

Notes on Bonds: Illiquidity Feedback During the Financial Crisis

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We trace the evolution of extreme illiquidity discounts among Treasury securities during the financial crisis, when bond prices fell more than 6% below more liquid but otherwise identical notes. Using high-resolution data on market quality and trader identities and characteristics, we find that the discounts amplify through feedback loops, where cheaper, less-liquid securities flow to longer-horizon investors, thereby increasing their illiquidity and thus their appeal to these investors. The effect of the widened liquidity gap on transactions costs is further amplified by a surge in the price liquidity providers charge for access to their balance sheets in the crisis. (*JEL* E43, G01, G12, G14)

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The rapid contraction of the financial industry in 2007–09 pulled many prices out of their usual orbits. Of the many resulting anomalies, perhaps none was as stark as the disparity 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 6% of face value, even with cash flows matched exactly. So extreme a violation of the law of one price indicates another strong force differentiating asset prices, and the notable remaining difference between off-the-run notes and bonds is that the notes are more liquid. In this paper we ask how this seemingly modest liquidity

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difference, which normally commands a very small price, came to command such a large price during the crisis.

Our investigation adapts the analysis by Dow (2004) of the role of investor clientele in amplifying illiquidity discounts. In Dow (2004), investors with more private information about securities' payoffs select less-liquid securities, and this selection lowers the liquidity further, which in turn increases the selection; thus, asymmetric information about payoffs can power a feedback loop that amplifies liquidity differences. We adapt this analysis to a setting where the power comes not from investors' private information about payoffs, but, as in Amihud and Mendelson (1986), from the investors' need for liquidity. That is, we ask whether the feedback could instead be that investors who expect to hold a security longer select less-liquid securities, which lowers liquidity and further increases the selection. The market for off-the-run Treasuries, where this price divergence occurred, presents an ideal opportunity to find out.

The off-the-run Treasury market is ideal for three reasons. First, the precise equivalence between Treasury securities promising the same future cash flows isolates the effect of liquidity differences; their payments come from the same obligor with the same seniority, they are denominated in the same currency, they are subject to the same tax schedules, their trades settle the same way, they are equally valid as repo collateral, and are otherwise the same in every meaningful way. But, the ease with which the securities trade is free to vary. Second, the liquidity indeed varies widely; despite the consistently high liquidity of on-the-run Treasuries, liquidity differences among off-the-run Treasuries are large. As we document later, off-the-run bonds trade at twice the bid-ask spread of off-the-run 10-year notes on average,¹ and the average of the time since the last buy or sell of a bond, on the platform that provided our data, is almost three days, over eight times longer than the same average for a 10-year note. And finally, for a large and varied group of Treasury traders—that is, every U.S. insurance company—we see not only all their trades but also extensive data on their circumstances, particularly those relevant to investment horizons. Therefore, given the nature of the securities and the available data, the off-the-run Treasury market is ideal to examine whether less-liquid securities fall to a further disadvantage by flowing to those insurers with less need for liquidity and relatively longer horizons.

Our Treasury market data source is key to this study, because the usual sources (e.g., eSpeed, Brokertec) reveal almost nothing about the off-the-run market. This is because the market segment they represent, the interdealer market, is not where off-the-run transactions take place. For example, one could not infer from interdealer data sources, and probably would not even suspect, that days go by between trades of an off-the-run bond. The major venue for off-the-run

¹ Throughout the paper, we refer to securities originally issued with n years to maturity as n -year securities.

trading is not the interdealer market but rather the customer-to-dealer market, as shown on the TradeWeb platform,² an online request-for-quote platform backed by the largest Treasury dealers. This is the source of our database, which gives key metrics of market quality, including bids and asks for each CUSIP, as well as the time since each CUSIP last traded. Thus, we not only see the transactions costs charged by liquidity providers to demanders, but also have a good proxy for how long the liquidity providers can expect to wait before a later trade takes any new supply off of their books.

Figure 1 shows the evolution of the anomaly we study. Each line in panel A represents the price of a 10-year note minus the price of a replicating portfolio that matches cash flows exactly, composed of a bond and the bond's principal STRIP.³ For example, the red line represents three securities that mature on February 15, 2015: 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, which is the net revenue from shorting the note and buying a portfolio with identical cash flows. Beginning in August 2007, the price of the note rises relative to the price of the replicating portfolio, and this price difference continues over the next two years to follow the familiar contours of the crisis.⁴ The pattern repeats across all pairs of notes and bonds extant at the time. Panel B shows the average price difference across all of the maturity-matched bonds and notes in our sample.

The implicit arbitrage is significantly profitable even net of repo-market financing costs. When we assemble the components of the arbitrage from a database of concurrent repo transactions, we find that funding the short side of the trade offsets only a small fraction of the gross profit, so the explicit costs to establish the trade are small change relative to the price divergence.

We analyze the divergence in three stages, the first of which identifies the cross-sectional determinants of illiquidity discounts. We start by subtracting from each security's price the price implied by a smoothed yield curve, to then relate the cross-section of relative prices to the underlying liquidity drivers, such as issue size, and the manifestations of liquidity, such as bid-ask spreads.

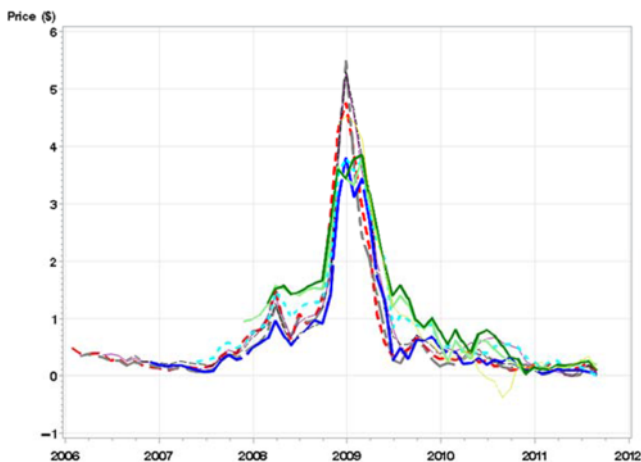
We find a strong negative relation between measures of a security's liquidity and the security's relative price. Securities that are older, have smaller outstanding quantities, have been stripped more, have lower trading volume and higher bid-ask spreads, all of which distinguish bonds from notes, trade at larger

² 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% of total fixed income trading volume is executed electronically, and that 45% of institutional investors use electronic platforms for at least part of their fixed income transactions.

³ 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.

⁴ A short time-series animation 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>.

Panel A: Individual Maturity-Matched Pairs



Panel B: Average of Maturity-Matched Pairs

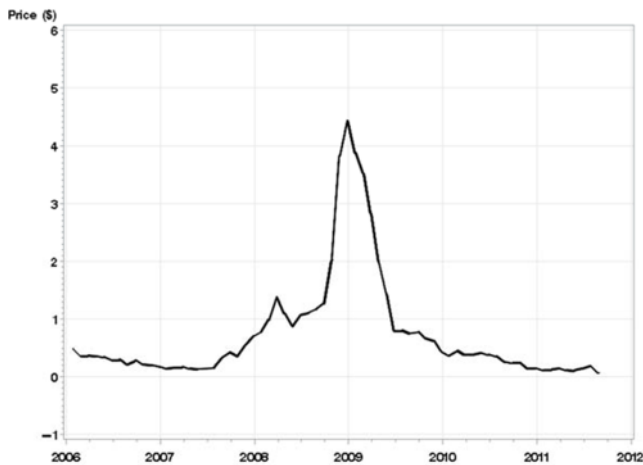


Figure 1

Price difference between maturity-matched treasury securities

Panel A shows the monthly average in price difference of maturity-matched Treasury security portfolios with identical cash flows; each pair is represented by a separate line. Each price difference 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 a STRIP that matures on the same date. Each series starts with the date that the pair's 10-year original issue note becomes off-the-run. The maturity dates of the nine pairs range from February 2, 2015, to May 15, 2015. Panel B shows the cross-sectional average over the spreads shown in panel A.

discounts. These relations become substantially stronger when market-wide liquidity declines, as happened during the crisis. Controlling for the aggregate state of liquidity over time, these security-specific liquidity variables account for most of the widening of the bond/note price gap.

The second stage of the analysis identifies the investor clienteles attracted to the more- or less-liquid securities. The key database for this identification is the universe of transactions in Treasury securities by all U.S. insurance companies, which we combine with extensive information on the insurers' financial conditions. This database allows us to follow each insurer's activity over twelve years, including the date, direction, and identity of each security purchased or sold, while tracking the insurer's changing circumstances, such as its leverage. Collectively, insurers hold about 3% of the stock of U.S. Treasuries,⁵ so they are not the largest aggregate clientele for these securities, but their circumstances vary in ways that we can observe, and that can influence their relative demand for more- or less-liquid assets. Prior research has also shown that insurance companies, particularly life insurers, faced difficulties during the financial crisis that induced extraordinary behavior.⁶ Thus, we can identify the investor characteristics and circumstances driving demand for the more-liquid securities at their premium prices.

Our principal result is that the insurers with more appetite for liquidity tilt increasingly toward the more-liquid and more-expensive securities as their premia increase. Those paying up for the liquid securities include those investors that generally trade more, and those with financial circumstances, such as high leverage, that indicate a need for more-liquid investments. This result bears out the prediction of Amihud and Mendelson (1986) that less-liquid securities attract investors with longer horizons (distinct from the relationship between expected returns and liquidity that has been well documented in the literature), and because the selection increases with the premium price, it also bears out the view that the selection powered a feedback loop, amplifying the liquidity difference.

The third stage asks how the liquidity difference came to command such a high price in the crisis. We answer this question by decomposing the cross-section of bid-ask spreads into two prices charged by the liquidity provider: the price charged to finance the position until the next trade, and the price charged to bear the position's interest rate risk over that time. We can do this because we have a large cross-section of securities that differ in interest rate risk and

⁵ The Federal Reserve's Financial Accounts data, Table L.209, shows the combined holdings of Life Insurers and Property and Casualty Insurers, as of December 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>).

⁶ Kojien and Yogo (2015) show that life insurers drastically underpriced insurance policies in order to raise statutory capital; Ellul et al. (2015) show that insurers sold corporate bonds with the largest unrealized capital gains to increase statutory capital; and Merrill et al. (2012) show that insurers sold recently downgraded bonds to avoid higher statutory capital requirements.

also an excellent proxy for the expected time to a security's next trade—that is, the time since its last trade. We achieve the decomposition by regressing the cross-section of spreads on the securities' durations and the times since their last trades. Based on the estimated coefficients, the regression shows a sharper spike in the price charged for financing a position over a longer expected holding period than the price charged for bearing interest rate risk. That is, liquidity providers showed a particular aversion at the peak of the crisis to expanding their balance sheets to bridge the arrival of trades, and a less pronounced increase in aversion to bearing the securities' price risk over this period. These prices fall and stabilize after the crisis, but while the price charged per unit of financing has remained stable, the quantity of financing risk has increased—that is, more time elapses between trades—and this has widened average spreads and the difference in spreads between more- and less-liquid Treasury securities. This effect persists until the end of our sample period.

Putting the evidence together, the Treasury market experienced a large price divergence that presented a substantial arbitrage opportunity, net of funding costs, to willing traders. Differences in liquidity that normally command low prices came to command very high prices, which resulted in notable differences in bid-ask spreads within the market for off-the-run Treasury securities. Contributing to this amplification was a feedback loop driven by the selection of longer-horizon traders into less-liquid securities that intensified as the liquidity premia increased. The resulting differences in liquidity premia led to large differences in prices for identical securities. These results suggest that policies to offset the liquidity feedback effect in less-liquid securities, such as increased activity in the Federal Reserve's securities lending or additional security reopenings by the U.S. Treasury, could help mitigate a potential illiquidity spiral.

1. Background and Data

In this section we first review the existing literature that relates liquidity to asset prices and discuss the findings on price discrepancies in the Treasury market. Next, we introduce the data that we use for our analysis. We describe our data set of secondary-market Treasury security prices, which we complement with additional security-level data to form proxies for relative liquidity. We also describe the secondary market trading activity and portfolio holdings of Treasuries for U.S. insurance companies, which we use to gain insight into the trading activity of a large end-buyer of Treasuries.

1.1 Literature review

Amihud and Mendelson (1986) provide a formal treatment of the relation between bid-ask spreads and security prices. Since the bid-ask spread represents a cost of trading a security, it affects the ultimate return realized by investors. Amihud and Mendelson (1986) show that expected asset returns are increasing

in the bid-ask spread, as investors demand a discount to buy securities that are more costly to trade. This effect persists when investors have different holding period horizons, but it is somewhat muted. Clienteles with longer horizons rationally purchase securities with higher bid-ask spreads, since the longer horizons make the higher expected return attractive relative to the higher trading cost. Conversely, clientele with shorter horizons purchase securities with lower bid-ask spreads, since the shorter horizons make the lower trading cost more attractive. This selection of investors results in an increasing and concave relation of expected returns to bid-ask spreads, which Amihud and Mendelson (1986) confirm empirically using stocks traded on the New York Stock Exchange (NYSE).

Dow (2004) endogenizes bid-ask spreads in a model with clientele that vary based on private information and shows that there are strategic complementarities between investor security demand and the bid-ask spreads posted by market makers. Investors with less private information congregate in securities with lower spreads, which are justified due to the lack of adverse selection risk. Conversely, investors with more private information choose securities with higher spreads to capitalize more fully on their private information, which justifies the higher spreads and crowds out less-informed traders. Dow (2004) shows that multiple equilibria are possible, with similar securities having either low or high liquidity. We conjecture that a similar feedback mechanism could operate through heterogeneity in investors' trading horizons.

Amihud and Mendelson (1991) empirically examine the relationship between bid-ask spreads and yields on Treasury securities. They compare the pricing of Treasury bills, which have an original maturity less than one year, and Treasury notes that have only six months remaining until maturity and thus are past their penultimate coupon payments. Both are pure discount Treasury securities, so a straightforward arbitrage relation exists. They find that the notes have wider bid-ask spreads and higher yields, so they allow profits for traders who do not try to unwind their positions before maturity. Thus the authors conclude that this is an illiquidity premium available to patient capital.⁷

A related 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 their greater liquidity (e.g., Fleming 2003; Goldreich, Hanke, and Nath 2005; Barclay, Hendershott, and Kotz 2006; and Pasquariello and Vega 2009). There is a predictable convergence that patient capital can wait for, in that the new security becomes old, and thus likely to trade in line with the existing old securities, when the next security is floated. Krishnamurthy (2002) finds that the cost of borrowing the new bond

⁷ 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. Also, Strebulaev (2002) argues against the relationship between liquidity and relative prices.

to short it tends to offset much of the profitability of this trade. 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 is correlated with various measures of funding liquidity. Hu, Pan, and Wang (2013) also construct an aggregate measure of liquidity from the Treasury market, which they term "noise," as the square root of the mean squared deviation of individual Treasury yields from a smoothed curve. They interpret the measure as capturing liquidity shocks, which among other things show a local peak around the collapse of Bear Stearns and the global peak after the Lehman bankruptcy apparent in Figure 1.

Matched-maturity comparisons are also possible between other securities that share the same creditworthiness. One such comparison is that of Refcorp bonds, which arose from the Savings and Loan crisis, with Treasuries, both of which are backed by the full faith and credit of the U.S. federal government. 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 (2017) shows that the yield spread between comparable German federal government and KfW agency securities, which have an identical guarantee, is a real-time, tradable proxy for market liquidity and liquidity risk. 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.

There is also a literature examining the relationship between liquidity and yields of corporate bonds, which includes Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter and Lando (2012). It is more challenging to precisely pin down the liquidity component in yields of corporate bonds due to the influence of credit risk on bond prices. Liquidity tends to correlate with creditworthiness in the corporate market, making it difficult to completely distinguish the effect of liquidity from credit.

To summarize, there is generally a liquidity premium in securities markets, including in the Treasury market. Newer securities are more liquid and expensive than older, and the newest securities, the on-the-run, are the most expensive of all, due presumably to the intense focus of traders on these particular securities. Our analysis avoids confusion with this on-the-run effect by focusing exclusively on the off-the-run Treasury security-date observations.

1.2 Data

1.2.1 Treasury transactions on the TradeWeb platform. We construct a data set 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. We have this data from May 3, 2004, through September 30, 2011. We use TradeWeb, rather than the usual interdealer data (eSpeed, BrokerTec, and GovPX) because the customer-to-dealer market is the primary venue for off-the-run Treasury market transactions. TradeWeb data capture the trades of a variety of market participants (e.g., hedge funds, pension funds, insurers) with differing motives for trading. The database flags the dates that each security is on-the-run, and we exclude those security-date pairs from our analysis; all of our empirical analysis is based on off-the-run Treasury security-date observations.

TradeWeb follows a request-for-quote format in which a customer first sees indicative quotes, then solicits hard quotes from a set of dealers to buy or sell some quantity of a security, and finally decides whether to accept one of these quotes. The TradeWeb data report indicative quotes averaged across market makers at four moments each day: 8:05 a.m., 3:00 p.m., 4:00 p.m., and 4:45 p.m. (EST). From June 2008 onward, the data also report for each security the time since the last buy and the last sell. We average these two times to form *TTT* (time-to-trade). For our daily observations we choose the 3:00 p.m. snapshot for two reasons. First, the time since the last trade is likely to be more informative as an indicator of a security's liquidity near the end of the trading day when most trades have occurred. And second, the 3:00 p.m. snapshot is likely more representative of general intraday liquidity as it is still within the window of high intraday trading volume and moderate bid-ask spreads, before the end-of-day deterioration in market conditions (Fleming and Remolona 1997).⁸

We complement the TradeWeb data with a database of special repo transactions from a large interdealer broker. Our repo sample contains all transactions intermediated by the broker from April 1, 2004, through March 1, 2009. For each repo we see the identity of the specific security that served as collateral for the repo, the repo rate, the trade date, the settlement date, and the term. Not all securities are repoed on each day; on average, 20% of the maturity-matched bonds and notes have observable repo rates. To this repo database we add the daily general collateral (GC) rate reported by Bloomberg.

1.2.2 Additional liquidity variables. In addition to *TTT* we calculate three additional measures of a security's current liquidity. From the TradeWeb data we have the percentage bid-ask spread, *Bid-Ask*, which is $\frac{Ask - Bid}{(Bid + Ask)/2}$ as of 3:00 p.m. For volume and relative trading volume, there is no publicly available data for trading of individual Treasury securities, so we use the insurance data described below. For each security on each day, we construct *Volume* as the sum of buys and sells of the security by insurers, scaled by the sum of all Treasury security trades by insurers that day.

⁸ None of our results are sensitive to this choice.

We gather data on security characteristics from the Treasury Department's Monthly Statement of the Public Debt. We collect each security's initial size and the fluctuation over time due to repurchases and reopenings. We also see fluctuations in the effective issue size due to stripping and reconstitution. These data are all end-of-month, which we match with the corresponding month of our daily variables. We construct $\ln(Out)$ as the log of the principal outstanding and $Share\ Stripped$ as the share of the security's principal outstanding held in stripped form. From the issuance and maturity dates, we calculate $\ln(Age)$ as the log of the time since issuance and $\ln(TTM)$ as the log of the time remaining until maturity. The last two variables are computed daily.

Table 1 reports summary statistics for the liquidity variables, along with some additional information about the securities, and it highlights significant variation across securities with different original-issue maturities. Thirty-year bonds, in particular, are notably less liquid by all of the measures. The average quoted percentage bid-ask spread is 3 basis points on average across all securities, but nearly 7 basis points for bonds alone. Bonds also trade far less frequently than other Treasuries; their average TTT is almost 3 days, compared with 8 hours for a 10-year note. Bonds are also much smaller, older, and more stripped, on average, than other securities. Consistent with prevailing interest rates at their time of issue, bonds also have higher coupons and shorter duration, on average, than notes.

1.2.3 Trading and holdings data for insurance companies. Our final data set reports the transactions in and holdings of Treasury securities by U.S. insurance companies, from January 1, 1998, through December 31, 2011. 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 of each security. These data are packaged and resold by eMaxx.⁹ We limit our sample to the 2,327 insurers that show holdings and transactions in coupon Treasury securities, including STRIPS, and that also can be matched with accounting data from SNL Financial over the same sample period as our Treasury price data, from 2006 through 2011.¹⁰ We define $Buys_{ijt}$ to be the quantity of security i , purchased by insurer j , at time t , $Sells_{ijt}$ are the analogous sales, and NP_{ijt} (i.e., net purchases) are $Buys_{ijt} - Sells_{ijt}$. We also define $Buys_{it}$, $Sells_{it}$, and NP_{it} to be their respective averages across insurers.

For each insurer we calculate two statistics summarizing its trading activity over the sample period. To measure how long an insurer tends to hold a position,

⁹ The original data from eMaxx is at the level of insurer-date-CUSIP-investment adviser, 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.

¹⁰ We construct our insurer trading style variables with the 1998 through 2011 sample period, but for all of our analysis, we use the 2006 through 2011 sample period.

Table 1
Treasury security characteristics

Panel A: Means and standard deviations

	Bid-ask spread (basis points)		Amount out (\$bn)		Share stripped (share of security)		Age (years)		TTM (years)		Volume/day (\$mn)		Coupon (%)		Duration (years)		Time-to-trade (days)	
	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
All coupons	3.24	3.11	23.88	11.03	0.04	0.09	5.08	6.58	4.29	3.53	44.80	75.95	4.31	2.19	3.62	2.53	0.92	1.78
2-year	1.61	0.65	32.12	7.78	0.00	0.00	0.94	0.50	1.06	0.50	41.33	132.90	2.82	1.62	1.05	0.49	0.35	0.61
3-year	1.90	0.64	31.38	7.68	0.01	0.01	1.26	0.76	1.74	0.76	19.33	57.68	2.40	1.46	1.70	0.74	0.46	0.82
5-year	2.58	1.18	20.35	8.42	0.01	0.02	2.31	1.33	2.69	1.33	82.24	206.64	3.65	0.93	2.55	1.22	0.79	1.27
10-year	3.44	1.67	28.24	11.92	0.02	0.03	4.53	2.69	5.48	2.69	85.43	191.01	4.50	0.76	4.80	2.21	0.33	0.76
30-year	6.89	6.14	12.08	6.14	0.21	0.15	19.69	2.84	10.32	2.85	16.94	94.01	8.55	1.06	7.40	1.63	2.86	3.25
STRIPS	11.65	8.28	0.85	0.65	N/A	N/A	N/A	N/A	4.84	2.84	4.13	19.51	N/A	N/A	4.84	2.84	6.18	5.36

Panel B: Correlations

	Bid-ask spread	Amount out	Share stripped	Age	TTM	Volume	Coupon	Duration	Time-to-trade
Bid-ask spread	1.00								
Amount out	-0.33	1.00							
Share stripped	0.35	-0.50	1.00						
Age	0.43	-0.61	0.60	1.00					
TTM	0.38	-0.24	0.42	0.24	1.00				
Volume	-0.10	-0.02	0.03	0.00	0.01	1.00			
Coupon	0.45	-0.75	0.68	0.76	0.36	0.03	1.00		
Duration	0.39	-0.24	0.52	0.32	0.94	0.01	0.52	1.00	
Time-to-trade	0.20	-0.41	0.31	0.36	0.09	0.02	0.36	0.09	1.00

Panels A and B show summary statistics for our liquidity proxies, which differ for each individual Treasury security. Panel A shows the means and standard deviations of our variables in aggregate (*All Coupons*), 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.

we calculate *Holding Horizon* as the volume-weighted average number of days between the purchase and sale of each Treasury security that the insurer trades over the sample.¹¹ Panel A of Table 2 shows the average number of years that an insurer holds a position in our sample is about 2.5 years. For a measure of portfolio turnover we compute *Churn*, which is an insurer’s sample-average trading volume in Treasury securities divided by its sample-average holding of Treasury securities, computed at the monthly frequency.¹² The mean value of *Churn* is 4.13 in panel A of Table 2 and indicates that the typical insurer trades about 4% of the portfolio each month. As an insurer trades more, *Holding Horizon* tends to decrease and *Churn* to increase, which is shown in the -0.52 correlation across insurers, reported in Table 2, panel B.

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.¹³ Kojien and Yogo (2015) show that life insurers with very high leverage were most aggressive in underpricing their policies to boost their regulatory capital and confirm that leverage is the characteristic most strongly related to their measure of the shadow cost of capital. *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 Kojien and Yogo (2017), variable annuities generated significant losses for insurers during the financial crisis due to falling stock prices and low interest rates. McMenamin et al. (2012) also note that 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 ratio of actual capital to risk-based capital, measuring the insurer’s capital adequacy, is greater than the median for all insurers in our sample, and 0 otherwise.¹⁴ Finally, *Net Income* is an indicator variable equal to 1 if the insurer’s net income is positive, and 0 otherwise. The underlying accounting data is available quarterly, and we linearly interpolate to create monthly values in the subsequent analysis.

11 Holding horizon measures the average number of days that insurer j holds a security i in its portfolio. $Horizon_j = \frac{\sum_{i=1}^I (Q_{i,j} Days_{i,j})}{\sum_{i=1}^I Q_{i,j}}$ where $Q_{i,j}$ is the quantity that is both bought and subsequently sold of security i for insurer j , and $Days_{i,j}$ 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.

12 $Churn_j = \frac{1}{N} \times \sum_{t=1}^T \sum_{i=1}^I (Buy_{i,j,t} + Sell_{i,j,t})}{\frac{1}{T} \times \sum_{t=1}^T \sum_{i=1}^I Holding_{i,j,t}}$, where $Holding_{i,j,t}$ is the level of holdings of CUSIP i for insurer j on day t , T is the number of days in the sample, and N is the number of months in the sample.

13 The vast majority of insurers are private, so it is impractical to use market values.

14 Merrill et al. (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. Insurers with low risk-based capital were also more likely to underprice policies during the financial crisis (Kojien and Yogo 2015).

Table 2
Insurer characteristics

Panel A: Means and standard deviations

	# of Insurers	Assets (\$bn)		Capital/assets (%)		Annuity (%)		RBC (%)		Net income (%)		Churn (%)		Holding horizons (years)	
		Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
All insurers	2327	3.21	17.11	45.65	25.83	4.41	20.54	50.04	50.00	76.29	42.53	4.13	3.66	2.53	1.49
Health	330	0.35	0.91	59.09	20.41	0.00	0.00	31.70	46.53	75.82	42.82	4.54	3.88	2.10	1.11
Life	571	10.85	32.97	30.79	27.28	18.38	38.74	53.36	49.89	71.02	45.37	4.52	4.35	2.50	1.64
P&C	1426	0.90	4.64	48.39	23.66	0.00	0.00	52.90	49.92	78.43	41.13	3.88	3.28	2.63	1.49

Panel B: Correlations

	Assets	Capital/assets	Annuity focus	RBC >Median RBC	Net income >0	Churn	Holding horizon
Assets	1.00						
Capital/assets	-0.22	1.00					
Annuity focus	0.38	-0.24	1.00				
RBC >median RBC	-0.03	0.43	-0.01	1.00			
Net income >0	-0.01	0.12	-0.05	0.11	1.00		
Churn	0.19	-0.18	0.16	-0.13	0.02	1.00	
Holding horizon	-0.10	0.12	-0.05	0.14	0.01	-0.52	1.00

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 its 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. *Churn* is the ratio of an insurer's monthly average trading volume relative to holdings. *Holding Horizon* is the volume-weighted average number of years that an insurer holds a Treasury security. The sample period is January 1, 2006, through September 30, 2011.

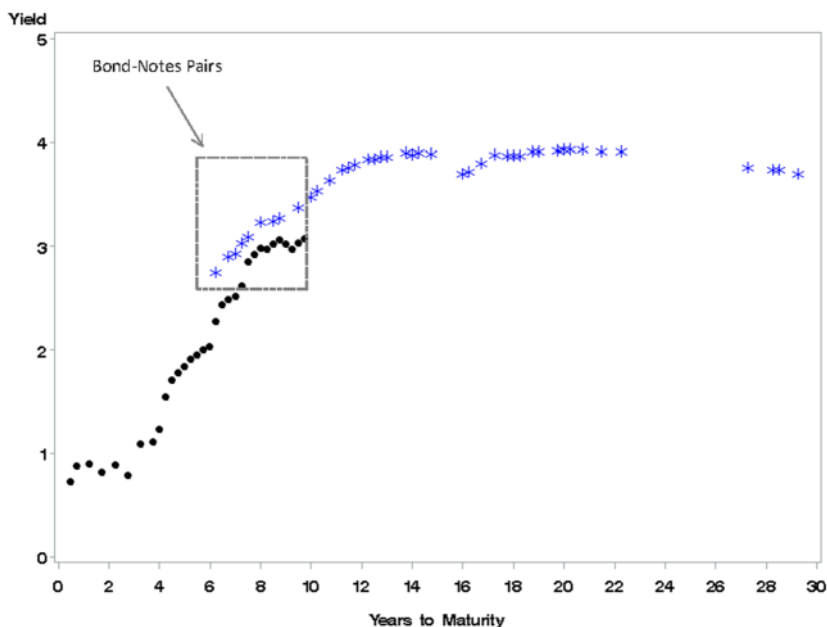


Figure 2
Notes versus bonds, November 20, 2008

This figure shows the yield curve for 10-year and 30-year original-issue Treasury notes and bonds 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 years-to-maturity are in years on the horizontal axis.

2. Explaining Relative Price Differences in the Cross-Section

2.1 The divergence and the arbitrage

In this section we document the divergence and gauge the cost of trading on it, which is determined by the relevant repo rates. In the days after the Lehman bankruptcy, there are additional considerations arising from the high propensity of delivery fails.

On November 20, 2008, Treasury coupon securities closed the day at the yields displayed in Figure 2. The figure highlights nine bonds (shown with blue asterisks) that share a maturity date with a note (black dots). All of the matching notes are 10-year Treasuries. Because their maturity dates match, they pay principal and coupons on the same dates. But, the bonds date from an era of higher rates, and thus have larger coupons, which imply lower yields with an upward-sloping yield curve. However, the bond yields on this date are instead much higher. So the bonds appear to be significantly cheap relative to the notes, and the coupon difference makes the differential even more surprising.¹⁵

¹⁵ The bonds with more than 10 years remaining to maturity follow a curve largely consistent with the nine highlighted bonds, but the absence of matching notes prevents a precise comparison of their prices.

For an exact comparison we construct an exact match by using the bond's principal STRIP. The cash flows of a note with coupon C_N are replicated by a portfolio with (C_N/C_B) of a bond with coupon C_B and $(1 - C_N/C_B)$ of the bond's principal STRIP.¹⁶ We subtract the price of this replicating portfolio from that of the note (using the midpoint of bid and ask prices), yielding the time-series plots in Figure 1 that show the large divergence.

Did this divergence offer a profitable trading opportunity? To trade on the divergence, one must short the note, buy the matching portfolio of the bond and its STRIP, and wait for convergence. Shorting the note is generally accomplished through the repo market by lending cash and accepting the note as collateral. The interest rate earned on the loan depends on the demand to borrow the specific security. For generic securities that are not in high demand, the repo rate is the GC rate. For securities in high demand—those deemed “special”—the repo rate will fall below the GC rate. The bond purchase can also be financed through the repo market, where the GC rate is the highest rate one would generally pay. The net cost of financing the arbitrage trade is the difference between the GC rate paid to finance the purchase of the bond and the potentially special rate received from shorting the note.

We gauge this carrying cost by reference to the rates in the repo database. On each day, we take the repo rate for any of the notes in Figure 1 to be the average rate across the repos of any of those notes on that day. If there are no repos of those notes that day (the database does not show a repo transaction for each security on each day),¹⁷ we take the repo rate for any of the notes to be zero, which is the lowest rate shown in the database.¹⁸ So our estimate assumes the worst-case scenario when no rates are observed, since the notes are likely to be special due to the arbitrage opportunity (Duffie 1996). We further assume the worst-case scenario for financing the long leg by assuming the trader pays the GC rate—that is, the rate that imputes no scarcity rents because the money lender is indifferent to which Treasuries are provided as collateral.

The financing rates are plotted in panel A of Figure 3, which shows the GC rate as the dotted blue line and the note rate as the solid black line, throughout our repo sample period. The key quantity, the trade's net funding cost, is the difference between these rates, which is generally small; it is between 0 and 23 basis points on 75% of the days in our sample period. It spikes on occasion, but not in late 2008, which is the period of greatest divergence

¹⁶ We use bond principal strips throughout, as note principal strips are relatively scarce (see Table 1).

¹⁷ 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. In our database, 82% of the transactions are overnight, so we estimate the realized financing costs of a hypothetical investor by stringing together a series of overnight rates. Both Duffie (1996) and Jordan and Jordan (1997) use exclusively overnight repo data, and Keane (1996) states that term repos longer than 90 days are in practice not available.

¹⁸ There are 834 zero-rate overnight Treasury transactions in our repo database, but none with a negative rate.

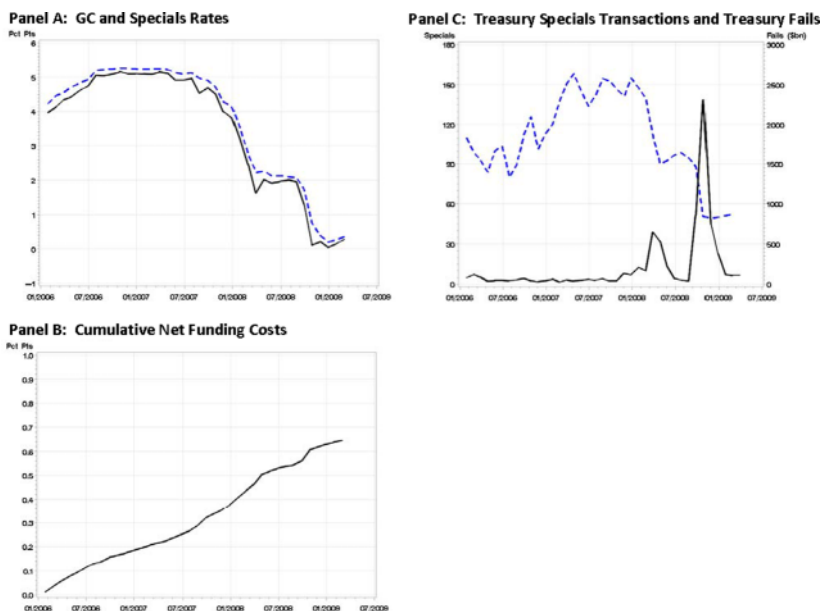


Figure 3
Overnight Treasury funding market

All panels in this figure represent monthly averages. Panel A shows overnight repo rates in percentage points, annualized. The solid black line is the overnight special repo rate averaged across the off-the-run Treasury notes comprising the nine matched portfolios in our sample, using transaction rates from a large inter-dealer broker. The dotted blue line is the overnight Treasury GC repo rate, obtained from Bloomberg. Panel B shows the running sum of the GC minus specials rate from Panel A, the cumulative net funding cost to the bond/note trade. In Panel C, the dashed blue line shows the number of overnight Treasury special repo transactions in our sample, referencing the scale on the left vertical axis. The solid black line shows the monthly average volume of weekly Treasury fails in \$ billions, referencing the scale on the right vertical axis. The fails data shown are the monthly average of the cumulative weekly fails (average of the fails to receive and fails to deliver), as reported by primary dealers to the Federal Reserve Bank of New York.

between prices in the cash market. At that time, the latitude for high net funding costs narrowed, as the overnight GC rate declined in line with the policy-driven overnight fed funds rate, and the special repo rate did not become negative. The carry cost of the trade was therefore reduced to almost zero. Panel B of Figure 3 plots the cumulative funding cost, from the beginning to the end of the sample period, as implied by the difference in rates from panel A. The realized financing cost of the trade, from February 22, 2008, the date the average divergence across bond/note pairs first rose above 1%, to the end of our specials data sample on March 1, 2009, is just 0.21%. A perfectly timed opportunistic trade, established at the very peak of the average divergence, on December 16, 2008, and unwound at the end of our sample, would have cost only 0.05%.

As a robustness check, we consider borrowing costs for the same set of maturity-matched notes from the Federal Reserve’s securities lending

operations.¹⁹ For the subsample starting on February 22, 2008, there are 414 security-date loans of the maturity-matched notes from the Federal Reserve's portfolio, which show an average annualized net funding cost equal to 0.26%. Lengthening the sample period by one additional year, during which the federal funds policy rate remains close to zero, brings the net funding cost to 0.18% on average over 674 loans. From this we conclude that the financing costs were small relative to the apparent arbitrage opportunity.

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. Krishnamurthy (2002) shows that the financing costs borne by well-positioned traders are in the neighborhood of the gross profit implied by the on-the-run Treasury premium. In a time of extreme market stress, it stands to reason that some traders would not have access to financing, even collateralized. Thus, the costs in Figure 3 are best characterized as those faced by a large trader.

Another question raised is why the specials rates do not fall below zero when there is likely strong demand to borrow particular securities. Repo rates are not bounded below by law or regulation, and indeed, negative rates have occurred after the sample period. The answer likely lies in a trader's alternative to fail to deliver a shorted Treasury—that is, to simply not deliver the security to the buyer, who would then not pay for it until it is delivered. As Evans et al. (2009) note, a delivery fail is economically equivalent to a repo rate of 0, plus any expected cost of getting bought in—that is, the expected cost arising from the trader's prime broker buying the security in order to deliver it, thereby ending the short and generating transactions costs.²⁰ Besides this buy-in risk, fails can also exacerbate counterparty credit risk and add to operational costs, and these frictions encourage borrowing at a negative specials rate in order to avoid failing (Fleming and Garbade 2005). However, borrowers are aware of the high likelihood that the lender will fail to deliver in a negative rate repo contract (Fleming and Garbade 2004). So, a short-seller could easily choose to fail, rather than borrow at a negative market rate.

That the alternative to fail was available and attractive is apparent in the incidence of both Treasury repos and Treasury delivery fails (as reported by the Federal Reserve Bank of New York), shown in panel C of Figure 3. In late 2008, the number of weekly repo transactions in our database drops steeply, suggesting a combination of low demand to arbitrage (e.g.,

¹⁹ The Federal Reserve lends securities to dealers on a daily basis against general Treasury collateral (GC), and so the securities lending fee can be considered equivalent to the net funding cost for the borrowed security, the GC repo rate minus the specials repo rate. These data are available at <https://apps.newyorkfed.org/markets/autorates/seclend-search-page>. As a counterparty, the Federal Reserve is perceived to be "guaranteed" to deliver. For this reason, securities lending rates implied by the Federal Reserve's lending fees are sometimes negative even when market rates remain non-negative (Fleming and Garbade 2004).

²⁰ A new market convention adopted in May 2009 made it much more costly to fail to deliver a Treasury security by imposing a penalty for failing (Garbade et al. 2010).

Gorton and Metrick 2012; Mitchell and Pulvino 2012) and reluctance to arbitrage specifically through the repo market. The steep concurrent rise of fails indicates that at least some of this drop reflects substitution from repos to failing, and the option to fail limited the cost of financing the arbitrage in the period that the relative price divergence between bonds and notes rose to its peak.

To summarize, the carry cost we estimate from repo transactions is low relative to the price divergence. The low carry cost in the months after Lehman is likely best representative of the best-situated traders, so there could have been traders who wanted to profit from the divergence but could not exploit it. The low cost was supported by the option at that time to fail to deliver, which effectively put a zero lower bound on repo rates. Traders could have expected costs to run higher, and for the divergence to expand or persist more than it did, but to the extent the data can reveal, the relative prices of notes and bonds presented a feasible arbitrage opportunity for patient capital. The next subsection addresses the role of relative liquidity in relative pricing by analyzing the relation between liquidity and prices for the full set of off-the-run Treasury securities.

2.2 Relative pricing of all Treasury securities

In this section, we relate the pricing of Treasury securities to their liquidity. We consider both the standard measures of liquidity, such as bid-ask spreads, and the potential fundamental drivers of liquidity, such as issue size and age. The goal is to establish both the general cross-sectional relation and also the change over time through the sample period, which runs from 2006 to 2011, so from before to after the crisis. For this estimation we expand our sample from the maturity-matched pairs to the universe of off-the-run coupon Treasury securities.

To expand the analysis beyond same-maturity pairs, we need to first calculate a baseline price for each security on each day. We do this by first fitting a smooth yield curve to all the securities, using the six-parameter model of instantaneous forward rates developed by Svensson (1994),²¹ then computing for each security the price implied by this curve, and finally subtracting this implied price from each security's actual price. We call this difference the security's "fitting error" for that day, denoted FE_{it} for security i on day t . The mean fitting error is by construction close to zero (not precisely zero, since prices are not linear in yields), and the root mean square of the fitting errors on each day is similar to the aggregate noise measure in Hu, Pan, and Wang (2013). The fitting errors line up well with the price differences of the exactly-matched pairs in Figure 1; the average fitting error across 30-year bonds becomes significantly negative during the crisis while the average

²¹ See Gürkaynak, Sack and Wright (2006) for a discussion of the methodology: <http://www.federalreserve.gov/pubs/feds/2006/200628/200628abs.html>.

across 10-year notes becomes significantly positive, and the difference peaks at around 6% on the same dates.

We relate the fitting error to liquidity with pooled cross-sectional, time-series regressions. Each independent variable differs across securities in ways that could affect their relative liquidity. We include *Bid-Ask* and *Volume* to capture the variation of realized liquidity across securities and time. Existing research identifies both age (Amihud and Mendelson 1991; Fontaine and Garcia 2012) and principal amount (Longstaff, Mithal, and Neis 2005) as potential drivers of liquidity, so we include $\ln(\text{Age})$, time-to-maturity as $\ln(\text{TTM})$, issue size outstanding as $\ln(\text{Out})$, and *Share Stripped* in the analysis. While existing research does not, to our knowledge, associate coupon with liquidity,²² the difference in coupons between bonds and notes is quite large, so we include *Coupon* as a control variable. Panel B of Table 1 shows that age, coupon, and share stripped are all highly correlated, which makes it difficult to distinguish their separate effects in a multiple regression. Accordingly, we run simple regressions on each. Finally, we include an indicator for the maturity-matched bond/note pairs. This *Net Long Matched Pair* indicator is set to 1 for the notes in the pairs and -1 for the bonds, so that the estimated coefficient captures half of the average difference in prices between the maturity-matched securities.

The regression model to explain relative prices takes the general form:

$$FE_{it} = \mu_i + \omega_t + \beta Liq_{it} + \varepsilon_{it} \quad (1)$$

where μ_i and ω_t are fixed effects for security i and day t , respectively, and Liq_{it} is a set of liquidity variables specific to security i on day t . Because FE increases with the security's relative price, a positive loading on a variable indicates a liquidity premium associated with that variable. We report the results, in panel A of Table 3, from a simple regression for each independent variable and three multiple regressions with different sets of the independent variables.

The simple regressions find premia consistent with the literature: securities are more expensive when they are newer, larger and less stripped, and when they have lower spreads or trade more frequently. The price is also higher for securities with lower coupons, which also distinguish notes from bonds due to the high 30-year yields (and thus high-issue coupons) in the 1980s. In the multiple regressions, most of the premia persist, but the effects of coupon, age and time-to-maturity are not stable. The note/bond price difference detected by the matched-pair indicator alone is nearly cut in half with these dimensions of liquidity controlled for.

The model in panel A fits static coefficients and thus captures the general relation of the liquidity variables to prices in the cross-section. However, we

²² Conceivably, high-coupon securities could be bid up by agents investing on behalf of consumers who don't understand the trade-off between higher current yield and bigger subsequent capital losses (see, e.g., Donnelly 1988).

Table 3
Continued

Dependent variable: *Fitting Error*_{*it*}
Panel B: *Security characteristics interacted with aggregate liquidity*

AggLiq × Bid-Ask _{<i>it</i>}	-0.63*** (0.17)																		-0.24** (0.12)	-0.46*** (0.10)
AggLiq × ShmStrip _{<i>it</i>}	-60.75*** (7.88)																		-47.72*** (8.69)	-39.00*** (6.86)
AggLiq × Volume _{<i>it</i>}	15.18*** (4.78)																		1.28 (3.14)	0.53 (3.14)
AggLiq × ln(Age) _{<i>it</i>}																			-0.15 (4.12)	-0.27 (3.14)
AggLiq × ln(TTM) _{<i>it</i>}																			2.66*** (1.01)	2.75*** (0.88)
AggLiq × ln(Out) _{<i>it</i>}																			0.98 (0.91)	0.94 (0.94)
AggLiq × Coupon _{<i>it</i>}																			9.14*** (3.08)	6.48*** (2.40)
AggLiq × Pair _{<i>it</i>}																			0.62 (0.58)	0.55 (0.55)
Bid-Ask _{<i>it</i>}	1.58 (1.15)																		11.53*** (3.07)	8.43*** (2.22)
ShmStrip _{<i>it</i>}	71.88*** (23.56)																		1.17 (0.93)	3.42*** (0.77)
Volume _{<i>it</i>}																			59.33*** (18.92)	-18.31 (26.72)
ln(Age) _{<i>it</i>}																			14.19 (11.13)	6.77 (8.74)
ln(TTM) _{<i>it</i>}																			1.98 (2.33)	-2.25 (2.47)
ln(Out) _{<i>it</i>}																			5.57*** (2.23)	-21.10** (4.77)
Coupon _{<i>it</i>}																			-15.45*** (6.95)	
Pair _{<i>it</i>}																			-0.67 (1.71)	
Day fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	19.00** (7.49)	
CUSIP fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes		
R ² , % (total)	43.46	47.56	38.86	46.42	39.03	46.30	46.38	45.94	46.38	45.94	51.99	51.99	55.74	55.74	55.74	55.74	55.74	55.74		
R ² , % (within)	7.66	14.36	0.15	12.50	0.44	12.31	12.43	11.72	12.43	11.72	21.59	21.59	27.71	27.71	27.71	27.71	27.71	27.71		
Observations	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873	207,873		

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 of par value. *Volume* is trading volume of U.S. insurance companies; *Volume* for each security on each day is the ratio of the trading volume for that security relative to the sum of volume for all securities on that day. *Coupon* is measured in percentage points per year. *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, and security CUSIP fixed effects are included in the regressions as indicated. R² values show the total and within variation explained by the fixed effects specification. Standard errors (in parentheses) account for clustering within security *i* and within day *t*; *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

are interested in understanding how differences in liquidity contributed to the widening of price differences during the crisis. Panel A of Figure 4, which tracks the average fitting error of each size quartile, suggests that the impact of fundamental differences strengthened during the crisis. It shows the lower average prices of smaller securities that we see in the regression, but it also shows that this cross-sectional difference in prices varies widely over time and follows a pattern quite similar to that of the bond/note pairs alone.

To capture time-series variation in the contribution of liquidity to prices, we allow the coefficients in Equation (1) to vary over time with an index of market-wide liquidity. A positive loading on this interaction means that the variable's contribution is bigger when aggregate liquidity is worse. Our index, labeled $AggLiq_t$ for day t , is the average bid-ask spread across the universe of securities that day, shown in panel B of Figure 4. The average spread rises from around 2 basis points pre-crisis to much higher levels around Lehman before drifting back down, though not all the way to where it started. This pattern is stronger among the less-liquid bonds, whose spreads exceed 20 basis points at the widest. These Treasury-market results are consistent with the equity-market results in Acharya and Pedersen (2005), where the most illiquid securities show higher sensitivity to changes in market liquidity.

The model including market-wide liquidity also includes security and day fixed effects, and the specification is:

$$FE_{it} = \mu_i + \omega_t + \beta Liq_{it} + \gamma Liq_{it} \times AggLiq_t + \varepsilon_{it} \quad (2)$$

where $AggLiq_t$ is the measure of market-wide liquidity. We repeat each regression from panel A with this expanded specification; results are in panel B of Table 3.

The specifications on the left-hand side of panel B find a consistent result: the interactions of the individual liquidity variables are significant in the same direction as was found for the uninteracted coefficients in panel A, but the R^2 values increase. As aggregate liquidity worsens, these variables explain even more of the general relation between liquidity and pricing. For example, the coefficient on $BidAsk$ in panel A is -2.99 , so on average, a 1-basis-point wider spread associates with a 2.99-basis-point lower price. In panel B, the coefficient on the interaction of $BidAsk$ with $AggLiq$ is -0.63 . Since $AggLiq$ increases by about 6 basis points during the crisis peak (from 2 basis points pre-crisis to 8 at the peak of the crisis), this implies that the price discount associated with a 1-basis-point wider spread increases by $(6)(0.63) = 3.78$ basis points at the peak of the crisis.

In the multiple regressions, our first specification includes only explanatory variables that are determined outside of market dynamics; age, time to maturity, size, coupon, and matched maturity date pairs. Issue size stands out as a driver of price divergence in both panels. We can get a back-of-the-envelope sense of this contribution by combining the point estimates from the regression with the summary statistics from Table 1. The average amount outstanding is 12.08

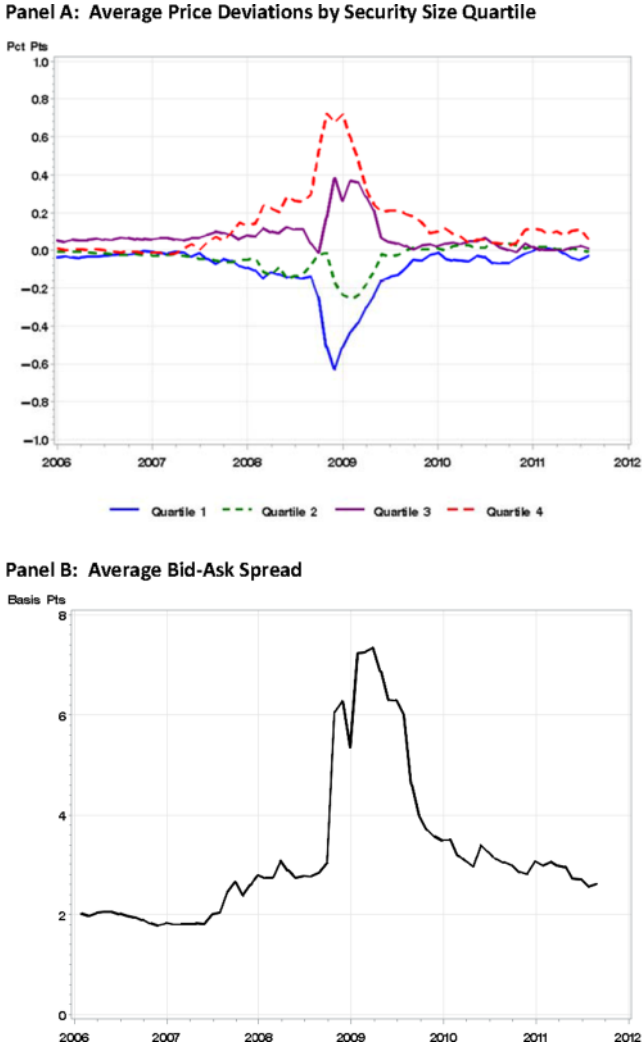


Figure 4

Security Liquidity Characteristics

Panel A shows the monthly average fitting error for each security size quartile. The solid blue line represents the quartile with the smallest securities, and the dashed red line represents the quartile with the largest securities. The vertical axis is measured in percentage points. Panel B shows the monthly average bid-ask spread (in price terms) for all off-the-run Treasury security observations in our sample. The data are from the TradeWeb platform. The vertical axis is measured in basis points.

for bonds and 28.24 for 10-year notes, and $\ln(12.08) - \ln(28.24) = -0.85$. So the coefficient of 6.12 on the interaction of *AggLiq* with $\ln(\text{Out})$ associates the 6-basis-point increase in *AggLiq* with a $(6.12)(6)(-0.85) = 31$ -basis-point decrease in the price of bonds relative to 10-year notes. Security size remains key to understanding relative prices even when we add the bid-ask, share stripped, and volume as regressors, with and without security fixed effects, as shown in the final two columns of the table. The relation of the share stripped to the fitting error is consistent and strong. To put the estimates into context, 21% of the average bond is stripped, compared with just 2% of the average 10-year note, so the increase in *AggLiq* implies a $(-39)(6)(0.21 - 0.02) = 44$ -basis-point decrease in bond prices relative to 10-year notes.

These liquidity variables explain more than a third of the bond/note disparity. In the regression including only the bond/note pair indicator, the 14.01 loading on the indicator implies a divergence of 1.7 due to the decrease in aggregate liquidity; that is, $14.01(6)(1 - [-1]) = 1.7\%$. However, when we include the liquidity variables in the regression, the loading falls to 12.32, which implies just a 1.0% divergence not explained by these liquidity measures.²³

To summarize, we find that relative liquidity—as reflected in both the underlying drivers of liquidity such as issue size and the manifestations of liquidity such as bid-ask spreads—explains much of the general price difference in the cross section of Treasury securities, and in particular, explains most of the widening of prices to their extreme disparity during the crisis. In the next section we address the dynamics of this widening, in particular the feedback from the trading horizons of investors buying the different securities to the securities' subsequent liquidity.

3. Liquidity Feedback Generated by Investor Trades

With the insurer data, we can line up an investor's decision to buy or sell notes or bonds with, on the one hand, the securities' current relative prices, and on the other hand, the investor's general trading style and its current financial stress. We can therefore see how the demand for the more-liquid security evolves as the price of liquidity changes and as the investor's liquidity needs change.

We gauge an insurer's trading style from its trading history and its financial stress from its balance sheet. The trading variables are designed to reflect liquidity needs arising from an insurer's style: *Churn* increases with an insurer's portfolio turnover and thus likely reflects its general demand for liquid securities, and *Holding Horizon* increases with an insurer's propensity to hold onto its investments, and thus likely decreases with its demand for liquid securities. The financial-stress variables include *Capital/Assets*, *RBC*, and *Net Income*, which increase with the health of the insurer and thus point to lower

²³ For robustness, we include results for Table 3, applied to only the matched-maturity bond/note pairs, in the Online Appendix.

stress, and *Annuity*, which indicates that the insurer is potentially subject to the need for emergency security liquidation. As in Coval and Stafford (2007), the financial stress that these variables capture likely increases the insurers' demand for liquidity in their investments.

We begin by assessing how the average insurer tends to trade in response to a security's relative price, as estimated by the fitting error. Due to the sparseness of off-the-run trades, we aggregate trades and fitting errors across the days in each month. The dependent variable is the average net purchase by all insurance companies of security i in month t —that is, $NP_{it} = Buys_{it} - Sells_{it}$. The independent variable of interest is the average fitting error for security i during month t , and the regression takes the form

$$NP_{it} = \mu_i + \omega_t + \beta FE_{it} + \varepsilon_{it} \quad (3)$$

where μ_i and ω_t are fixed effects for the security and month. The security fixed effects account for security-level, time-invariant factors that affect insurance companies' demand for a security, such as the original issue maturity or amount issued of the security. The month fixed effects account for time series variation in the aggregate demand for all Treasury securities for the average insurer. Together, the fixed effects imply that β is identified by the variation of the time series of fitting errors across securities, as highlighted in Figure 4. As before, FE_{it} is measured in price terms, so a positive value indicates a relatively rich security.

The identification strategy assumes that insurer transactions are responding to relative Treasury prices rather than affecting them. This assumption reflects the relatively small scale of insurer holdings and transactions, relative to the size and volume of the Treasury market. During 2008, there was \$6.1 trillion in publicly held U.S. Treasury debt, with an average issue size of \$23.9 billion (Table 1), and the daily average aggregate transaction volume in U.S. Treasuries exceeded \$550 billion.²⁴ Meanwhile, insurers hold 3% of Treasuries, and their average Treasury security transaction size, in our sample, is \$12.6 million, which is about one-half of one percentage point of the average Treasury issue size. There is substantial variation in Treasury transactions across insurers, and any single insurer's transactions are a small piece of the overall market.

We estimate the regression in Equation (3) first for the entire set of insurers, and then for each of the three insurer types separately. Results are shown in Table 4.²⁵ The first column indicates that the average insurer demands a Treasury security more when its price is relatively high. The next three columns show that this relationship is particularly pronounced for life insurers. To give

²⁴ www.sifma.org/research/statistics.aspx (Securities Industry and Financial Markets Association).

²⁵ Standard errors in Table 4 are heteroscedasticity-robust but not clustered. Abadie et al. (2017) argue that standard errors should not be clustered unless the treatment (regressor) is clustered, which is not the case in Table 4 since the fitting error varies by CUSIP and month. Nonetheless, the inferences from Table 4 are unchanged if we cluster by CUSIP or month.

Table 4
Insurer transaction patterns

Dependent variable: Net purchase of $Treasury_{it}$

Insurer type:	All	Health	Life	P&C
<i>Fitting Error</i> _{it}	5.07*** (1.12)	1.99*** (0.49)	14.56*** (2.94)	2.06** (0.99)
CUSIP fixed effects	Yes	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes	Yes
R^2 , % (total)	30.51	56.11	30.48	27.94
R^2 , % (within)	0.69	0.96	0.69	0.19

This table presents a pooled regression of insurance companies' monthly average net purchases of Treasury security i in month t on the fitting error for each security i at time t . 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 of par value. Net purchases are in \$1,000s. The sample period is January 1, 2006, through September 30, 2011. Fixed effects for security i and month t are included as indicated in the table. R^2 values show the total and within variation explained by the fixed effects specification. Standard errors are shown in brackets beneath the coefficient estimates; *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

an economic interpretation to the estimate in the first column, it implies that a one-percentage-point increase in a security's relative price leads to a \$5,070 increase in net purchases of the security by the average insurer, which would total \$11.8 million across all 2,327 insurers. The magnitude of this estimate for life insurers, 14.56, shows that they are roughly seven times more sensitive to relative security price changes than health or property & casualty insurers. Our data show that insurers in aggregate tend to be net buyers of the relatively liquid and expensive securities. Though insurers are relatively long-horizon investors, they value the ease of transactions in off-the-run notes rather than bonds. On balance, insurers have traded in the direction that would widen, rather than narrow, the price differentials among different Treasury securities. We next examine variation among insurers to help inform us as to what drives the relationship between an insurer's trading strategies and relative security prices.

To identify the role of an insurer's individual circumstances in affecting demand, we use disaggregated data and modify Equation (3) to allow the coefficient on the fitting error to vary across insurers as a function of their characteristics. The regression equation becomes

$$NP_{ijt} = \mu_{it} + \alpha_j + \varphi \chi_{jt} + \gamma \chi_{jt} FE_{it} + \varepsilon_{ijt} \tag{4}$$

where j denotes insurers, and the vector χ_{jt} includes measures of the trading-style and financial-stress circumstances of the insurer.²⁶ The μ_{it} are security-by-month fixed effects, and the α_j are insurer fixed effects. The security-by-month fixed effects are feasible because there remains variation in net purchases across insurers for a given security in a given month. We include these fixed effects because they are at the same level of variation as FE_{it} and can account for any factors that might simultaneously affect the

²⁶ Some of the insurer characteristics vary over time (at a monthly frequency), and some do not.

Table 5
Who engages in the arbitrage?

Dependent variable: *Net Purchases_{ijt}*
 Insurer characteristics interacted with fixed effects

<i>Capital/Assets_{jt} * FE_{it}</i>	-0.11***						-0.08***
	(0.03)						(0.03)
<i>RBC_{jt} * FE_{it}</i>		-1.90*					0.78
		(1.14)					(1.47)
<i>Net Income_{jt} * FE_{it}</i>			0.07				1.70
			(1.17)				(1.32)
<i>Annuity_j * FE_{it}</i>			16.80**				13.27*
			(7.47)				(7.60)
<i>Churn_j * FE_{it}</i>				0.93***			0.42**
				(0.20)			(0.18)
<i>ln(Hold Horizon_j) * FE_{it}</i>						-5.61***	-3.23***
						(1.10)	(0.98)
CUSIP × Month fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>R</i> ² , % (total)	1.33	1.33	1.33	1.33	1.33	1.33	1.33
<i>R</i> ² , % (within)	0.001	0.000	0.000	0.001	0.001	0.001	0.002

Observations = 31,895,540

This table presents results from a pooled regression of an insurance company's monthly average 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 minus the fitted price based on a smoothed yield curve, measured in basis points of par value. The sample period is January 1, 2006, through September 30, 2011. Fixed effects for security *i* interacted with fixed effects for month *t*, and fixed effects for insurer *j* are included as indicated in the table. Insurer characteristics that vary over time, not interacted with the fitting error, are also included in the regressions. *R*² values show the total and within variation explained by the fixed effects specification. Standard errors are clustered at the insurer level, and are shown in brackets beneath the coefficient estimates; *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level. Note that coefficients on annuity, churn, and holding horizon are not identified in cases where insurer fixed effects are included.

relative price of a security and the demand for the security.²⁷ The insurance company fixed effects account for time-invariant factors that affect a particular insurance company's demand for Treasury securities overall, which would control for differences in insurer type such as life or health. To account for any constant insurer-level unobserved factors that affect net purchases through the error term, reported standard errors are clustered by insurer. The main object of interest is the coefficient on the interaction term, γ , as it tells us whether an insurer's particular circumstances make it more or less likely to buy the relatively expensive securities. The coefficient is identified by variation in net purchases across insurers for a given security in a given month.²⁸

The results from estimating γ in Equation (4) are shown in Table 5, with the insurer characteristics, χ_{jt} , entering individually in the first six columns, and together in the last column (the coefficient estimates of uninteracted terms

²⁷ For robustness, we include additional combinations of interacted and uninteracted fixed effects in the Online Appendix. The coefficient estimates are quite stable across the various regression specifications.

²⁸ Because of the insurer fixed effects, the coefficient is identified by time-series deviations from the insurer-level average.

are not reported in Table 5). The top set of estimates on the insurer's financial variables show that insurers with higher stress demand the more expensive securities. Insurer leverage and exposure to annuities are both robustly related to the demand for expensive securities; even in the multiple regression, these variables retain the same sign and significance as in the simple regressions. The coefficient estimates suggest that insurers with high leverage (low *Capital/Assets*) are much more likely to buy expensive securities. Based on the simple regression, a two-standard-deviation decrease in *Capital/Assets* increases the coefficient on *FE* by 5.9 ($25.83 \times 2 \times 0.11$). This change implies roughly a doubling of the coefficient on *FE* for the average insurer, as estimated in Table 4. Similarly, the estimated coefficient on the *Annuity* dummy variable shows that the propensity to buy overpriced securities is about four times larger for annuity providers. Annuity-focused insurers are concentrated within life insurers, which helps to explain why life insurers show a particularly high degree of sensitivity to the fitting error in Table 4.

The coefficients in the fifth and sixth rows of Table 5 show that the trading-style variables are also associated with buying the relatively expensive securities. Investors with shorter average holding periods (*Holding Horizon*) and more frequent portfolio turnover (*Churn*) both have a greater sensitivity of net purchases to fitting error. For instance, a two-standard-deviation decrease in the log holding horizon of an insurer (meaning that an insurer's weighted average holding horizon shortens by 3.3 years) implies a 6.7 ($-0.59 \times 2 \times -5.61$) increase in the fitting error sensitivity, which is comparable to the impact of leverage. A two-standard-deviation increase in the *Churn* variable (meaning that an insurer that transacts an extra 8% of its holdings in a given month) shows a comparably increased propensity, 7.7 ($0.97 \times 2 \times 3.94$), to purchase the relatively expensive Treasury securities.

These results show that liquid securities migrate to financially stressed clienteles as the price of liquidity, the price differential between relatively liquid and illiquid securities, grows. This gives new and direct empirical evidence of the clientele prediction from the Amihud and Mendelson (1986) model of the bid-ask spread; less-liquid assets are allocated in equilibrium to portfolios with longer expected holding periods.²⁹ It is also in the spirit of Brunnermeier and Pedersen (2008), in that their model connects varying investor constraints to rapid increases in the price of liquidity.³⁰

To summarize, the insurance company transactions show that investors select into securities according to their need for liquidity, and that this accelerates

²⁹ The clientele prediction differs from the positive and concave relationship between an asset's bid-ask spread and its return, which is consistent with our finding in Section 2, Equations (1) and (2), and has already been empirically tested in the literature.

³⁰ The Brunnermeier and Pedersen (2008) model relies on differences in margin requirements between securities. Krishnamurthy (2010) shows that repo haircuts for short-term Treasury securities averaged 2% from the spring of 2007 through the spring of 2009, and haircuts for long-term Treasury securities ranged from 5% to 6% over the same period.

as the price of liquidity increases. Self-selection of insurers that trade less frequently into less-liquid securities would tend to lower the securities' liquidity even further as they become even less traded. This is consistent with a feedback loop where an illiquidity discount begets a larger discount, due to the expectation that the security will trade less, and this expectation should correspondingly widen bid-ask spreads. For this mechanism to work, spreads should widen over time as trading slows down. Thus, the last empirical section asks how the changing rate of trading affects the change in bid-ask spreads over time.

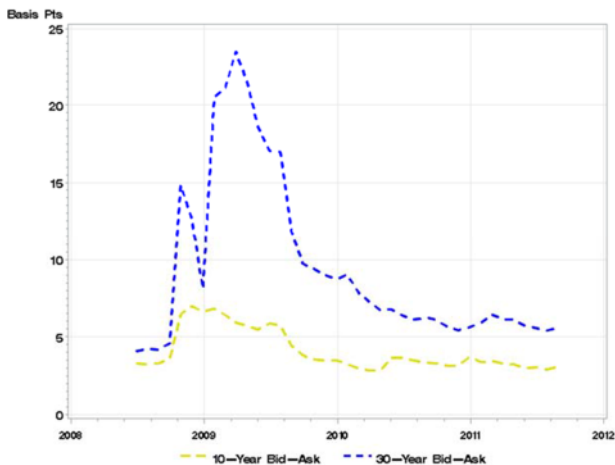
4. Liquidity Provider Risk Pricing

A security's bid-ask spread includes the price charged by liquidity providers to absorb temporary imbalances in security supply and demand. Panel B of Figure 4 shows a near quadrupling in the average bid-ask spread from before the crisis to its peak, and panel A of Figure 5 shows a particularly dramatic spike in the average bid-ask spread for 30-year bonds relative to 10-year notes. This variation across securities and over time raises two main questions. First, how much of the spike reflects a higher price charged to provide the same liquidity, and how much represents a change in the quantity of liquidity being provided? And second, which elements of liquidity provision are responsible for the high spreads? Is it the price of carrying the position on the balance sheet until the next trade, or the price of bearing the security's interest rate risk exposure? We address these questions by examining the evolution of the relationship between bid-ask spreads and two fundamental costs of providing liquidity: securities' interest rate risk and the expected time between trades.

A market maker builds the expected costs of its services, including financing a position and bearing its price risk, into the bid-ask spread charged to customers. We use two variables to capture these costs. The first is time-to-trade, TTT , as defined in Section 1.2. The realized time since the last trade serves as a proxy for the expected time that the liquidity provider must wait until another trade arrives to take the position off his hands. To reduce the noise in this proxy, while still allowing it to pick up high-frequency changes in the trading environment, we average TTT over the time since the last sell and the time since the last buy. The second variable is the duration of the security, Dur , which represents the price risk per unit of time borne by the liquidity provider between trades. The intuition is that the cross-section of the securities' interest rate risks is roughly proportional to the securities' durations.

Panel B of Figure 5 plots the monthly average levels of TTT and Dur . There is a strong upward trend in the time between Treasury transactions, more than doubling from mid-2008 to mid-2011. The drop in transaction frequency 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 and anecdotal evidence point strongly to a

Panel A: Average Bid-Ask Spread



Panel B: Average TTT and Duration

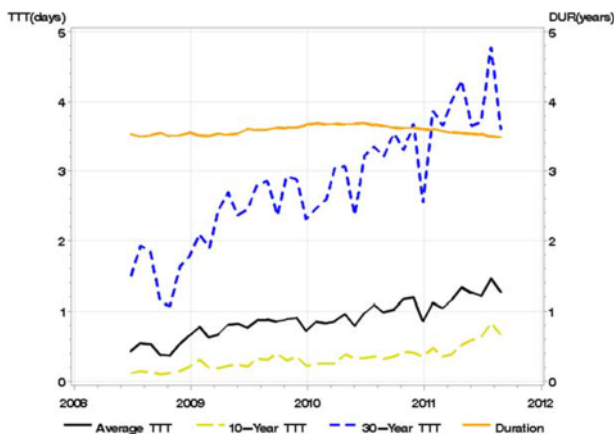


Figure 5
Liquidity fundamentals

This figure shows the monthly average of the *Bid-Ask Spread*, *TTT*, and *Duration* for various coupon-paying Treasury securities in our sample. Panel A shows the *Bid-Ask Spread*. Panel B shows *TTT* and *Duration*. In both panels A and B, the dashed yellow and blue lines represent average values over 10- and 30-year Treasury securities, respectively. In panel B, the solid black line shows average *TTT*, which is measured in days, referencing the scale on the left vertical axis, over all bonds and notes in our sample. This panel also shows the average level of *TTT* for 10-year notes, and the average level of *TTT* for 30-year bonds in our sample. The solid orange line shows average *Duration*, referencing the scale on the right vertical axis. *Duration* is measured in years.

general trend of worsening market conditions, while the market share of electronic platforms such as TradeWeb has likely expanded.³¹ The time between trades reaches a local peak around the end of 2008, as does the level of interest rate risk, which spikes again in mid-2009.

We relate bid-ask spreads to the two variables with the following regression model:

$$Spread_{it} = \alpha_t + \beta_{1,t} TTT_{it} + \beta_{2,t} Dur_{it} + \varepsilon_{it} \quad (5)$$

where $Spread_{it}$ denotes the bid-ask spread for security i on day t . To allow the relation to change over time, we run a separate cross-sectional regression for each day t in the sample. The coefficient on TTT_{it} , $\beta_{1,t}$, provides an estimate of the price charged per unit of time, on date t , to finance a position until the expected arrival of the next trade. The coefficient on Dur_{it} , $\beta_{2,t}$, estimates the price charged over this same holding period to bear the position's interest rate risk. We present the results graphically in Figure 6, which has one bold line for each of the two coefficients along with lighter dashed lines showing confidence bounds. The graph shows monthly averages of the coefficient and confidence bounds from the daily regressions.

The time series of coefficients make two main points. First, the price charged per unit of financing time ($\beta_{1,t}$) surged when bid-ask spreads surged; both peak in September 2008, when Lehman failed, and both are higher in the first half of 2009 compared with the second half. Second, the price charged per unit of holding-period price risk ($\beta_{2,t}$) increased in late 2008 and again in early 2009, which contributed to the increase and slow decline of spreads in 2009, particularly for longer duration securities.

So to the question of why spreads increased so much when prices diverged so much, these results deliver an answer with two parts. First, the price charged by market makers for financing—that is, for access to their balance sheets—spiked dramatically after the Lehman bankruptcy and again in early 2009. In combination with a rise in the quantity of financing needed, due to the slowdown in trading (Figure 5B), bid-ask spreads increased for particularly illiquid securities. Second, the price charged for interest rate risk rose, which increased spreads for more risky securities.

The spike in the price charged for financing can help explain the divergence between bond and note prices.³² Bonds traded less often than similar notes, and the price charged for this difference in liquidity increased. To put the effect in perspective, in the first month of our sample (June 2008), the average estimated

³¹ TradeWeb launched its Treasury platform in 1998. Greenwich Associates (2015) estimated TradeWeb's market share of Treasuries on multi-dealer electronic trading systems to have grown to 56%. Greenwich also reports that electronic trading as a share of overall Treasury market volume increased from 33% in 2005 to 42% in 2015. These figures suggest that the increasing time between the electronic trades at TradeWeb reflects a general downward liquidity trend, and not a trend away from electronic trading platforms such as TradeWeb.

³² Interest rate risk cannot explain the difference in bid-ask spreads since the replicating portfolios have identical duration by construction.

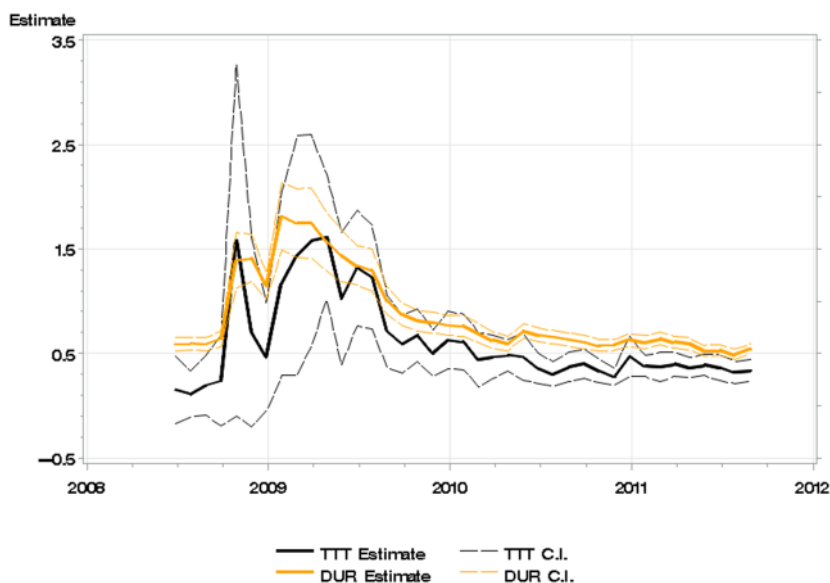


Figure 6
Monthly regressions of bid-ask spread on TTT and duration
Monthly regression coefficient estimates (dependent variable: $Bid-Ask Spread_{it}$)

The figure shows the monthly averages of coefficient estimates and 95% confidence intervals for a series of daily, cross-sectional multivariate regressions of the $Bid-Ask Spread_{it}$ onto TTT_{it} and Dur_{it} for each security i on each day t , where the $Bid-Ask Spread_{it}$ is measured in basis points. The solid black line shows the point estimates for TTT . The solid orange line shows the point estimates for Dur . The corresponding color thin-dashed lines show the confidence intervals for the respective coefficient estimates.

coefficient on TTT is 0.15, and at the peak of the bid-ask spread (March 2009), the coefficient reaches 1.58, a more than 10-fold increase. Based on the sample-average value of TTT (0.92 days), this increase implies a 1.3-basis-point increase in the bid-ask spread for an average security. Combined with a widening of the gap in TTT between bonds and notes shown in Figure 5B, the estimates attribute 4 basis points of the gap in bid-ask spreads between bonds and notes to a slowdown in trading and an increase in the price charged by market makers to bear this risk. As shown in Figure 5A, the actual gap in bid-ask spreads reached nearly 15 basis points in early 2009, which suggests that additional factors beyond those in our model—such as increased scope for adverse selection, which is generally associated with spreads in other markets—also contributed to differences in bid-ask spreads across the bonds and notes.

The feedback model helps explain the change in TTT in Figure 5B in terms of the levels of the bid-ask spreads in Figure 5A, in particular the co-occurrence of the widening of the TTT gap with the elevated spreads, both of which run from late 2008 to the end of 2010. As long as the bonds are more expensive to trade, the Amihud and Mendelson (1986) argument sees the patient traders

disproportionately selecting into the bond, and thus the bond's trades continuing to slow down. So, elevated spreads should co-occur with growing TTT , and a return to normal spreads should halt the growth, with the bonds now in the portfolios of traders with no plans to trade soon.

Interest rate risk changes little over the sample period, but there is a big change in the price to bear it, captured by the tripling of the coefficient on Dur from the start to early 2009. This increase accounts for about three-quarters of the increase in the average security's spread, from trough to peak, shown in Figure 4B. The remainder is due to the increases in average TTT and the coefficient on TTT .³³

In the June 2008 to March 2009 subsample, the regression results attribute most of the changes in the distribution of bid-ask spreads to changes in prices rather than changes in quantities of financing or interest-rate risk. Figure 6 shows the average predicted bid-ask spread for all 10-year notes in our sample as compared with the average predicted spread for all 30-year bonds. Bid-ask spreads for the less-liquid securities are clearly higher, and this divergence increases in the crisis period.³⁴ The larger contribution of price vis-à-vis quantity is consistent with the empirical facts reported in Adrian (2013), which states "bid-ask spreads increased dramatically during the financial crisis, despite the sharp increase in volume. The increase in bid-ask spreads reflect uncertainty at that time, as well as the reduced balance sheet capacity of dealers." Our results find a more pronounced effect on illiquid securities, resulting in spreads increasing more for 30-year bonds than for 10-year notes.

The estimates shown in Figure 6 also shed some light on why average bid-ask spreads end up higher in late 2011 than they started before the Lehman bankruptcy, as shown in Figure 4. The estimated coefficients on TTT and Dur largely returned to their pre-crisis levels by the end of 2009, which we interpret as a reversion of prices charged by liquidity providers to bridge the arrival of traders back to their pre-crisis levels. The rise in average bid-ask spreads is attributable, therefore, to the steady slowdown in trader arrival over the period, particularly for 30-year bonds. The result is a "new normal" of larger bid-ask spreads post-crisis for the sparsely traded off-the-run securities.³⁵

5. Conclusion

The financial crisis moved many pricing relationships far out of line. It is generally understood that the demand for liquidity played a role in this movement, but the nature of this role is not so well understood. Since issuers,

³³ The duration of the average security remained roughly constant during the sample period.

³⁴ Since this analysis includes securities other than the maturity-matched pairs, the 30-year bonds have longer average duration, which contributes to the difference in predicted bid-ask spreads.

³⁵ Adrian et al. (2017) find that spreads for on-the-run securities in the interdealer market returned to pre-crisis levels.

practitioners, and regulators all benefit from understanding the relation between liquidity and pricing, both in normal and in crisis times, it is crucial to learn what we can from this episode. We explore the role of liquidity demand and supply in asset pricing by analyzing one of the cleanest and largest misalignments, the bargain price of bonds relative to notes in the off-the-run Treasury market. This is clean because the price difference is between exactly-matched cash flows from the same issuer, and because credit risk plays no role, and it is large because both the price difference and the market are large. Furthermore, this market allows a wide-ranging exploration because we can see not only the relevant spreads at which liquidity is supplied, but also the cost of financing long and short positions and also all the trades and relevant circumstances of an important group of investors, U.S. insurance companies.

Our analysis makes several contributions. We document the note/bond misalignment, which is not only large, reaching 6% of principal value, but also systematic, encompassing all pairs of bonds and notes, and persistent, evolving throughout the crisis. We show that the cost of arbitraging the misalignment—that is, the cost of borrowing the notes and financing the bonds—is small compared with the misalignment itself. We find a feedback loop, in the spirit of Amihud and Mendelson (1986) and Dow (2004), magnifies the effect of liquidity on pricing: investors demanding more liquidity (those expecting to transact more frequently) select into the expensive and more-liquid notes, and those demanding less liquidity (those with longer holding horizons) select into the cheaper and less-liquid bonds, which widens the liquidity gap and thus feeds back into subsequent self-selection. We also find that liquidity providers amplify the self-selection by raising the price they charge for access to their balance sheets—that is, the price they charge per day to carry positions between trades.

One lesson of these findings is that, as suggested by Dow (2004), a security's liquidity is not uniquely determined by its fundamentals, because multiple equilibria are possible. The same security could be cheap, have a large bid-ask spread and trade infrequently, or be rich, have a low spread, and trade a lot.

Long-standing price relationships break down in crises, and it is critical for investors and policymakers to understand why. Investors pursue strategies based on these relationships, central banks infer conditions in financial markets from them, and bank regulators look to them for signs of stress. We show that differences in liquidity, combined with the actions of investors and liquidity providers during a crisis, can contribute to sharp and long-lasting deviations, even in the relationships that seem most susceptible to arbitrage. Our results indicate that policies to enhance liquidity in specific securities, such as a reopening or a securities lending program, could dampen the illiquidity feedback that might otherwise spiral to an extreme. Strategies to bolster market resilience to liquidity shocks are especially relevant as investors adjust to more conservative post-crisis market norms and liquidity providers navigate still-evolving regulatory-related costs to make markets.

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