>
<td>0.65</td>
<td>32.09</td>
<td>7.76</td>
<td>0.00</td>
<td>0.00</td>
<td>0.95</td>
</tr>
<tr>
<td>3-Year</td>
<td>1.89</td>
<td>0.64</td>
<td>31.26</td>
<td>7.69</td>
<td>0.01</td>
<td>0.01</td>
<td>1.29</td>
</tr>
<tr>
<td>5-Year</td>
<td>2.57</td>
<td>1.18</td>
<td>20.34</td>
<td>8.41</td>
<td>0.01</td>
<td>0.02</td>
<td>2.33</td>
</tr>
<tr>
<td>10-Year</td>
<td>3.43</td>
<td>1.67</td>
<td>28.21</td>
<td>11.92</td>
<td>0.02</td>
<td>0.03</td>
<td>4.56</td>
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<td>30-Year</td>
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<td>5.47</td>
<td>12.41</td>
<td>5.84</td>
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<td>STRIPS</td>
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<td>15.13</td>
<td>1.24</td>
<td>1.80</td>
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<td>N/A</td>
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#### Panel B: Correlations (entire sample)

<table>
<thead>
<tr>
<th></th>
<th>Bid-Ask Spread</th>
<th>Amount Out</th>
<th>Share Stripped</th>
<th>Age</th>
<th>Trading Volume</th>
<th>Coupon</th>
<th>Time-to-Trade</th>
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</thead>
<tbody>
<tr>
<td>Bid-Ask Spread</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amount Out</td>
<td>-0.26</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Share Stripped</td>
<td>0.27</td>
<td>-0.40</td>
<td>1.00</td>
<td></td>
<td></td>
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<td></td>
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<tr>
<td>Age</td>
<td>0.51</td>
<td>-0.52</td>
<td>0.62</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Trading Volume</td>
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<td>0.01</td>
<td>-0.01</td>
<td>-0.02</td>
<td>1.00</td>
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<td></td>
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<tr>
<td>Coupon</td>
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<td>-0.67</td>
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<td>0.00</td>
<td>1.00</td>
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<tr>
<td>Time-to-Trade</td>
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<td>-0.34</td>
<td>0.36</td>
<td>0.46</td>
<td>-0.02</td>
<td>0.43</td>
<td>1.00</td>
</tr>
</tbody>
</table>

**Table I.** Panels A and B show sample statistics for our liquidity proxies, which differ for each individual Treasury security. Panel A shows the means and standard deviation of our variables in aggregate, and also by original issue maturity bucket. The share of a security that is stripped and the dollar amount outstanding are from the Treasury’s Statement of Monthly Debt. Bid-ask spreads are from the TradeWeb trading platform. Trading volume is that of U.S. insurance companies.
Table II. Fitting Errors and Treasury Security Liquidity

<table>
<thead>
<tr>
<th>Dependent Variable: Fitting Errori,t</th>
<th>Panel A: Characteristics that Differ by Security</th>
<th>Panel B: Characteristics Interacted with Daily Average Bid-Ask Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bid-Ask Spreadi,t</td>
<td>-3.30*** (0.31)</td>
<td>-2.68*** (0.28)</td>
</tr>
<tr>
<td>log(Outstanding)i,t</td>
<td>18.90*** (2.83)</td>
<td>16.16*** (4.83)</td>
</tr>
<tr>
<td>Share Strippedi,t</td>
<td>-53.98*** (11.53)</td>
<td>-26.91*** (13.75)</td>
</tr>
<tr>
<td>log(Age)i,t</td>
<td>-4.60*** (0.85)</td>
<td>0.93 (1.10)</td>
</tr>
<tr>
<td>Trading Volumei,t</td>
<td>18.12*** (4.59)</td>
<td>12.31*** (3.12)</td>
</tr>
<tr>
<td>Couponi,t</td>
<td>-3.43*** (0.38)</td>
<td>-0.35 (1.11)</td>
</tr>
<tr>
<td>Net Long Matched Pairi</td>
<td>30.89*** (2.96)</td>
<td>27.06*** (3.33)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.078</td>
<td>0.076</td>
</tr>
<tr>
<td>Observations</td>
<td>221,867</td>
<td>221,867</td>
</tr>
</tbody>
</table>

| Bid-Ask Spreadi,t                   | -0.79 (0.71)                                     | 2.88*** (0.83)                                                   |
| log(Outstanding)i,t                 | -38.19*** (5.96)                                 | -28.43*** (8.33)                                                |
| Share Strippedi,t                   | 137.64*** (21.82)                                | 84.98*** (28.45)                                                |
| log(Age)i,t                         | 11.19*** (1.90)                                  | 2.24 (3.09)                                                      |
| Trading Volumei,t                   | -21.87 (13.52)                                   | -5.08 (9.47)                                                     |
| Couponi,t                           | 7.00*** (0.76)                                   | -2.99 (2.57)                                                     |
| Net Long Matched Pairi             | -39.59*** (5.00)                                 | -27.95*** (7.00)                                                |
| AggLiq*Bid-Aski,t                   | -0.41*** (0.10)                                  | -0.48*** (0.10)                                                 |
| AggLiq*log(Outi,t)                  | 17.62*** (2.52)                                  | 14.26*** (3.65)                                                 |
| AggLiq*ShrStripi,t                  | -66.67*** (8.52)                                 | -44.31*** (11.81)                                               |
| AggLiq*Agei,t                       | -4.83*** (0.77)                                  | -0.31 (1.25)                                                     |
| AggLiq*Volumei,t                    | 12.41** (4.98)                                   | 4.62 (3.35)                                                     |
| AggLiq*Couponi,t                    | -3.17*** (0.32)                                  | 1.01 (1.11)                                                     |
| AggLiq*Pairi,t                      | 21.10*** (2.00)                                  | 16.34*** (2.79)                                                 |
| R-Squared                           | 0.083                                           | 0.190                                                            |
| Observations                        | 221,867                                         | 221,867                                                          |
Table II. This table presents a panel regression of fitting errors on security characteristics. The Fitting Error, the dependent variable, is defined as the difference between the actual price of the security and the fitted price based on a smoothed yield curve, measured in basis points. Trading Volume for each security on each day is the ratio of the trading volume for that security relative to the average trading volume for all securities on that day, divided by 100. Trading volume is that of U.S. insurance companies. Coupon is measured in percentage points per year. Net Long Matched Pair is a dummy equal to 1 for a note and -1 for a bond in cases where both the note and bond have the same maturity date, and 0 for all other securities. Panel A shows univariate and multivariate results for characteristics that differ by security. Panel B shows results for specifications that include interaction effects between security characteristics and AggLiq, which is a time series proxy for market-wide liquidity. The variable AggLiq is the average bid-ask spread over all securities in our sample on day t. Calendar day fixed effects are included in each regression. Standard errors (in parentheses) account for clustering within security i and arbitrary heteroskedasticity; *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.
Table III. Insurer Characteristics

Panel A: Means and Standard Deviations

<table>
<thead>
<tr>
<th># of Insurers</th>
<th>Assets (#bn)</th>
<th>Capital / Assets (%)</th>
<th>Annuity Focus (%)</th>
<th>RBC &gt; Median (%)</th>
<th>Net Income &gt; 0 (%)</th>
<th>Churn (ratio)</th>
<th>Buys To Sells (ratio)</th>
<th>VW Hold Horizon (years)</th>
</tr>
</thead>
<tbody>
<tr>
<td>All Insurers</td>
<td>2321</td>
<td>3.24</td>
<td>17.21</td>
<td>45.67</td>
<td>49.70</td>
<td>0.07</td>
<td>0.36</td>
<td>2.53</td>
</tr>
<tr>
<td>Health</td>
<td>329</td>
<td>0.35</td>
<td>0.91</td>
<td>59.16</td>
<td>31.00</td>
<td>0.08</td>
<td>0.16</td>
<td>0.40</td>
</tr>
<tr>
<td>Life</td>
<td>570</td>
<td>10.93</td>
<td>33.16</td>
<td>27.32</td>
<td>53.09</td>
<td>0.09</td>
<td>0.16</td>
<td>0.30</td>
</tr>
<tr>
<td>P&amp;C</td>
<td>1422</td>
<td>0.91</td>
<td>4.67</td>
<td>48.40</td>
<td>52.60</td>
<td>0.06</td>
<td>0.38</td>
<td>2.63</td>
</tr>
</tbody>
</table>

Panel B: Correlations

<table>
<thead>
<tr>
<th></th>
<th>Assets</th>
<th>Capital / Assets</th>
<th>Annuity</th>
<th>RBC &gt; Median</th>
<th>Net Income &gt; 0</th>
<th>Churn</th>
<th>Buys To Sells</th>
<th>VW Hold Horizon</th>
</tr>
</thead>
<tbody>
<tr>
<td>Assets</td>
<td>1.00</td>
<td>0.38</td>
<td>0.03</td>
<td>-0.01</td>
<td>0.01</td>
<td>0.26</td>
<td>-0.14</td>
<td>-0.10</td>
</tr>
<tr>
<td>Capital / Assets</td>
<td>-0.22</td>
<td>1.00</td>
<td>-0.01</td>
<td>0.06</td>
<td>0.12</td>
<td>0.14</td>
<td>0.10</td>
<td>0.13</td>
</tr>
<tr>
<td>Annuity</td>
<td>0.38</td>
<td>-0.24</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RBC &gt; Median</td>
<td>-0.03</td>
<td>0.43</td>
<td>-0.01</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Net Income &gt; 0</td>
<td>-0.01</td>
<td>0.13</td>
<td>-0.06</td>
<td>0.12</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Churn</td>
<td>0.26</td>
<td>-0.14</td>
<td>0.14</td>
<td>-0.08</td>
<td>0.01</td>
<td></td>
<td>-0.29</td>
<td>0.41</td>
</tr>
<tr>
<td>Buys To Sells</td>
<td>-0.14</td>
<td>0.18</td>
<td>-0.08</td>
<td>0.10</td>
<td>-0.02</td>
<td>-0.37</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>VW Hold Horizon</td>
<td>-0.10</td>
<td>0.13</td>
<td>-0.05</td>
<td>0.14</td>
<td>0.01</td>
<td></td>
<td>-0.37</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Table III. This table shows summary statistics for insurer-level characteristics. Annuity is an indicator variable equal to 1 if an insurer has a business focus on annuities, and 0 otherwise, defined based on the insurer writing more than 50% of business in annuities. RBC is an indicator equal to 1 if an insurer has an RBC ratio above the median insurer ratio, and 0 otherwise. Net Income is an indicator variable equal to 1 if net income is positive, and 0 otherwise. Buys To Sells is a measure of volume purchased relative to volume sold. Churn is the ratio of an insurer’s trading volume relative to holdings. VW Hold Horizon is the volume-weighted average number of years that an insurer holds a Treasury security. The sample period is January 1, 2006 through December 31, 2011.
Table IV. Insurer Transaction Patterns

<table>
<thead>
<tr>
<th>Insurer Type:</th>
<th>All</th>
<th>Health</th>
<th>Life</th>
<th>P&amp;C</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fitting Error_{ij,t}</td>
<td>2.67***</td>
<td>1.39***</td>
<td>7.03***</td>
<td>1.25**</td>
</tr>
<tr>
<td></td>
<td>(0.62)</td>
<td>(0.22)</td>
<td>(2.18)</td>
<td>(0.53)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.0032</td>
<td>0.0099</td>
<td>0.0037</td>
<td>0.0020</td>
</tr>
<tr>
<td>Observations</td>
<td>32,329,801</td>
<td>4,358,217</td>
<td>7,788,288</td>
<td>20,183,296</td>
</tr>
</tbody>
</table>

Table IV. This table presents a pooled regression of insurance companies’ monthly net purchases of Treasury security $i$ for insurer $j$ in month $t$ on the fitting error for each security $i$ at time $t$. Net purchases are measured per $1$ billion of the security’s original issue size. The fitting error is defined as the difference between the actual price of the security and the fitted price based on a smoothed yield curve, measured in basis points. Month fixed effects and insurer type fixed effects are included in all regressions. The sample period is January 2006 through August 2011. Standard errors are shown in brackets beneath the coefficient estimates; *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.
### Table V. Who Engages in the Arbitrage?

<table>
<thead>
<tr>
<th>Dependent Variable: Net Purchases of Treasury_{i,t}</th>
<th>Capital/Assets_{i,t} * FE_{t}</th>
<th>-0.10***</th>
<th>-0.08***</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(0.02)</td>
<td>(0.03)</td>
<td></td>
</tr>
<tr>
<td>Capital/Assets_{i,t}</td>
<td>0.85</td>
<td>1.01</td>
<td>(1.19)</td>
</tr>
<tr>
<td></td>
<td>(0.93)</td>
<td>(0.93)</td>
<td></td>
</tr>
<tr>
<td>Annuity_{j} * FE_{t}</td>
<td>13.58***</td>
<td>10.41***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.99)</td>
<td>(3.28)</td>
<td></td>
</tr>
<tr>
<td>Annuity_{j}</td>
<td>-301.17**</td>
<td>-280.33**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(117.10)</td>
<td>(124.12)</td>
<td></td>
</tr>
<tr>
<td>RBC_{i,t} * FE_{t}</td>
<td>-1.98</td>
<td>0.46</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.28)</td>
<td>(1.49)</td>
<td></td>
</tr>
<tr>
<td>RBC_{i,t}</td>
<td>-24.62</td>
<td>-63.30</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(47.04)</td>
<td>(55.80)</td>
<td></td>
</tr>
<tr>
<td>Net Income_{j,t} * FE_{t}</td>
<td>1.51</td>
<td>3.10**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.27)</td>
<td>(1.36)</td>
<td></td>
</tr>
<tr>
<td>Net Income_{j,t}</td>
<td>13.09</td>
<td>18.64</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(49.39)</td>
<td>(52.57)</td>
<td></td>
</tr>
<tr>
<td>Churn_{j} * FE_{t}</td>
<td>78.26***</td>
<td>21.78***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(5.97)</td>
<td></td>
</tr>
<tr>
<td>Churn_{j}</td>
<td>-411.56***</td>
<td>84.32</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(214.50)</td>
<td></td>
</tr>
<tr>
<td>Buys To Sells_{j} * FE_{t}</td>
<td>-4.19***</td>
<td>-0.29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(1.51)</td>
<td>(1.83)</td>
<td></td>
</tr>
<tr>
<td>Buys To Sells_{j}</td>
<td>110.44**</td>
<td>119.89*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(55.00)</td>
<td>(66.59)</td>
<td></td>
</tr>
<tr>
<td>VW Hold Horizon_{j} * FE_{t}</td>
<td>-1.50***</td>
<td>-0.64</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.42)</td>
<td>(0.50)</td>
<td></td>
</tr>
<tr>
<td>VW Hold Horizon_{j}</td>
<td>11.95</td>
<td>-0.03</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(15.37)</td>
<td>(18.42)</td>
<td></td>
</tr>
<tr>
<td>FE_{t} (Fitting Error)</td>
<td>7.19***</td>
<td>2.05***</td>
<td>3.69***</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(0.64)</td>
<td>(0.90)</td>
</tr>
<tr>
<td>R-Squared</td>
<td>0.0033</td>
<td>0.0033</td>
<td>0.0033</td>
</tr>
</tbody>
</table>

Table V. This table presents results from a pooled regression of an insurance company’s monthly net purchases of Treasury security $i$ for insurer $j$ in month $t$ on the fitting error for each security $i$ at time $t$ interacted with various characteristics of the insurance company. The fitting error is defined as the difference between the actual price of the security and the fitted price based on a smoothed yield curve, measured in basis points. Net purchases are measured per $1$ billion of the security’s issue size. The sample period is January 1, 2006 through December 31, 2011. Month fixed effects and insurer type fixed effects are included in all regressions. Standard errors are in parentheses; *** indicates significance at the 1 percent level, ** at the 5 percent level, and * at the 10 percent level.