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Asset mispricing☆

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ABSTRACT

We use a unique sample of corporate bonds guaranteed by the full faith and credit of the US to test recent theories about why asset prices may diverge from fundamental values. A key feature of our study is access to proprietary data on the haircuts, funding costs, and inventory positions of the primary dealers making markets in the individual bonds. The results provide strong support for the cross-sectional implications of the safe-asset, intermediary-constraints, and search-frictions literatures. Furthermore, the results indicate that network topology may also play an important role in explaining mispricing.

1. Introduction

One of the central doctrines of modern financial theory is that the price of a security should equal the present value of its cash flows. Recently, however, this paradigm has been challenged by evidence of asset prices that appear to diverge from their fundamental values, particularly during financial crises and major market events.

A number of important recent studies examine the time series properties of these apparent violations of the law of one price in financial markets. One stream of this literature focuses on the convenience yield incorporated into near-money assets such as Treasury securities. Key examples include Longstaff (2004), Krishnamurthy and Vissing-Jorgensen (2012), and Nagel (2016). Another stream focuses on the role that intermediary balance sheet constraints may play in asset pricing. An important recent example is Du et al. (2018) who show that covered interest rate parity violations are directly related to the proximity to the end of a quarter.

This paper extends the literature in a new direction by studying the cross-sectional variation in mispricing within an asset class. In this study, we use a unique data set of corporate bonds explicitly guaranteed by the full faith and credit of the United States to shed light on the factors at play in allowing asset mispricing to occur. A key advantage of this data set is that since these bonds have the same credit risk as Treasury bonds, deviations from fundamental values can be observed directly by contrasting their prices with those of comparable Treasury bonds. We also have proprietary data on the funding costs, haircuts, and inventory positions of the individual primary dealers making markets in each bond as well as data on the trading ac-

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tivity and network topology of each bond. Thus, this panel data set is ideally suited for exploring the cross-sectional implications of a number of recent theoretical models of asset mispricing.

We find that there is significant and persistent mispricing among the guaranteed corporate bonds in the data set during the 2008–2012 sample period. The overall average value of the mispricing during the sample period is 20.07 basis points, which is highly significant both statistically and economically. We also show that there is dramatic variation in the amount of mispricing over time as well as across bonds. We note that the pattern of correlations in mispricing across bonds is unlikely to be explained by a single factor.

We begin the analysis by considering the cross-sectional implications of the various classes of theoretical models in the literature. In particular, we consider the cross-sectional implications of the Treasuries-as-money, intermediary-constraints, search-frictions, and microstructure-related literatures. This task is made somewhat challenging by the fact that a number of the theoretical models are developed in settings with only one asset and/or a single representative intermediary. Thus, in a strict sense, some models in their current format may only have meaningful implications for the time series properties of mispricing.[1]

The empirical results provide a number of important insights into the underlying reasons and economic mechanisms allowing persistent mispricing to occur in this market. First, we find that mispricing is strongly related to the duration of the matching Treasury bond used in the estimation. This result is consistent with Krishnamurthy and Vissing-Jorgensen (2012) who present a model in which the near-money convenience yield in Treasury securities can vary across maturities. Second, we find that mispricing is significantly related to the credit default swap (CDS) spreads and haircuts of the primary dealers making markets in the bonds. These results support the implications of many current intermediary-based models of asset pricing. Third, we show that the structure of the dealer/customer network is related to mispricing in ways consistent with a number of recent theoretical network models. Finally, we find little evidence that traditional liquidity measures such as bid-ask spreads are related to mispricing in our sample.

Having found support for the Treasuries-as-money, intermediary-constraints, and search-friction theories, we conduct a number of additional tests to examine whether the patterns of mispricing are consistent with the underlying mechanisms of each model. First, we test whether the term structure of mispricing is linked to the convenience yield in Treasury securities. The results provide strong additional support for the Treasuries-as-money literature. In particular, we find that it is the interaction of measures of the near-money premium in Treasuries with duration—and not duration itself—that best explains the term structure of mispricing.

Second, we test whether the relation between mispricing and dealer CDS spreads and haircuts operates through an inventory channel as implied by many current intermediary asset pricing theories. In particular, models such as Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), He and Krishnamurthy (2012, 2013), and others share a common underlying economic mechanism: an adverse shock to the capital and/or funding capacity of a financial intermediary reduces its risk-bearing ability that, in turn, leads to reductions in its security positions and a corresponding increase in mispricing. We find support for both parts of this economic mechanism. Increases in dealer CDS spreads and haircuts are both followed by significant declines in dealer inventory positions. In turn, an instrumental variables (IV) analysis shows that declines in dealer inventory are significantly related to increases in mispricing. The results also indicate, however, that shocks to dealer CDS spreads and haircuts may not operate exclusively through the inventory channel—that intermediary constraints may have broader effects than current models suggest.

To examine the implications of the intermediary-constraints literature at a more fundamental causal level, we study the impact of two separate events that resulted in major exogenous shocks to the amount of capital available to dealers, to the access of dealers to funding for their inventory positions, and to the liquidity of the bonds. One of these occurred in April 2009 after the Fixed Income Clearing Corporation (FICC) announced that the guaranteed bonds would be eligible for the general collateral finance (GCF) Repo market. This event represented a major positive funding shock for dealers that now faced lower effective haircuts in financing inventory positions via the repo market. We show that the cross-sectional patterns of changes in mispricing following this event are directly related to the funding and capital costs faced by dealers.

The other event is the announcement of the financial stress tests (the Supervisory Capital Assessment Program, or SCAP) for major dealers in the market in February 2009. This resulted in a significant decline in the market value of the impacted dealers on the day of announcement, representing a large exogenous negative shock to their capitalization. We again find that the cross-section of changes in mispricing is directly related to the differences in the size of the negative capital shock suffered by dealers on the announcement date.

Third, one of the central implications of the search-frictions/network-structure literature such as Duffie et al. (2005, 2007), Duffie (2010), Babus and Hu (2017), Üslü (2019), and others is that mispricing is more likely in networks in which the meeting rate of participants is lower. We find strong empirical support for this hypothesis. Specifically, using an IV approach, we find that an increase in the frequency at which participants meet and trade is associated with a significant decline in mispricing.

In summary, this paper contributes to the literature in three important ways. First, by being among the first papers to focus on the cross-section of mispricing, we are able to test the implications of current theoretical models in ways not possible using only time series data. Second, the results indicate that there are multiple sources for asset mispricing—no single theory completely explains the cross-sectional patterns of mispricing observed in the

[1] We are grateful to the referee for this insight.

data. In particular, we find strong empirical support for the implications of both the intermediary-constraints and the search-frictions/network-structure literatures. Furthermore, we also find evidence that the convenience yield incorporated into Treasury securities plays a significant role in accounting for the apparent mispricing of guaranteed corporate bonds relative to Treasuries. Finally, our results suggest a number of possible new directions for future theoretical models. In particular, the results highlight the need for models that allow for intermediary heterogeneity across assets as well as for theoretical frameworks in which balance sheet constraints may impact asset pricing in ways other than through the traditional inventory channel.

2. Cross-sectional implications of the literature

In this section, we summarize some of the broad themes that appear in the theoretical literature on asset mispricing and consider the potential implications of these themes for the cross-sectional characteristics of mispricing.

2.1. Treasuries as money

An important recent literature highlights the unique safe-asset or near-money characteristics of Treasury securities—we denote this as the Treasuries-as-money literature. Longstaff (2004), Krishnamurthy and Vissing-Jorgensen (2012), Nagel (2016), and others show that Treasury securities trade at premium prices relative to other securities with similar credit risk and liquidity features. As discussed by Krishnamurthy and Vissing-Jorgensen (2012), this premium may reflect the store-of-value or medium-of-exchange role that Treasury securities can play during flights to safety in the financial markets.

Krishnamurthy and Vissing-Jorgensen (2012) use a framework in which agents derive utility from holding a convenience asset to model the near-money premium in Treasury securities. A key insight of their model is that the near-money premium may vary across Treasury bonds with different levels of price risk. Recall that the price risk of a Treasury bond is directly related to its maturity or duration. While Krishnamurthy and Vissing-Jorgensen (2012) do not provide specific predictions about the relation between duration and the safety/liquidity premium, they do make the important point that these premia may differ between less-risky short-term assets and riskier long-term assets. In particular, they state on page 240 that “our specification emphasizes that the safety attributes may differ across short- and long-term assets and thus lead to differences in convenience value in long-term assets relative to short-term assets.” Thus, a natural implication of their model is that there may be some type of term structure to the near-money premia in Treasury securities.[2] We note also that this implication is also consistent with classic limits-to-arbitrage theory. In particular, limits to arbitrage are more likely to bind for riskier securities. In turn, this suggests the possibility of a cross-sectional relation between the duration of Treasury securities and the size of the near-money premium incorporated into their prices. Since we estimate mispricing from the difference between the prices of Treasury-guaranteed corporate bonds and matched-maturity Treasury bonds, this suggests the following:

Cross-sectional implication 1:

Mispricing is positively related to the price risk of the matched-maturity Treasury security.

2.2. Intermediary balance sheet constraints

A rapidly-growing literature addresses the relation between asset prices and balance sheet constraints faced by financial intermediaries. One stream of this literature focuses specifically on the effect of equity or capital constraints on asset pricing. Important examples include Xiong (2001), Kyle and Xiong (2001), He and Krishnamurthy (2012, 2013), Brunnermeier and Sannikov (2014), He et al. (2017), and Kondor and Vayanos (2019). Although differing in details, these models share a common underlying economic mechanism: an adverse shock to the capital of a financial intermediary reduces its risk-bearing capacity which, in turn, leads to reductions in their security positions and a corresponding increase in mispricing.

A second stream of the literature focuses on the effects of the margin or leverage constraints faced by a financial intermediary on asset pricing. Key examples include Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), Adrian et al. (2014), and Morelli et al. (2019). The common economic mechanism in these models is that an adverse shock to the ability of intermediaries to fund leveraged security positions again reduces their risk-bearing capacity, which is then followed by declines in their holdings of securities and an increase in the mispricing of assets.

One challenge we face in identifying the implications of this literature for the cross-section of mispricing is that most of the models are developed in settings with only one asset and/or a single representative intermediary. Thus, these models may only have meaningful implications for the time series properties of mispricing. For example, applying Brunnermeier and Pedersen (2009) or Gârleanu and Pedersen (2011) to the market we study implies that mispricing should literally be constant across bonds.[3] Motivated by the spirit of this literature, however, we take the broader interpretation that intermediary balance sheet constraints could still be relevant if these models were extended to more realistic settings allowing for heterogeneity in intermediaries across assets. For example, this type of heterogeneity could occur endogenously in models of network formation in which intermediaries choose to specialize on the basis of asset-specific characteristics. Alternatively, this type of fragmentation could oc-

[2] Other research showing that some Treasury securities trade at a premium relative to others includes Amihud and Mendelson (1991), Kamara (1994), Duffee (1996), Krishnamurthy (2002), Fleckenstein et al. (2014), and Fleckenstein and Longstaff (2020).

[3] This follows since the intermediary—who faces the same tri-party repo margin across all guaranteed corporate bonds in this market—equilibrates the ratio of mispricing to margin across all bonds in these models.

cur if intermediaries faced exogenous frictions that limited their ability to make markets across all securities in an asset class. These considerations suggest the following patterns for mispricing across assets:

Cross-sectional implication 2:

Mispricing is larger for assets whose primary intermediaries face

- higher capital costs or
- higher margins.

2.3. Search frictions and network structure

Another important literature focuses on the microstructure of decentralized markets such as those in which the guaranteed bonds we study trade. There are at least three major streams of this literature.

First, an important recent stream focuses on the role of search frictions in financial markets. Important examples include Wolinsky (1990), Duffie et al. (2005, 2007), Vayanos and Wang (2007), Weill (2007), Vayanos and Weill (2008), Duffie and Strulovici (2012), and Duffie et al. (2015a). In these types of models, trading occurs as investors search for intermediation in opaque over-the-counter markets. In many of these models, intermediation occurs through the random pairwise matching of market participants. As a result, the meeting rate of network participants becomes a critical asset pricing factor. For example, in (Duffie, 2010, pg. 1242) “the size of the immediate price reaction and the halflife of its reversal are decreasing in the mean rate at which investors locate suitable counterparties.”

Second, another stream considers the impact of network structure as investors search for intermediation in financial markets. Important recent examples of this rapidly growing literature include Atkeson et al. (2015), Babus (2016), Di Maggio et al. (2017), Babus and Hu (2017), Farboodi (2017), Babus and Kondor (2018), Sambalaibat (2018), Afonso and Lagos (2015), Neklyudov (2019), Üslü (2019), Eisfeldt et al. (2019). While few of these models focus exclusively on asset pricing, a number of them suggest that specific network features may be related to equilibrium prices. One such feature is the interconnectivity of dealers at the center of a core-periphery network. For example, Sambalaibat (2018) uses a directed-search model of network formation to show that dealer interconnectiveness results in higher dealer volume, improves bond market liquidity, and alleviates misallocations. Another feature is network centrality. In particular, the results in Babus and Hu (2017), Üslü (2019) and Eisfeldt et al. (2019) suggest that deviations from fair value may be related to the concentration of dealer positions at the core of the network. We note, however, that the sign of the effect of changes in dealer centrality varies across models in the current literature.[4] Finally, a number of models share the implication that the core of the network consists of a set of investors that function as intermediaries because they experience higher meeting rates (for either endogenous or exogenous reasons) than investors in the periphery. Key examples include Farboodi et al. (2020) and Üslü (2019). In these types of models, equilibrium prices may depend on the size of the core relative to that of the periphery (e.g., the number of dealers versus the number of customers or the ratio of dealer trading volume to customer trading volume). Although current network models are typically developed in a single-asset setting, we again hypothesize that they could be embedded in broader settings in which heterogeneity in network structure could potentially help explain differences in mispricing across assets.

A third stream focuses on the role of slow-moving capital in asset pricing. Key examples of this literature include Pagano (1989), Caballero (1995), Lynch (1996), Gabaix and Laibson (2001), Mitchell et al. (2007), and Chien et al. (2012). Another important example is Duffie (2010), who presents a model in which intermediaries trade every period, but some fraction of their customers are inattentive over an extended period after trading. When supply or demand shocks occur, the resulting limited depth of the market requires price concessions to obtain immediacy. These price concessions are gradually reversed over time as inattentive customers eventually return to the market. One implication of this framework is that mispricing may be larger during periods characterized by low levels of customer trading activity.

The key implications of the various streams of this literature can be summarized as follows:

Cross-sectional implication 3:

Mispricing is larger for assets with

- longer search times/lower meeting rates,
- networks with either higher or lower dealer concentration, or
- lower relative customer trading activity.

2.4. Liquidity models

Finally, there is an extensive literature considering the impact of transaction costs and illiquidity on security prices. In these models, investors may face significant trading costs or other types of illiquidity that prevent them from arbitraging away mispricing. Examples of research focusing on the implications of transaction costs and illiquidity for asset prices include Demsetz (1968), Amihud and Mendelson (1986), Boudoukh and Whitelaw (1993), Vayanos (1998), Vayanos and Vila (1999), Acharya and Pedersen (2005), Amihud et al. (2005), Huang and Wang (2009, 2010), and Chen et al. (2018b). This literature suggests the following:

Cross-sectional implication 4:

Mispricing is larger for assets with higher transaction costs/lower liquidity.

3. The Federal Deposit Insurance Corporation Debt Guarantee Program

Our approach to identifying asset mispricing is to compare the yields on corporate bonds that are explicitly guar-

[4] For example, Li and Schürhoff (2019) state: “By contrast, network-based models show that trading costs depend on dealer centrality. Predictions of a centrality premium or discount, however, are ambiguous in both types of models.”

anteed by the full faith and credit of the United States with those of comparable US Treasury bonds. This approach closely parallels Longstaff (2004), who studied the relative pricing of Refcorp and US Treasury bonds.

In particular, we focus on the pricing of corporate bonds that were issued under a debt guarantee program administered by the Federal Deposit Insurance Corporation (FDIC). In the wake of the failure of Lehman Brothers, and as part of a coordinated response within the US government to prevent what was described as the possible collapse of credit markets, the FDIC introduced the Temporary Liquidity Guarantee Program (TLGP) on October 14, 2008. This program consisted of two parts: the Transaction Account Guarantee Program, which involved an FDIC guarantee in full of all non-interest-bearing accounts, and the Debt Guarantee Program which involved a guarantee of certain newly-issued unsecured debt. The bonds we consider were issued as part of the Debt Guarantee Program.

The goal of the Debt Guarantee Program was to allow institutions to roll over senior unsecured debt by issuing new debt in their own name, backed by a government guarantee. The program provided a guarantee for debt issued by FDIC-insured depository institutions as well as their parent bank holding companies.[5] The guarantee was for newly issued debt only, and (ultimately) that debt needed to be issued before the end of October 2009; the guarantee expired on December 31, 2012.[6]

US Treasury bonds are guaranteed by the full faith and credit of the United States. It is important to note that the FDIC guarantee under the Debt Guarantee Program is also explicitly backed by the full faith and credit of the United States. Specifically, the FDIC's Final Rule, issued in November 2008, states that the FDIC's guarantee of qualifying credit debt under the Debt Guarantee Program is subject to the full faith and credit of the United States pursuant to Section 15(d) of the Federal Deposit Insurance (FDI) Act, 12 USC 1825(d).[7]

In fact, the Master Agreement for the Debt Guarantee Program contains the requirement that the following text be included, exactly as written, in each security issued under the program:

> The parties to this Agreement acknowledge that the Issuer has not opted out of the debt guarantee program (the "Debt Guarantee Program") established by the Federal Deposit Insurance Corporation ("FDIC") under its Temporary Liquidity Guarantee Program. As a result, this debt is guaranteed under the FDIC Temporary Liquidity Guarantee Program and is backed by the full faith and credit of the United States. The details of the FDIC guarantee are provided in the FDIC's regulations, 12 CFR Part 370, and at the FDIC's website, www.fdic.gov/tlgp. The expiration date of the FDIC's guarantee is the earlier of the maturity date of this debt or June 30, 2012.

Furthermore, the Master Agreement is explicit that bondholders receive timely payment of principal and interest even if a default occurs. In particular, Section 370.12 of the Final Rule states:

> Upon the occurrence of a payment default, the FDIC shall satisfy its guarantee obligation by making scheduled payments of principal and interest pursuant to the terms of the debt instrument through maturity (without regard to default or penalty provisions).

Thus, for the lifetime of the guarantee program, payments will continue as scheduled regardless of the default of the issuer—the timing of principal and interest cash flows is guaranteed to be unaffected by a default.[8] The guarantee is not only for the bond's principal; the full schedule of cash flows from the bond itself is guaranteed.

Finally, we observe that the explicit full faith and credit guarantee of corporate debt issued under the FDIC program was honored ex post. In particular, the FDIC reported in its summary of the TLGP that it fully covered the losses suffered by debtholders from the defaults by six financial institutions that participated in the program. The total amount of the defaulted principal and interest payments covered by the FDIC was $153 million.[9]

4. The data

Our objective is to examine the asset pricing implications of the literature using the cross-section of these guaranteed corporate bonds. A unique feature of our study is the availability of several proprietary data sets that provide us direct measures of key variables including the inventory positions and margins of individual dealers in the market.[10]

4.1. The transactions data

We were given access to a confidential version of the Trade Reporting and Compliance Engine (TRACE) database. This database contains all over-the-counter trades in publicly traded US corporate bonds, including those issued under the Debt Guarantee Program. This version differs from the public version of TRACE in that it explicitly identifies the dealers involved in each transaction and includes the actual size of each transaction.[11] An important advantage

[5] Savings and loan corporations with certain business models and other financial entities were also allowed to participate subject to case-by-case approval.

[6] Both the issuance window and the end of the guarantee given here are the result of deadline extensions that occurred in 2009.

[7] The Appendix provides additional details about the FDIC guarantee including the legislative background establishing its full faith and credit nature.

[8] Though allowed by the Debt Guarantee Program, no one issued debt under the program for longer than the guarantee period, so this guarantee was applicable through the full lifetime of all of the bonds used in our study.

[9] The six defaulting institutions (and the par amount of defaulted debt) were Integra Bank ($51 million), Bradford Mid-Tier Company ($2 million), Coastal Community Bank ($3.8 million), Washington First Financial Group ($34.4 million), the Park Avenue Bank ($20 million), and Superior Bank ($40 million).

[10] The Appendix and Internet Appendix provide additional details about how the variables are constructed as well as the data sets.

[11] In contrast, the public version of TRACE data used in most other studies is subject to a dissemination cap of $5 million per transaction, and all transactions in excess of $5 million are disseminated as "$5MM+."

of this is that we can infer directly the inventory holdings of each dealer in the market for each of the bonds in the sample. Furthermore, the TRACE data set also includes an indicator for whether the transaction is between a dealer and another dealer or between a dealer and a customer. This allows us to identify both total customer trading volume and total interdealer trading volume (which we denote simply as dealer trading volume) for each of the bonds in the sample.

4.2. Corporate bond data

The sample of guaranteed corporate bonds consists of 63 fixed coupon bonds issued under the Debt Guarantee Program of the FDIC and publicly traded during the sample period from December 2008 to December 2012. As required by the terms of the program, all of the bonds have fixed principal and bullet maturity terms, are senior in the capital structure, and have no special features such as call, put, sinking fund, or conversion provisions. The data source for bond characteristics such as the bond type, issue date, outstanding amount, maturity, and coupon rate is the Fixed Income Securities Database (FISD). We limit the sample to bonds that make fixed, semi-annual coupon payments and have at least 180 days to maturity, and thus the data used in the study concludes with trades occurring on June 28, 2012. The data on secondary-market transactions and prices of these bonds are from the confidential version of TRACE described above. We compute the closing transaction price for each trading day based on institutional-sized trades with a volume of at least $100,000. These trades account for more than 98% of the total trading volume.

4.3. Dealer capital constraints

To measure dealer capital costs, we focus on the CDS spreads of a set of 12 dealers that represent the main intermediaries in our sample. We designate these dealers as the primary dealers. Each of these dealers was the largest inventory holder for at least one of the sample bonds at some point during the sample period. These primary dealers account for 82% of the total inventory holdings for the bonds in the sample. They are also major participants in the tri-party repo market. The dealer CDS spread is used as a measure of intermediary capital constraints in a number of other studies including Gilchrist and Zakrajšek (2012) and Copeland et al. (2014). We obtain daily market prices for five-year CDS contracts for the primary dealers. The source of the CDS data is Markit.

It is important to recognize that CDS spreads are based on the total financial risk of the dealers. For the primary dealers in our sample, however, the amount of guaranteed bonds held in inventory represents only a tiny fraction of their total balance sheet. For example, Federal Reserve Weekly Reports of Dealer Positions (FR 2004A) indicate that dealers' inventory holdings of guaranteed bonds during the sample period represented only 1.5% of their total holdings of bonds. Thus, primary dealer CDS spreads should be free from reverse causation effects from mispricing since any mispricing of the guaranteed bonds would not have any material impact on the financial position of the dealer.

4.4. Dealer margins

We also have access to a confidential data set from the Federal Reserve Bank of New York that identifies the margin or haircut that each dealer must pay to obtain repo financing for corporate bonds. This data set consists of disaggregated data on haircuts for corporate bond collateral posted by individual dealers in the tri-party repo market. We note that the tri-party repo market is a major source of funding for the inventory holdings of large dealers. Later in the paper, we also consider the role of an alternative source of funding for dealer inventory holdings, namely the GCF Repo service of the FICC.

An important feature of the tri-party repo market is that the haircut for an individual dealer is determined at the asset class level—in this case, the corporate bond asset class—rather than at the individual bond level. This means that a dealer financing inventory in the tri-party repo market faces the same haircut for all corporate bonds—the haircut is not specific to the guaranteed bonds in the sample. Because of this, the haircuts faced by individual dealers in this market should also be free of reverse causation effects from mispricing since a dealer's guaranteed bond holdings represent only a small fraction of the dealer's total corporate bond portfolio.[12]

4.5. Network measures

The inventory and trading volume data obtained from the confidential TRACE data set also provides us with the ability to identify a number of key measures for the networks in which the individual guaranteed bonds trade. For example, we identify the number of dealers in the network for a specific bond by simply counting the number of dealers holding inventory positions in that bond. Similarly, knowing the inventory held by each dealer in a network allows us to estimate dealer centrality or concentration measures for that network. In particular, we calculate the dealer centrality measure as the ratio of the total inventory held by the primary dealer for a bond to the total inventory held by the set of the 12 primary dealers for the bond. This ratio provides a measure of the degree of concentration within the core of the network. Having dealer and customer trading volume data for each bond also allows us to measure the relative amount of trading activity involving the core and periphery of the network.

Specifically, we compute the dealer share of trading volume as the ratio of total dealer trading volume to total trading volume. This ratio provides a measure of the relative activity of the core versus the periphery of the network. Alternatively, this ratio can also be viewed as a measure of the length of the intermediation chain because more interdealer trading activity may imply that the bond

[12] For example, over the sample period, the set of all 63 guaranteed bonds in the sample accounts for only 4.3% of the total corporate bond trading volume reported in TRACE.

passes through several dealers before it ultimately reaches the customer.

Finally, we collect data on the total number of institutions that hold positions in the individual guaranteed bonds from the eMAXX database. This data source provides quarterly measures of the amount of each bond in the sample that is held by institutions such as insurance companies, mutual funds, public pension funds, endowment funds, and foundations.

4.6. Liquidity measures

We use a number of metrics to measure bond liquidity. First, we include the daily effective bid-ask spread as a direct measure of transaction costs for each bond. The effective bid-ask spread is estimated from the individual transactions in the confidential TRACE data set. Second, we also estimate the Amihud (2002) measure using the individual transactions in the confidential TRACE data set. Finally, we include standard measures of bond liquidity used in the literature such as the age of the bonds as well as the total notional amount of the bond outstanding.[13]

4.7. Descriptive statistics

Table 1 provides summary statistics for guaranteed bonds in the sample including a number of dealer-related variables used throughout the paper. The first three of these variables—dealer CDS, dealer margin, and dealer inventory—are based on the set of 12 primary dealers as described above. In particular, the dealer CDS and dealer haircut measures used in the study are the inventory-weighted average CDS spreads and haircuts for the set of primary dealers holding inventory positions in a specific bond, where the weights are based on the total inventory held by the set of primary dealers at the end of the previous month. Similarly, dealer inventory is defined as the percentage of the total bond issue held by the set of primary dealers. In contrast, the number of dealers is defined as the total number of dealers that transact in a specific bond (not just those in the set of primary dealers). Likewise, trading volume is based on the transactions of all dealers and customers (trading volume variables are normalized by the size of the bond issue unless otherwise specified).

Fig. 1 plots the cross-sectional distributions of dealer CDS spreads, margins, and inventory throughout the sample period. As shown, there is considerable cross-sectional variation across bonds in terms of the CDS spreads, margins, and inventory positions of the primary dealers for those bonds. Fig. 2 plots the average inventory holdings for the individual bonds for the top eight primary dealers (the plots for the other four smaller primary dealers are similar to those shown). As illustrated, there is significant heterogeneity across dealers in terms of their inventory holdings for individual bonds—different dealers appear to specialize in different bonds. This feature is important since it is this heterogeneity that will allow us to identify dealer effects in the cross-section. The distribution of dealer inventory holdings in Fig. 2 also suggests that the networks for these guaranteed bonds display a core-periphery structure similar to that observed in other markets.[14] Finally, Fig. 3 plots the cross-sectional distribution of the number of dealers, the number of institutional investors, and the trading frequencies for the individual bonds throughout the sample period.

5. Mispricing of guaranteed corporate bonds

We use a simple two-step procedure to identify mispricing. First, we take the difference between the yield on a guaranteed corporate bond and the yield on a matching Treasury bond with the identical coupon rate and maturity date. The yield on a guaranteed corporate bond for a given day is based on the final transaction price for that bond on that day. We note that the TLGP bond markets are relatively liquid and that 73.4% of the final transaction prices occur after 3:30 PM ET, while 83.4% occur after 2:30 PM ET. To determine the yields for these matching Treasury bonds, we use the daily spot curve constructed from off-the-run, fixed coupon Treasury securities with residual maturities of 90 days or more. The zero coupon Treasury curve is generated using the functional form proposed by Nelson and Siegel (1987) as extended by Svensson (1994) and is based on market prices observed at 3:30 PM ET. Thus, there should be relatively little mismatch in the timing of the TLGP and Treasury yields used to estimate mispricing. Furthermore, even if slight timing differences introduce some noise into our estimates of mispricing, they are unlikely to bias those estimates. A detailed description of the estimation methodology used to measure the zero coupon Treasury curve is given in Gurkaynak et al. (2006).

From the fitted Treasury spot curve, we calculate the price of a Treasury bond with the same coupon and maturity as the corporate bond and determine the yield spread. We compute the yield spread for each bond for each day in the sample period and provide descriptive statistics and further details in the remainder of this section. For analyses in later sections where some data are only available at the monthly frequency, we use the yield spread observed on the last trading day of the month as the monthly estimate of mispricing.

Second, we make a small adjustment to the yield spread due to the difference in the state income taxation of corporate and Treasury bonds. As discussed in Elton et al. (2001), corporate bonds are subject to state income taxation, while Treasury bonds are not. The Appendix shows that the state income tax effect on the yield spread is simply $c\ \tau_s\ (1-\tau)$, where c is the coupon rate, τ_s is the marginal state income tax rate, and τ is the marginal federal income tax rate. The Appendix also shows that the state income tax effect can be identified from a cross-sectional regression of yield spreads on coupon rates. The

[13] The liquidity measures are described in more detail in the Internet Appendix.

[14] For example, see Duffie et al. (2015b), Hollifield et al. (2017), and Li and Schürhoff (2019).

Table 1
Descriptive statistics for the guaranteed bonds.

This table presents descriptive statistics for the individual guaranteed bonds. Statistics are time series averages of month-end values for each bond. Issue size is in billions of dollars. Dealer CDS and Dealer haircut are inventory-weighted averages for the primary dealers and are expressed in basis points and percentages, respectively. Dealer inventory is total dealer inventory as a percentage of the issue size. Num of dealers denotes the average number of dealers that execute trades in a bond. Num of invest denotes the average number of institutional investors holding positions in the bonds. Dealer central denotes the ratio of primary dealer inventory to total dealer inventory. Ratio of volumes denotes the ratio of dealer trading volume to total trading volume. *N* denotes the number of observations. The sample is monthly from December 2008 to June 2012.

Issuer	Coupon	Maturity	Issue size	Dealer CDS	Dealer haircut	Dealer inventory	Num of dealers	Num of invest	Dealer central	Ratio of volumes	*N*
American Express	3.150	12–2011	3.50	138.04	5.78	6.59	18.44	68.80	0.40	0.19	25
Bank of America	2.100	04–2012	6.00	156.74	6.27	10.13	28.06	94.85	0.28	0.25	34
Bank of America	3.125	06–2012	8.25	159.04	6.15	8.49	39.41	111.11	0.39	0.27	37
Bank of America	2.375	06–2012	2.00	168.94	5.95	17.07	22.91	47.88	0.32	0.26	34
Bank of America NA	1.700	12–2010	3.75	135.93	5.55	11.07	24.63	38.63	0.40	0.35	19
Bank of the West	2.150	03–2012	1.00	176.17	5.98	10.80	9.77	29.94	0.57	0.26	31
Citibank	1.625	03–2011	1.00	140.89	5.81	16.85	12.06	18.06	0.47	0.33	16
Citibank	1.500	07–2011	1.75	141.23	5.48	15.40	14.16	27.00	0.25	0.28	19
Citibank	1.375	08–2011	2.50	147.93	6.02	8.15	18.39	27.83	0.51	0.14	18
Citibank	1.250	09–2011	1.50	146.41	6.26	10.81	15.21	23.47	0.68	0.20	19
Citibank	1.250	11–2011	1.25	150.04	6.13	21.35	12.00	15.75	0.62	0.25	20
Citibank	1.875	05–2012	2.25	167.92	5.95	13.44	18.00	42.87	0.51	0.21	30
Citibank	1.875	06–2012	1.30	175.73	6.21	8.54	10.17	31.80	0.48	0.30	30
Citigroup	1.375	05–2011	2.30	152.32	5.58	18.22	14.83	33.89	0.36	0.31	18
Citigroup	1.250	06–2011	1.40	135.78	6.05	9.63	10.72	14.06	0.42	0.39	18
Citigroup	2.875	12–2011	3.75	150.75	6.00	12.34	36.50	85.80	0.43	0.31	30
Citigroup	2.000	03–2012	1.00	179.00	6.29	17.26	14.42	33.00	0.65	0.35	31
Citigroup	2.125	04–2012	8.00	193.66	6.07	10.51	31.74	92.79	0.57	0.31	34
Citigroup	2.125	07–2012	1.75	184.86	6.24	10.00	14.68	49.23	0.69	0.22	31
Citigroup	1.875	10–2012	5.00	164.80	6.23	15.52	25.16	86.13	0.65	0.30	31
Citigroup	1.875	11–2012	2.50	172.79	6.35	14.82	16.00	51.30	0.72	0.25	30
Citigroup	2.250	12–2012	2.50	170.85	6.33	20.27	26.91	69.53	0.72	0.27	32
General Electric	1.625	01–2011	2.50	140.09	5.46	13.99	26.39	24.17	0.29	0.37	18
General Electric	1.800	03–2011	4.95	136.73	5.58	14.38	27.06	51.89	0.31	0.36	18
General Electric	3.000	12–2011	4.90	142.44	5.92	13.53	36.77	94.23	0.42	0.34	30
General Electric	2.250	03–2012	2.92	160.87	5.94	19.12	21.20	52.30	0.41	0.27	30
General Electric	2.200	06–2012	4.50	172.73	6.27	11.94	31.86	79.14	0.38	0.27	35
General Electric	2.000	09–2012	3.65	188.06	6.62	18.64	19.47	59.81	0.45	0.23	32
General Electric	2.450	12–2012	0.15	179.26	7.07	0.00	1.25	4.13	0.00	0.12	8
Goldman Sachs	1.700	03–2011	1.00	139.14	5.65	26.59	16.94	19.89	0.63	0.26	18
Goldman Sachs	1.625	07–2011	3.50	152.66	5.83	13.45	33.58	58.63	0.35	0.35	24
Goldman Sachs	2.150	03–2012	1.00	150.84	6.09	14.36	14.37	25.97	0.37	0.29	30
Goldman Sachs	3.250	06–2012	5.50	161.70	6.05	14.88	40.24	112.08	0.47	0.27	37
HSBC	3.125	12–2011	2.33	124.35	6.22	12.94	17.74	59.90	0.41	0.23	31
John Deere	2.875	06–2012	2.00	150.58	6.03	15.93	33.78	95.62	0.41	0.25	37
JP Morgan Chase	2.625	12–2010	3.00	113.70	5.55	15.20	33.72	39.67	0.26	0.45	18
JP Morgan Chase	1.650	02–2011	2.00	109.02	5.53	19.60	22.53	28.68	0.36	0.30	19
JP Morgan Chase	3.125	12–2011	5.00	131.39	5.92	11.48	38.87	87.17	0.40	0.31	30
JP Morgan Chase	2.200	06–2012	3.00	153.50	6.03	12.40	25.69	63.57	0.56	0.22	35
JP Morgan Chase	2.125	06–2012	3.00	150.62	5.77	14.42	23.35	61.05	0.36	0.25	37
JP Morgan Chase	2.125	12–2012	2.30	156.60	5.98	22.37	30.53	62.00	0.38	0.31	36
Keybank	3.200	06–2012	1.00	180.21	5.95	19.18	21.92	60.41	0.41	0.22	37
Morgan Stanley	2.900	12–2010	2.50	165.90	5.33	16.45	26.78	31.50	0.43	0.43	18
Morgan Stanley	2.000	09–2011	2.50	177.95	5.75	9.43	21.25	42.61	0.38	0.26	28
Morgan Stanley	3.250	12–2011	3.25	156.65	6.01	12.60	21.50	77.23	0.48	0.29	30
Morgan Stanley	2.250	03–2012	2.00	166.14	6.00	19.48	14.17	41.90	0.38	0.19	30
Morgan Stanley	1.950	06–2012	3.00	160.48	6.00	7.33	18.56	63.58	0.63	0.19	36
NY Comm Bank	3.000	12–2011	0.51	178.52	6.03	5.73	13.03	20.83	0.28	0.18	30
NY Comm Bank	2.550	06–2012	0.09	237.53	6.18	1.04	2.46	8.92	0.58	0.16	13
Oriental Bank	2.750	03–2012	0.11	199.13	6.89	0.53	2.07	2.50	0.43	0.22	14
PNC	1.875	06–2011	0.50	174.29	5.71	10.14	12.92	19.48	0.50	0.17	25
PNC	2.300	06–2012	2.00	164.62	5.96	10.54	26.68	87.57	0.33	0.22	37
Regions Bank	2.750	12–2010	1.00	148.25	5.59	25.18	22.89	17.78	0.45	0.46	18
Regions Bank	3.250	12–2011	1.99	138.27	6.10	16.40	28.10	80.13	0.31	0.28	30
Sovereign Bank	2.750	01–2012	1.35	170.38	5.92	11.03	15.91	53.13	0.41	0.25	32
Sovereign Bank	2.500	06–2012	0.25	194.32	5.90	5.45	5.17	6.23	0.79	0.20	35
State Street	1.850	03–2011	1.00	137.90	5.43	18.93	16.56	25.78	0.50	0.22	18
State Street	2.150	04–2012	1.50	149.72	6.08	12.53	20.41	69.44	0.34	0.23	32
Suntrust	3.000	11–2011	2.24	169.45	5.92	7.14	21.33	52.37	0.37	0.23	30
US Bancorp	2.250	03–2012	1.10	145.43	6.04	10.75	25.63	32.43	0.38	0.23	30
US Bancorp	1.800	05–2012	1.08	167.79	5.98	7.53	12.93	26.20	0.63	0.20	30

(*continued on next page*)

Table 1 (*continued*)

Issuer	Coupon	Maturity	Issue size	Dealer CDS	Dealer haircut	Dealer inventory	Num of dealers	Num of invest	Dealer central	Ratio of volumes	*N*
Wells Fargo	3.000	12–2011	3.00	153.34	5.81	19.16	36.63	85.57	0.33	0.31	30
Wells Fargo	2.125	06–2012	1.75	169.26	6.26	12.16	17.91	49.29	0.35	0.28	34
Average				159.20	5.98	13.19	21.18	49.06	0.44	0.27	27

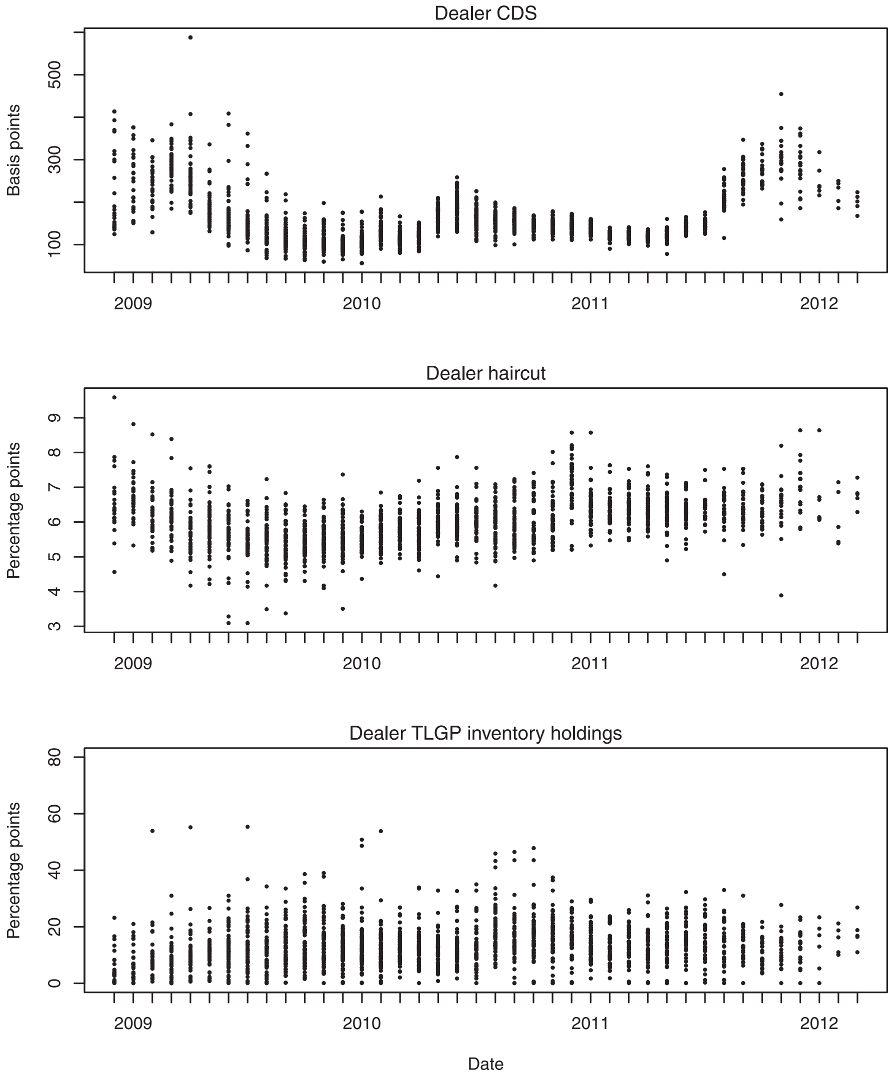

Fig. 1. Cross-sectional distribution of dealer CDS spreads, dealer haircuts, and dealer inventory.
This figure plots the monthly cross-sectional distribution of the dealer CDS spreads, dealer haircuts, and dealer inventory for the individual guaranteed bonds.

resulting estimate of $\tau_s(1-\tau)$ is 1.655%. We control for the state income tax effect by subtracting 0.01655 times the coupon rate of the bond from the yield spread. Because of the low coupon rates of the bonds, the average size of the state income tax effect is small, just 3.8 basis points.

Table 2 provides summary statistics for the mispricing of each of the bonds in the sample. The average mispricing is positive and highly statistically significant for all 63 bonds in the sample. The average mispricing across all bonds is 20.07 basis points. The median mispricing across all bonds is 14.07 basis points. Furthermore, 91.72% of all mispricing estimates are positive. These results provide strong evidence that guaranteed bonds with the same cash flows as Treasury securities traded at a significant spread to Treasuries during most of the sample period—a clear violation of the law of one price. These results are consistent with previous empirical research in the literature showing that essentially riskless securities often trade at a spread relative to Treasury securities.[15]

[15] For example, see Longstaff (2004) (guaranteed Refcorp bonds), Krishnamurthy and Vissing-Jorgensen (2012) (commercial paper),

Table 2
Summary statistics for the mispricing of the guaranteed bonds.
This table presents summary statistics for the mispricing of the guaranteed bonds in the sample. The mispricing is measured as the basis point yield spread of the guaranteed bonds in the sample over Treasury bonds, adjusted for the effect of state income taxes. The columns titled 10%, 50%, and 90% denote the 10th, 50th, and 90th percentiles of the distribution. *N* denotes the number of observations. The sample is daily from December 1, 2008 to June 28, 2012.

Issuer	Coupon	Maturity	Mean	St. dev	10%	50%	90%	N
American Express	3.150	12–2011	12.83	16.93	−0.33	10.32	24.40	411
Bank of America	2.100	04–2012	21.33	22.18	0.96	15.74	47.21	643
Bank of America	3.125	06–2012	24.56	28.19	2.78	15.66	72.56	736
Bank of America	2.375	06–2012	16.84	16.99	0.44	13.37	34.39	487
Bank of America NA	1.700	12–2010	18.65	25.40	−1.64	7.47	59.69	337
Bank of the West	2.150	03–2012	18.78	17.85	0.08	14.97	40.05	263
Citibank	1.625	03–2011	9.75	10.33	−1.59	8.35	21.46	167
Citibank	1.500	07–2011	12.74	10.26	−1.69	12.81	25.54	236
Citibank	1.375	08–2011	10.72	9.83	−2.36	10.32	23.08	280
Citibank	1.250	09–2011	8.42	8.96	−2.45	6.95	20.15	227
Citibank	1.250	11–2011	10.52	8.04	0.29	9.74	21.64	212
Citibank	1.875	05–2012	17.82	12.55	2.19	15.93	36.88	399
Citibank	1.875	06–2012	16.66	12.62	0.65	15.39	35.04	278
Citigroup	1.375	05–2011	12.84	10.75	−1.06	11.60	26.53	244
Citigroup	1.250	06–2011	12.12	10.94	−3.11	14.48	23.57	131
Citigroup	2.875	12–2011	26.76	30.61	2.15	17.17	79.53	572
Citigroup	2.000	03–2012	20.06	17.80	−0.06	15.54	41.56	340
Citigroup	2.125	04–2012	22.77	22.13	1.88	17.02	47.46	651
Citigroup	2.125	07–2012	14.81	11.18	1.03	13.40	30.67	425
Citigroup	1.875	10–2012	15.14	11.27	0.39	15.23	31.50	570
Citigroup	1.875	11–2012	12.86	10.20	−1.81	13.09	28.14	430
Citigroup	2.250	12–2012	14.10	10.96	−1.10	14.07	27.98	605
General Electric	1.625	01–2011	20.14	21.39	2.25	10.33	56.84	323
General Electric	1.800	03–2011	16.11	17.88	−0.60	11.20	38.66	341
General Electric	3.000	12–2011	26.73	30.42	2.98	17.32	83.04	615
General Electric	2.250	03–2012	19.14	18.91	0.80	15.03	40.26	498
General Electric	2.200	06–2012	23.32	22.99	3.29	17.41	54.19	678
General Electric	2.000	09–2012	13.29	10.72	−0.66	12.89	28.74	533
General Electric	2.450	12–2012	14.62	13.74	2.42	11.90	44.51	9
Goldman Sachs	1.700	03–2011	13.94	16.50	0.16	8.20	41.24	256
Goldman Sachs	1.625	07–2011	19.07	20.74	−0.99	14.47	56.38	469
Goldman Sachs	2.150	03–2012	17.23	17.90	−0.03	13.37	35.40	325
Goldman Sachs	3.250	06–2012	24.21	27.44	2.13	15.84	69.10	740
HSBC	3.125	12–2011	23.47	28.10	0.56	13.53	77.62	526
John Deere	2.875	06–2012	22.05	23.55	2.05	14.40	64.02	681
JP Morgan Chase	2.625	12–2010	21.02	29.04	−0.63	8.10	60.88	342
JP Morgan Chase	1.650	02–2011	16.11	17.89	1.35	9.31	46.58	296
JP Morgan Chase	3.125	12–2011	25.11	30.69	3.95	14.34	75.12	614
JP Morgan Chase	2.200	06–2012	19.36	18.20	2.14	15.36	40.33	559
JP Morgan Chase	2.125	06–2012	23.12	23.59	1.39	16.41	65.52	607
JP Morgan Chase	2.125	12–2012	11.97	11.16	−0.67	10.77	24.14	728
Keybank	3.200	06–2012	22.83	25.63	0.55	15.32	69.14	600
Morgan Stanley	2.900	12–2010	22.61	30.87	0.00	10.20	60.42	351
Morgan Stanley	2.000	09–2011	21.73	27.54	−0.40	11.66	72.89	476
Morgan Stanley	3.250	12–2011	25.98	32.09	1.66	14.70	77.46	553
Morgan Stanley	2.250	03–2012	19.38	19.04	1.28	14.88	41.19	424
Morgan Stanley	1.950	06–2012	21.21	21.98	2.05	15.32	54.64	568
NY Comm Bank	3.000	12–2011	37.30	37.38	1.46	22.35	99.11	291
NY Comm Bank	2.550	06–2012	19.48	28.34	−1.95	12.94	49.28	29
Oriental Bank	2.750	03–2012	40.33	38.16	4.66	25.60	107.54	29
PNC	1.875	06–2011	26.47	29.58	−3.47	18.06	77.73	243
PNC	2.300	06–2012	22.22	23.83	1.39	14.79	66.99	647
Regions Bank	2.750	12–2010	23.92	30.96	−0.32	10.09	65.56	278
Regions Bank	3.250	12–2011	26.43	32.09	0.96	15.86	84.46	552
Sovereign Bank	2.750	01–2012	27.69	30.55	1.93	16.29	87.95	418
Sovereign Bank	2.500	06–2012	29.69	29.06	2.26	19.87	81.52	159
State Street	1.850	03–2011	13.81	16.20	−0.72	9.35	35.62	250
State Street	2.150	04–2012	18.64	19.89	0.34	14.69	40.64	517
Suntrust	3.000	11–2011	24.99	29.21	0.72	16.24	79.43	517
US Bancorp	2.250	03–2012	16.76	17.17	−0.32	13.60	34.54	409
US Bancorp	1.800	05–2012	15.05	11.76	1.47	13.78	31.59	314
Wells Fargo	3.000	12–2011	22.95	25.72	2.44	15.24	68.81	585
Wells Fargo	2.125	06–2012	14.45	13.29	0.27	11.86	29.97	488
All			20.07	23.13	0.71	14.07	46.58	26,482

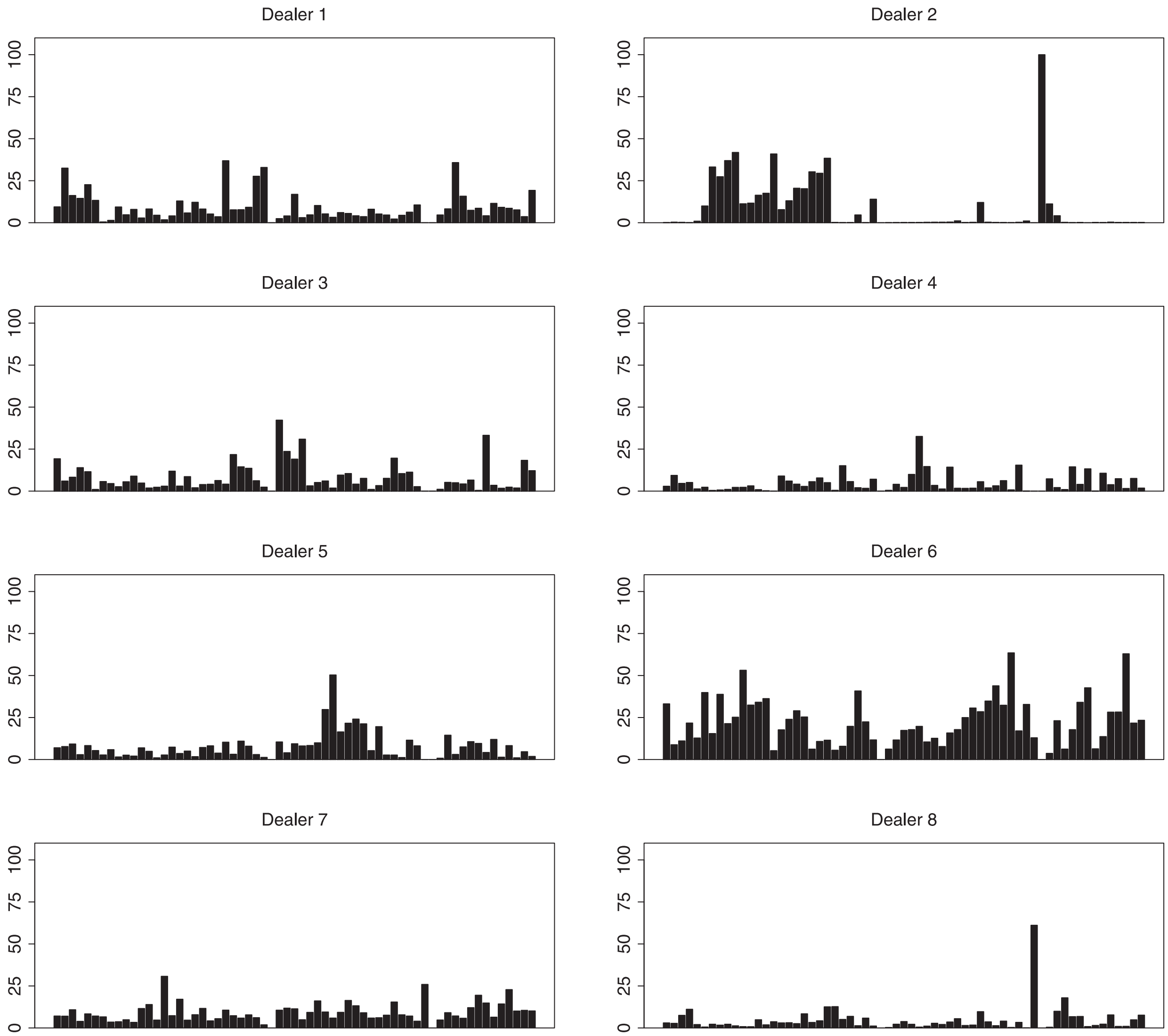

Fig. 2. Average inventory holdings of top primary dealers.
This figure plots the average inventory holdings of the top eight primary dealers for each of the individual guaranteed bonds as a percentage of the total inventory held by dealers for each bond.

Fig. 4 plots the time series of mispricing estimates for all the bonds in the sample. As shown, there is considerable variation in mispricing over time. Mispricing often exceeds 100 basis points during early 2009 but then shows a declining trend during most of the sample period. By the end of the sample period, mispricing generally appears to converge to near zero. A notable feature of the data, however, is the large dispersion of mispricing across bonds at any given point in time. During much of the sample period, the cross-sectional standard deviation of mispricing is in the range of 20 to 30 basis points. Even near the end of the sample period when average mispricing has converged to nearly zero, we still see evidence of significant cross-sectional dispersion in mispricing estimates for individual bonds.

To provide additional perspective on this cross-sectional dispersion, we compute pairwise correlations for mispricing of the bonds in the sample. In particular, we compute the correlation between the levels of mispricing for all pairs of bonds for which there are at least 20 days with data for both bonds during the sample period. This results in a set of 1811 pairwise correlations. The average pairwise correlation is 73.19%. These results indicate that while there is a strong common dimension to mispricing, mispricing is unlikely to be fully explained by a single common factor. Thus, there is significant cross-sectional variation in mispricing that needs to be explored.[16]

Nagel (2016) (repo loans), Nagel (2016) and Anderson et al. (2019) (interest on excess reserves), and Frame et al. (2015) (agency debt).

[16] The Internet Appendix provides a number of additional results about the cross-sectional pattern of mispricing across bonds. For example, the

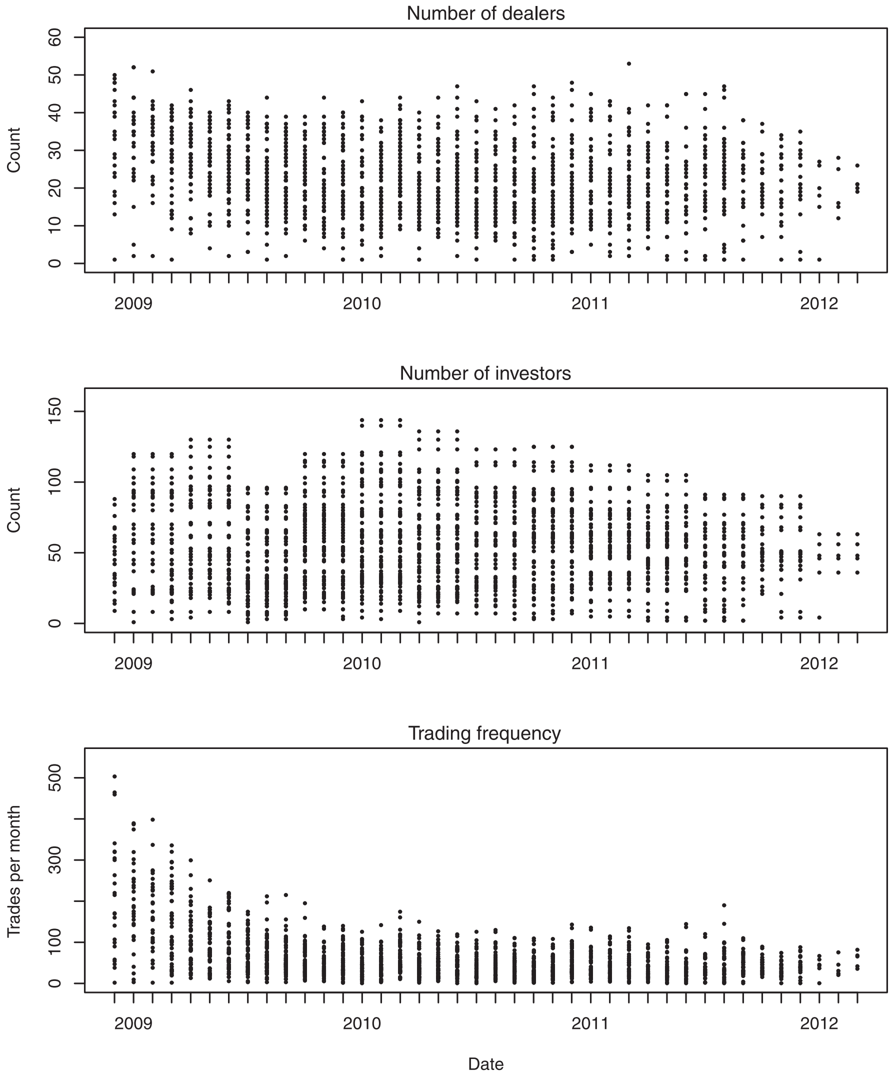

Fig. 3. Cross-sectional distribution of the number of dealers, number of institutional investors, and trading frequencies.
This figure plots the monthly cross-section of the number of dealers, number of institutional investors, and trading frequencies for the individual guaranteed bonds. Trading frequency is the number of times a bond trades during a month.

6. The panel regression tests

We turn next to testing the cross-sectional implications of the alternative models in the literature. In particular, we estimate a panel regression in which we regress mispricing on various measures of the price risk, intermediary balance sheet constraints, network structure, and liquidity of the bonds in the sample. In this panel regression, we include only explanatory variables that are unlikely to experience reverse causation effects from mispricing. In subsequent sections, however, we will also explore the relation between mispricing and potentially endogenous measures such as inventory and trading activity using IV techniques. Since most of our explanatory variables are observed monthly, we conduct this analysis at a monthly frequency using the mispricing observed on the last trading day of the month as the dependent variable. Thus, the basic observational unit in this analysis is bond-month. We note, however, that with much more granular intramonth data for the explanatory variables (e.g., institutional holdings, haircuts), it might also become possible to conduct the analysis at the bond-dealer-transaction level. Given the limitations of our data set, however, this extension must be left to future research.

In this panel regression, we include several controls for bond-specific characteristics. First, we include the coupon rate of the bond as a control for any residual marginal state income tax effects. Second, as discussed earlier, the credit risk of the issuer should not affect the pricing of the bond given the full faith and credit guarantee by the US. We include the CDS spread of the issuer, however, as a control

Internet Appendix shows that the first principal component captures only 57.10% of the variation in mispricing across bonds.

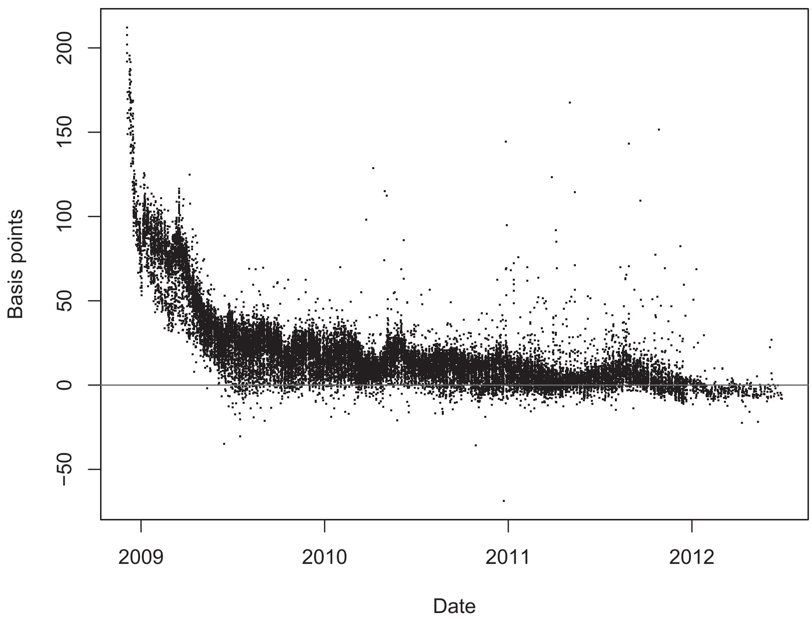

Fig. 4. Mispricing of individual bonds.
This figure plots the mispricing of the individual guaranteed bonds over time. Mispricing is measured in basis points.

for the possibility that investors may still believe that issuer credit remains a factor. Finally, since the panel regression is estimated in levels, we include monthly fixed effects to control for trends in the data. We note that the inclusion of monthly fixed effects also allows us to control for the potential effects of omitted common factors that may jointly impact mispricing and explanatory variables in the panel regression. In particular, while we have done our best to identify the key factors identified in the theoretical literature as driving mispricing, it is always possible that there are omitted factors. If so, and if these factors affect mispricing and explanatory variables in a purely time series way, then the monthly fixed effects should control for the effects of these excluded variables.[17]

To test the cross-sectional implications of the Treasuries-as-money literature, we require a measure of the price risk of the matching Treasury bonds used in estimating mispricing. Following standard practice in fixed income markets, we use the Macauley duration of the bond as the measure of its price risk.

To test the cross-sectional implications of the intermediary balance sheet constraints literature, we need measures of the balance sheet constraints facing the primary dealers holding positions in the guaranteed bonds. As a measure of the capital costs faced by these dealers, we use the inventory-weighted average of the CDS spreads for the primary dealers, where the inventory weights are determined at the end of the previous month. Similarly, as a measure of the leverage constraints faced by these dealers, we use the inventory-weighted average of the tri-party repo haircuts for the primary dealers.

To examine the relation between mispricing and network structure, we include several network measures in the panel regression. First, we include the number of dealers and the number of institutional investors holding positions in the individual bonds as of the end of the prior month. These variables provide measures of the relative sizes of the core and the periphery of the networks in which individual guaranteed bonds trade. Second, we include the ratio of the inventory held by the primary dealer to the total inventory held by all dealers as a measure of the degree of concentration in the core of the network. Third, we include the ratio of interdealer trading volume to all trading volume as a measure of the relative size of customer versus dealer trading activity in the network.

Finally, as measures of the trading costs and liquidity of the individual bonds, we include the age of the bond, the logarithm of the size of the bond issue, the effective bid-ask spread of the bonds, and the Amihud measure of the bonds in the regression.

The panel regression specification is given by Eq. (1):

$$\begin{aligned} Y_{it} = &\sum_{j=1}^{T} \alpha_j D_{jt} \ + \ \beta_1 \text{ Coupon}_i + \ \beta_2 \text{ Issuer CDS}_{it} \\ &+ \beta_3 \text{ Duration}_{it} + \ \beta_4 \text{ Dealer CDS}_{it} + \ \beta_5 \text{ Dealer haircut}_{it} \\ &+ \beta_6 \text{ Number of dealers}_{it} + \ \beta_7 \text{ Number of institutions}_{it} \\ &+ \beta_8 \text{ Dealer centrality}_{it} + \ \beta_9 \text{ Dealer share of volume}_{it} \\ &+ \beta_{10} \text{ Age}_{it} + \ \beta_{11} \text{ Issue Size}_i + \ \beta_{12} \text{ Bid-ask spread}_{it} \\ &+ \beta_{13} \text{ Amihud measure}_{it} + \epsilon_{it} \end{aligned} \quad (1)$$

[17] We acknowledge, however, that we are implicitly relying on the assumption that, if these omitted common factors also impact the cross-sectional distributions of mispricing and explanatory variables in the panel regression, the impact on the distribution of mispricing is conditionally independent of the impact on the distribution of the explanatory variables. We believe, however, that this assumption is unlikely to be violated in practice given the bond-specific nature of mispricing and the dealer-specific nature of most of the explanatory variables in the panel regression. We are grateful to the referee for raising this issue.

Table 3
Panel regression of mispricing on price risk, intermediary, network, and liquidity variables.

This table reports the results from the panel regression of mispricing on the indicated variables. Mispricing is measured in basis points. Coupon is expressed as a percentage. Issuer and dealer CDS spreads are measured in basis points. Duration is measured in years. Dealer haircut is expressed as a percentage. Number of dealers denotes the number of dealers executing trades in the bond during the month. Number of institutions denotes the number of financial institutions holding positions in the bond as of the end of the month. Dealer centrality denotes the fraction of total dealer inventory held by the primary dealer for the bond. Dealer share of volume denotes the trading volume of dealers divided by total trading volume. Age is expressed in years. Issue size denotes the logarithm of the total par amount of the bond outstanding expressed in billions of dollars. Bid-ask spread is measured in cents per 100 dollar par amount. The *t*-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively. The sample is monthly from December 2008 to June 2012.

Category	Variable	Coeff.	*t*-stat
Controls	Coupon	0.3130	0.35
	Issuer CDS	0.0044	1.10
Price risk	Duration	9.1312	7.61**
Intermediary	Dealer CDS	0.0396	3.91**
	Dealer haircut	1.4969	2.50**
Network	Number of dealers	−0.1000	−2.07**
	Number of institutions	0.0358	1.65
	Dealer centrality	−3.2347	−1.88*
	Dealer share of volume	−2.9168	−2.61**
Liquidity	Age	−0.1966	−0.10
	Issue size	−0.9945	−1.36
	Bid-ask spread	−0.5530	−0.06
	Amihud measure	−0.1789	−0.56
Monthly fixed effects			Yes
Adjusted R^2			0.873
Number of observations			1,727

where Y_{it} denotes the mispricing for bond i at the end of month t, D_{jt} is a monthly fixed effects dummy variable that takes a value of one for month t and zero otherwise, and ϵ_{it} denotes the regression residual. Table 3 reports the results from the panel regression. Standard errors are clustered by bond.

The results in Table 3 provide strong support for the cross-sectional implications of the Treasuries-as-money literature. As shown, mispricing is directly related to the duration of the matching Treasury bond used in the estimation. The positive relation is not only highly statistically significant but is also large in economic terms. In particular, an increase in the duration of a bond by one year maps into an increase in mispricing of 9.13 basis points. These results suggest the presence of a term structure to the near-money convenience yield of Treasury and are consistent with term structure implications of models such as Krishnamurthy and Vissing-Jorgensen (2012). Furthermore, these results are also consistent with the classic limits-to-arbitrage literature in which deviations from fair value may be more severe for riskier securities (for which these limits are more likely to be binding).

Table 3 also provides support for the key implications of the intermediary-constraints literature. As shown, the coefficient for the dealer CDS spread is positive and highly significant. The positive sign of the coefficient implies that mispricing is directly related to dealer capital costs as implied by the equity constraint hypothesis of He and Krishnamurthy (2012, 2013), He et al. (2017), and others. The effect is also economically significant. An increase of 100 basis points in the dealer CDS spread is associated with an increase in mispricing of 3.96 basis points. Similarly, the coefficient for the dealer haircut is also positive and highly significant. The positive sign for the dealer haircut implies that mispricing is larger for bonds that are primarily intermediated by dealers that face leverage constraints, consistent with Brunnermeier and Pedersen (2009), Gârleanu and Pedersen (2011), Adrian et al. (2014), and others. A one percentage point increase in the haircut maps into an increase in mispricing of 1.50 basis points. In summary, these cross-sectional results all appear broadly consistent with the implications of a number of current theoretical models in the intermediary-constraints literature (assuming, of course, that these models could be embedded into frameworks allowing for heterogeneity in intermediaries across assets).

The results in Table 3 also provide evidence that mispricing is related to differences in the network structure across bonds. First, the number of dealers holding positions in a bond is significantly negatively related to mispricing. This intuitive result suggests that intermediation has a beneficial effect on the quality of financial market prices. In particular, deviations from fair value are lower in markets with greater intermediary participation. The effect is also significant in economic terms—doubling the number of dealers reduces mispricing by an average of 2.12 basis points (see Table 1 for the average values of network variables). This result harmonizes well with the general implications of the search literature in that we would anticipate expected search times to be lower in markets in which more intermediaries are active.

Second, the number of institutional investors holding positions in a bond is positively related to mispricing, although the coefficient is marginally insignificant at the 10% level. Still, the positive sign is intriguing since it implies that broader institutional interest in a security might adversely impact its pricing. In terms of economic magnitudes, doubling the number of institutional investors increases mispricing by an average of 1.76 basis points. Third, dealer centrality is negatively related to mispricing and is significant (at the 10% level). The economic magnitude of the effect is also important—doubling the percentage of inventory held by the primary dealer reduces mispricing by an average of 1.42 basis points. This result is consistent with some network models of endogenous intermediation such as Üslü (2019) that suggest that intermediaries specialize in assets based on their risk-bearing capabilities. Thus, if the most-central intermediaries take larger positions because of their comparative risk-bearing advantage, this may be reflected in pricing of the bonds they intermediate.

Finally, the results show that the dealer share of volume is negatively and significantly related to mispricing. Doubling the share of total trading volume by dealers reduces mispricing by an average of 0.79 basis points. This implies that bonds that trade in networks with more interdealer trading relative to customer trading tend to have less mispricing. This result again appears consistent with an interpretation that higher interdealer trading results in shorter expected search times. In contrast, this result seems inconsistent with the inattentive-investor hypothesis in the slow-moving capital literature that implies mispricing should decrease as customers become more engaged in trading.

Table 3 shows that the liquidity and transaction cost measures are not related to the cross-sectional structure of mispricing. In particular, age, issue size, bid-ask spreads, and the Amihud measure are all insignificant in the panel regression. Furthermore, none of these variables are significant in economic terms—the coefficient estimates imply that doubling the magnitude of the liquidity variables impacts mispricing by less than a basis point. Finally, Table 3 shows that neither the bond coupon nor the issuer CDS spread variables are significant in the panel regression.

We conduct a number of robustness checks on these results by estimating alternative specifications. For example, to verify that our mispricing measure is robust to potential minor timing mismatches between the observed final trades of the TLGP bonds and the Treasury securities that are priced as of 3:30 PM ET, we estimate the panel regression using only observations for which the final transaction price for the TLGP bonds is observed after 2:30 PM ET and 3:30 PM ET, respectively. The results are very similar to those reported in Table 3. We also examine the robustness of the results in Table 3 to alternative ways of clustering standard errors. In particular, we also compute t-statistics using standard errors obtained by clustering by the primary dealer (as identified at the end of the previous month) and by double clustering by bond and the primary dealer. The results given by these alternative clustering approaches are very similar to those reported in Table 3. As a robustness check for the issuer CDS spread, we reestimate the panel regression over only the earlier part of the sample period through April 2009 when mispricing was the highest. The results are similar to those reported in Table 3. In particular, the coefficient for the issuer CDS spread is insignificant (t-statistic 0.70).

Finally, to explore the source of the identification of the variables included in the panel regression, we estimate both purely time series and cross-sectional versions of the panel regression. In particular, we estimate a time series version in which we include both bond and monthly fixed effects (to avoid collinearity with the bond fixed effects, this specification omits bond-specific variables such as the coupon rate, issue size). We also estimate a cross-sectional version by using a standard Fama and MacBeth (1973) specification. The Internet Appendix discusses the estimation of these alternative specification and presents the results. As shown in the Internet Appendix, the effects of dealer CDS, dealer haircuts, dealer centrality, and dealer share of volume are identified via time series variation; the effects of duration, dealer haircuts, and dealer centrality are identified via the cross-section; and the effects of the number of dealers are identified jointly via time series variation and the cross-section.[18]

[18] We are grateful to the referee for suggesting this identification analysis.

Table 4
Panel regression of mispricing on near-money premium variables.

This table reports the results from the panel regression on near-money premium variables. It reports the results from the panel regression of mispricing on the repo spread (the three-month repo rate minus the three-month Treasury bill rate) interacted with duration, on the AAA spread (the yield on ten-year AAA corporate bonds minus the ten-year AAA Treasury yield) interacted with duration, and on duration. Mispricing, repo spread, and AAA spread are measured in basis points. Duration is measured in years. The t-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively. The sample period is monthly from December 2008 to June 2012.

Variable	Coeff.	t-stat
Duration	−5.2129	−1.23
Duration × Repo spread	0.2641	2.14**
Duration × AAA spread	0.0581	2.71**
Monthly fixed effects		Yes
Adjusted R^2		0.866
Number of observations		1,727

7. Mispricing and near-money premia

The panel regression in the previous section provides support for the presence of a term structure in mispricing, consistent with the implications of models that focus on the moneylike nature of Treasury securities or the classic limits-to-arbitrage literature. In this section, we explore the relation between mispricing and the near-money premium or convenience yield associated with Treasury securities in greater depth.

Several recent papers provide empirical measures of the near-money premia in Treasury security prices. For example, Nagel (2016) uses the yield spread between three-month general collateral Treasury repo rates and three-month Treasury bills as a measure of the near-money premium in short-term Treasury bills. Krishnamurthy and Vissing-Jorgensen (2012) use the spread between ten-year AAA-rated corporate bonds and ten-year Treasury bonds to identify variation in the near-money premium for longer-term Treasury securities. Motivated by this literature, we begin by examining whether mispricing is related to these empirical measures of near-money premia in the way suggested by theory.

In particular, we test whether the strong relation between mispricing and duration is related to cross-sectional differences in the near-money premia incorporated into bonds. To do this, we regress mispricing on the interactions between duration and the three-month repo and AAA-rated corporate bond spreads. If the relation between mispricing and duration arises from differences in near-money premia across bonds rather than some other type of duration-related effect, then these interaction variables should subsume the explanatory power of duration by itself in this regression.

Table 4 reports the results from the panel regression of mispricing on duration, duration times the repo spread, and duration times the AAA-rated corporate bond spread. As shown, the coefficients for both of the interaction variables are positive and significant. In contrast, the coefficient for duration by itself is not significant. These results provide strong evidence that the relation between mispricing and duration is driven by cross-sectional differences in the near-money premia embedded into the prices of the matching Treasury bonds used to estimate mispricing. These results also make a compelling case that the Treasuries-as-money convenience yield may represent a major source of the mispricing observed in riskless securities when measured relative to Treasury securities. Finally, these results argue that there may be a significant term structure to the near-money premia embedded in Treasury securities, consistent with Krishnamurthy and Vissing-Jorgensen (2012).[19]

8. Intermediary constraints

In this section, we explore the implications of this literature in greater depth by testing whether the relation between mispricing and dealer CDS spreads and haircuts arises through the economic mechanisms common to many current intermediary-based models.

8.1. The economic mechanism

The panel regression in Table 3 provides evidence that mispricing is significantly related to the constraints faced by financial intermediaries as measured by dealer CDS spreads and margins. Recall from earlier discussion, however, that intermediary-based theories imply that dealer capital and haircuts should affect mispricing primarily through the dealer inventory channel. As discussed in Section 2, the intermediary literature generally implies that asset mispricing arises through a two-stage economic mechanism. In the first stage, an exogenous shock to intermediary capital or leverage results in dealers reducing their inventory holdings of securities. In the second stage, the reduction in dealer inventory leads to market prices that may diverge from economic fundamentals. Thus, the effects of shocks to dealer capital and leverage should impact mispricing exclusively through an inventory channel. To explore the specific implications of the literature at the most fundamental level possible, our approach will be to test separately whether each stage of the economic mechanism is consistent with the empirical evidence.

To study the first stage of the economic mechanism, we test whether exogenous shocks to dealer CDS and haircuts are associated with changes in dealer inventory in the way suggested by theory. Specifically, we regress changes in dealer inventory on its lagged values and on contemporaneous and lagged changes in dealer CDS spreads and dealer haircuts. Table 5 reports the results from this panel regression.[20]

Table 5
Panel regression of changes in dealer inventory on changes in dealer CDS spreads and haircuts.

This table reports the results from the panel regression of changes in dealer inventory on its lagged values and on contemporaneous and lagged changes in dealer CDS spreads and dealer haircuts. Dealer inventory is expressed as a percentage of the size of the bond issue. Dealer CDS spread is measured in basis points. Dealer haircut is measured as a percentage. The t-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively. The sample period is monthly from December 2008 to June 2012.

Variable	Coeff.	t-stat
Intercept	0.2818	2.81**
Change in Dealer inventory$_{t-1}$	−0.3762	−4.65**
Change in Dealer inventory$_{t-2}$	−0.1269	−2.07**
Change in Dealer inventory$_{t-3}$	−0.0491	−1.16
Change in Dealer CDS$_t$	−0.0131	−2.64**
Change in Dealer CDS$_{t-1}$	−0.0136	−3.39**
Change in Dealer CDS$_{t-2}$	−0.0026	−0.46
Change in Dealer CDS$_{t-3}$	0.0062	1.92*
Change in Dealer haircut$_t$	−0.4253	−0.95
Change in Dealer haircut$_{t-1}$	−0.2343	−0.74
Change in Dealer haircut$_{t-2}$	−0.9242	−2.35**
Change in Dealer haircut$_{t-3}$	−0.5535	−2.11**
Adjusted R^2		0.101
Number of observations		1,451

The results in Table 5 provide strong support for the first stage of the economic mechanism implied by the intermediary-based models. In particular, the coefficients for the contemporaneous and first lagged changes in dealer CDS spreads are negative and highly significant. The negative sign of these coefficients is consistent with a scenario in which intermediaries that face increased capital constraints and costs of holding inventories—as reflected by their CDS spreads—respond by reducing their inventories of securities. Similarly, the coefficients for the second and third lagged changes in dealer haircuts are negative and significant. The negative sign of these coefficients is likewise consistent with a scenario in which dealers reduce their inventory holdings when facing tighter leverage constraints.

Turning now to the second stage of the economic mechanism, our objective is to examine whether a decline in dealer inventory for a specific guaranteed bond results in an increase in mispricing for that bond. Furthermore, we also want to examine the implication that intermediary capital and leverage constraints affect mispricing exclusively through the inventory channel. It is important, however, to consider the potentially endogenous nature of dealer inventory choices in the analysis. In particular, while the intermediary-based literature implies that changes in inventory affect mispricing, it is also possible that mispricing affects inventory choices since prices and quantities are jointly determined in equilibrium.

To address these potential endogeneity issues, we use an IV approach in examining the relation between mispricing and dealer inventory. To begin, we instrument changes in dealers' inventory holdings of a guaranteed TLGP bond using changes in the same dealers' inventory holdings of

[19] As a robustness check, we also estimate the regression in Table 4 in changes rather than levels. The results are similar in that duration is again not significant, while both the interaction of duration and changes in the repo spread and the interaction of duration and changes in the AAA spread are positive and significant.

[20] Since the intermediary-constraints literature is framed primarily in terms of the impact of shocks (changes) in dealer capital and/or leverage on inventory and mispricing, we believe that it is much more interpretable to examine the economic mechanism in terms of changes rather than levels.

Table 6
Instrumental variables regression of changes in mispricing on changes in dealer inventory.

This table reports the estimates from the second stage of a two-stage least squares regression of changes in mispricing on instrumented changes in dealer inventory and on changes in dealer CDS spreads and dealer haircuts. Changes in dealer inventory are instrumented with changes in dealer inventory holdings of non-TLGP corporate bonds and three lags of TLGP inventory changes. Mispricing is measured in basis points. Dealer CDS spread is measured in basis points. Dealer haircut is expressed as a percentage. The t-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively. The sample period is monthly from December 2008 to June 2012.

Variable	Coeff.	t-stat
Intercept	−1.8444	−14.84**
Instrumented change in Dealer inventory	−0.4398	−1.70*
Change in Dealer CDS spread	0.0333	4.27**
Change in Dealer haircut	2.1983	3.63**
Number of observations		1,451

non-TLGP corporate bonds, and following the analysis in Table 5, we also include three lags of the change in TLGP inventory itself.[21] Intuitively, changes in non-TLGP inventory holdings should be a good instrument for their TLGP counterparts because they are driven by the same shocks to the capital and funding costs of a dealer. At the same time, non-TLGP inventories are unrelated to the characteristics of any specific TLGP bond other than through sharing the same dealer. Based on this intuition, we assume first that non-TLGP inventory is a valid instrument and cannot reject at the 5% level that the inventory lags are also valid.[22] Table 6 shows the results from the second stage of the IV regressions of changes in mispricing on the instrumented change in inventory as well as changes in dealer CDS spreads and haircuts. The results show that changes in mispricing are significantly related to changes in dealer inventory as suggested by the theory (at the 10% level). In particular, the negative sign on the coefficient for changes in dealer inventory implies that mispricing increases when dealer inventory declines. The effect provides support for the second stage of the mechanism driving mispricing in the intermediary-based literature.

In addition to the instrumented change in inventory, the second-stage regression in Table 6 also includes changes in dealer CDS spreads and haircuts. The evidence from Table 5 suggests that since dealer CDS and haircuts drive dealer inventory, their effect on mispricing might be subsumed by the inclusion of the instrumented dealer inventory into the second-stage regression. In fact, the intermediary-based theory suggests that dealer inventory should be the only channel through which dealer capital and funding costs affect mispricing. In the environment we have in our IV regression in Table 6, the question of whether an independent variable affects the dependent variable through the instrument only is a test of the exclusion restriction itself. In addition, where multiple instruments are being used for a single endogenous variable as they are here, tests for overidentifying restrictions in the IV regression can be used to test the validity of the exclusion restriction for the instruments.[23] We already have four excluded instruments in our specification, and so a test of whether or not constraints to dealer capital (proxied by CDS) or leverage (proxied by haircuts) affect mispricing solely through the inventory channel is possible by examining a sequence of specifications of the IV inventory-mispricing regression where we include these variables or their lags one at a time in the instrument list and check the resulting Hansen J statistic. Each specification with one of the additional CDS or haircut variables generates a large J statistic and a strong rejection of the hypothesis that these proxies for capital or leverage affect mispricing solely through the inventory channel.[24] Since dealer CDS and haircuts do not appear to satisfy the exclusion restriction, we include them as additional regressors in the second-stage regression in Table 6.

Overall, the results reported in Table 6 have several important implications for the economic mechanism at the center of the intermediary-based theories. On the one hand, the results show that increases in dealer inventory are associated with reductions in mispricing as suggested by the intermediary-based theory. On the other hand, the results indicate that the effects of intermediary capital and leverage constraints on mispricing do not happen exclusively through the inventory channel. Table 6 shows that even after controlling for changes in dealer inventory, changes in dealer CDS spreads and haircuts remain significantly related to mispricing. In particular, the coefficients for changes in dealer CDS spreads and dealer haircuts are both positive in sign and highly significant.

In summary, the empirical results provide support for both components of the economic mechanism underlying intermediary-based models of mispricing. In particular, increases in dealer CDS spreads and haircuts both lead to reductions in dealer inventories of the guaranteed TLGP bonds. In turn, a decline in dealer inventory is directly associated with an increase in mispricing for these bonds. The empirical results, however, also leave us with a puzzle. Specifically, these results suggest that dealer capital and leverage constraints impact mispricing not only through

21 We believe that controlling for the time series properties is particularly important in this context since the intermediary constraints literature is largely silent on the issue of how long it takes for shocks to dealer CDS and haircuts to result in changes in dealer inventory. The results are robust to whether the lagged changes are included or not.

22 Tests of specifications in which only non-TLGP inventory is used to instrument for TLGP inventory provide evidence that it is a valid instrument. The first-stage F-statistic in a specification with only non-TLGP inventory is large, and the second-stage regression results are very similar to those provided in Table 6. Additional discussion of this specification, as well as the overidentifying restrictions, is provided in the Internet Appendix.

23 More formally, under the null hypothesis that all the instruments are properly excluded, the Hansen J statistic will be distributed chi-squared with $K - L$ degrees of freedom, where K is the number of instruments and L is the number of endogenous variables (in our case $L = 1$, inventory).

24 Additional discussion and a table of these regression results are given in the Internet Appendix. To summarize the numerical results, the J statistics we find when contemporaneous CDS or haircuts are added (individually) to the baseline specification are both above 20. When we instead add lagged values of CDS or haircuts, the J statistics are 20 and 12, respectively. These values allow us to reject the hypothesis that the effects of capital or leverage constraints operate exclusively through the inventory channel.

the inventory channel but potentially through other types of mechanisms as well. One possibility is suggested by the model presented in Üslü (2019) in which investor trading decisions depend both on inventory and network meeting rates. If shocks to dealer capital or leverage impact not only their inventory decisions but also their meeting rates, then network frameworks such as Üslü (2019) may provide an additional theoretical channel for explaining how intermediary constraints may impact mispricing.

8.2. The GCF repo eligibility event

In the previous section, we explored the relation between mispricing and the economic mechanisms implied by current intermediary-based theories. In this section, we expand on previous results by using a major exogenous shock in the availability of repo financing to help identify the causal relation between changes in dealer constraints and the mispricing of the guaranteed bonds.

Prior to April 2009, the guaranteed bonds were not eligible for financing through the GCF Repo service of the FICC, making these bonds much more difficult to finance than US Treasury or agency bonds. On March 27, 2009, the FICC issued a notice announcing that effective April 1, 2009, it would begin accepting FDIC guaranteed corporate bonds for GCF Repo processing. After that point, participating dealers were able to trade and clear repo against guaranteed bond collateral on the same platform as repo backed by US Treasury and agency collateral.

The GCF Repo service was designed by the FICC to provide an efficient way for securities dealers to finance their inventories of US Treasury and agency bonds. The GCF Repo service exists alongside the tri-party repo platform but differs from it in a number of ways. One important difference is that GCF Repo trades do not involve the posting of margins or haircuts at the individual bond level. Thus, GCF Repo has the potential to significantly reduce the margins faced by some dealers.[25] Because the FICC acts as the central counterparty for all GCF Repo transactions, dealers do not face counterparty credit risk from each other. The amount credited to a cash lender's account equals the market value of the securities financed. The FICC relies on its clearing fund as a protection against default of a given counterparty. In contrast, tri-party repo transactions typically rely on haircuts to protect the cash lender in the event of a counterparty default.

GCF Repo also differs from other types of repo because the transactions are anonymous. GCF Repos are negotiated through interdealer brokers on a blind basis. This mechanism especially favors dealers that have high perceived counterparty risk, whose tri-party cash lenders may demand large haircuts. Furthermore, the efficient design of clearing and settlement for GCF Repos reduces transaction costs and enhances liquidity in the interdealer market (Agueci et al. (2014)). An additional difference is that GCF Repo is an interdealer market, while the tri-party market includes participation from other financial institutions such as money market funds. Finally, it is important to emphasize that the tri-party repo market and the GCF Repo markets exist side by side and neither dominates the other. Dealers are often active in both markets, and decisions about which repo market to use in financing a specific position may depend on the specifics of their portfolio as well as the net margins and financing costs they face.[26]

What is clear, however, is that the inclusion of the guaranteed bonds among the collateral classes eligible for GCF Repo represents a positive exogenous funding shock for these bonds. The eligibility event immediately resulted in an expanded set of financing options that could significantly reduce the haircuts faced by dealers that wanted to hold positions in the guaranteed bonds.[27] As discussed, the additional option of having access to the GCF Repo market was particularly valuable to dealers facing larger tri-party repo haircuts. The resulting positive shock to the ability of dealers to finance inventory positions in guaranteed bonds allows us to test directly the implications of the leverage constraint hypothesis.[28] In particular, the hypothesis implies that mispricing should decline the most for the bonds whose dealers face the most-severe leverage constraints in the form of the highest tri-party haircuts prior to the event.

To illustrate that dealers did, in fact, respond to the positive funding shock, the upper panel of Fig. 5 plots the change in dealer inventory holdings over the month surrounding the inclusion of the guaranteed bonds in the GCF Repo market. Specifically, Fig. 5 shows the change in the percentage of the individual bond issues held by primary dealers in inventory for the 44 bonds in the sample as of the end of March 2009. The changes in inventory holdings are measured from the end of March 2009 to the end of April 2009. As shown, dealer inventory holdings increase for 36 of the 44 bonds in the sample (81.82% of the bonds). At the end of March 2009, dealers held an average of 7.96% of the guaranteed bonds in their inventory. By the end of April 2009, dealers now held an average of 10.37% of the bonds in their inventory. This change represents more than a 30% increase in the amount of inventory held by dealers. This increase is highly significant from both an economic and a statistical perspective (t-statistic 2.67).

[25] In practice, however, some margin may still be required at the netted portfolio level. In particular, GCF netting members must maintain a deposit to the Clearing Fund with the FICC on an ongoing basis. Each business day, the FICC determines the margin requirement based on the value-at-risk of the member's portfolio. Since 2007, the FICC has also imposed an additional "GCF Premium Charge" on the GCF Repo portion of the Clearing Fund deposit that depends on the size and composition of the GCF portfolio.

[26] For discussions of repo markets, see Copeland et al. (2012), Krishnamurthy et al. (2014), and Infante (2019).

[27] One possible implication of this is that tri-party haircuts might matter less for the pricing of TLGP bonds after April 2009. To examine this, we reestimate Table 3 for the period before the GCF event and the period after the GCF event. The effect of tri-party haircuts on mispricing decreased following April 2009 after the bonds became eligible for GCF repo. The estimated effect of dealer haircuts on mispricing from Table 3 declines from 3.87 (t-statistic 2.13) before April 2009 to 1.11 (t-statistic 1.88) after April 2009 but remains significant (at the 10% level).

[28] A recent paper by Chen et al. (2018a) also uses an exogenous shock to the haircuts faced by participants in the Chinese corporate bond markets to identify the effects of asset pledgeability on security prices.

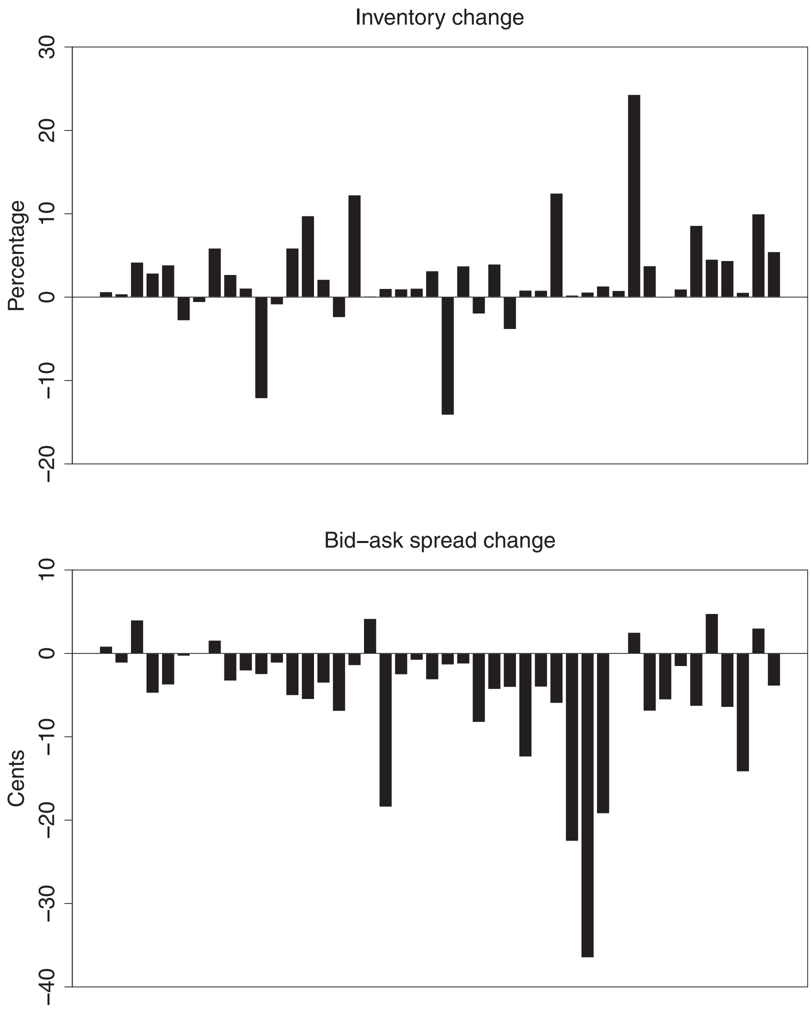

Fig. 5. Changes in dealer inventory and bid-ask spread associated with the GCF inclusion event.
The upper panel plots the percentage change in the amount of inventory held by primary dealers for each of the bonds in the sample during the GCF inclusion event in April 2009. The lower panel plots the change in the bid-ask spread for each of the bonds in the sample during the GCF inclusion event in April 2009.

The inclusion of the guaranteed bonds in the GCF Repo market also represents a positive exogenous shock to the liquidity of these bonds. One reason is that the bonds became more widely held among dealers. Prior to April 1, 2009, the 12 primary dealers accounted for 86% of the total inventory holdings for the guaranteed bonds, while other dealers accounted for 14%. The inventory share of the nonprimary dealers increased to 21% of the total by April 30, 2009, as repo financing for these bonds became more widely available through GCF Repo. The greater dispersion of inventory holdings among dealers likely lowered the search costs of finding dealer intermediation. The increased competition among dealers and the reduction of transaction costs in interdealer markets had the effect of reducing bid-ask spreads and increasing market depth. The resulting positive shock to the liquidity of the guaranteed bonds also allows us to test directly the impact of liquidity on mispricing. In particular, the literature on liquidity suggests that mispricing should decline more for the bonds that were less liquid prior to the inclusion.

To illustrate that there was in fact a positive liquidity shock associated with the GCF Repo eligibility event, the lower panel of Fig. 5 plots the change in the effective bid-ask spread for the individual bonds over the following month. As shown, the effective bid-ask spread declines for 37 of the 44 bonds in the sample (84.09% of the bonds). At the end of March 2009, the average effective spread is 17.98 cents per $100 par amount. At the end of April 2009, the average effective spread is 13.20 cents per $100 par amount. Thus, the average effective bid-ask spread declines by more than 26% in the month following the GCF inclusion event. Again, this decline is both economically and statistically significant (t-statistic - 4.16).

To test the implications of the intermediary-constraints literature, we regress the change in mispricing over the month following the GCF Repo eligibility event on ex ante measures of the dealer CDS spread and haircut. Since the effect of the eligibility event may be to reduce the dealer haircut to near zero in some situations, the ex ante value of the haircut is then essentially also the change in the

Table 7
Cross-sectional regression of the change in mispricing following the GCF Repo eligibility event.

This table reports the results from the regression of the change in mispricing in the month of April 2009, following the GCF repo eligibility event, on the indicated equity, leverage, and liquidity variables measured at end of March 2009. Mispricing is denoted in basis points. Dealer CDS spreads are measured in basis points. Dealer haircuts are measured as percentages. Bid-ask spreads are measured in cents per 100 par amount. Number of dealers denotes the number of dealers that execute trades in a bond. Issue size denotes the logarithm of the total par amount of the bond outstanding measured in billions of dollars. The t-statistics are based on robust standard errors. The superscripts * and ** denote significance at the 10% and 5% levels, respectively.

Variable	Coeff.	t-stat
Intercept	48.7544	3.49**
Dealer CDS spread	−0.0652	−2.09**
Dealer haircut	−9.1159	−3.95**
Bid-ask spread	0.0394	0.25
Number of Dealers	−0.0442	−0.29
Issue size	−5.8038	−1.31
Adjusted R^2		0.372
Number of observations		44

haircut associated with the event. Thus, this regression specification can be viewed as a standard difference-in-differences analysis of the effect of an exogenous change in dealer haircuts on the change in mispricing. Note that in this analysis, we are implicitly making the exclusion restriction assumption that the inclusion of the sample bonds among the collateral classes eligible for GCF Repo only impacted their mispricing through the dealer funding costs and liquidity channels. To test whether changes in liquidity and network structure impact mispricing in the manner suggested by the microstructure literature, we also include the ex ante bid-ask spread, issue size, and number of dealers as additional explanatory variables in the regression. To provide additional perspective for the results, we also note that the average level of mispricing for the bonds in the sample declines by about 28 basis points over the month following the inclusion event. Table 7 presents the results from the cross-sectional regression.

The regression results provide strong support for the empirical implications of the intermediary-constraints literature. The coefficient for the ex ante dealer CDS spread is significantly negative with a t-statistic of - 2.09. The negative sign of the coefficient implies that mispricing declined the most following the GCF eligibility event for the bonds whose dealers faced the highest ex ante capital costs. This result is both intuitive and consistent with intermediary-based theories. Similarly, the coefficient for the dealer haircut measure is highly significant with a t-statistic of - 3.95. The negative sign of the coefficient implies that mispricing decreases the most for the bonds whose dealers face the highest ex ante leverage or haircut constraints. This cross-sectional pattern following the exogenous funding shock represented by the GCF Repo inclusion event is again intuitive and fully consistent with the implications of the intermediary-constraints literature.

In contrast, the regression results provide little support for the implications of the microstructure literature. In particular, neither the ex ante bid-ask spread nor the number of dealers in the network is significant, similarly with the size of the bond issue.

8.3. The stress test announcement event

As a second way of identifying the causal relation between mispricing and intermediary constraints, we use the exogenous shock to dealer balance sheets that occurred with the announcement of bank stress tests. On February 10, 2009, Treasury Secretary Geithner announced the interagency Financial Stability Plan, a major component of which was the SCAP, "a forward-looking assessment of the risks on bank balance sheets and their capital needs" which came to be known as the "bank stress tests."[29] These tests aimed to assess whether or not the largest financial institutions (those with more than $100 billion in total assets) had the capital necessary to continue lending and to absorb the potential losses that could result from a severe decline in the economy. The announcement stated that banks subject to these "stress tests" would need to demonstrate that they had a sufficient capital buffer to survive hypothetical shocks to be stipulated within the soon-to-commence tests. If the tests showed that a bank failed to have sufficient capital, it would be expected to attempt to tap capital markets to increase its buffer or receive an "investment from Treasury in convertible securities."[30]

This announcement represented a major exogenous capital shock to the dealers in our study as it resulted in a sudden shift in the capital standards for the largest intermediaries. The amount of capital required to support their current balance sheet was to be reassessed under hypothetical macroeconomic and financial scenarios that were much more severe than the firms had already encountered. The market reaction to the announcement also resulted in an immediate capital loss for most US banks, with the severity of the reaction reflecting investor expectations of the capital shortfall of each firm. At the upper end of the spectrum were several US bank holding companies. Their equity valuations declined between 15 to 20 percentage points on the day. The stock prices of US banks that were considered to be less impacted by the new capital requirements decreased between 8 to 10 percentage points. At the other end of the spectrum were foreign banking organiza-

[29] See the Joint Statement By Secretary of the Treasury Timothy F. Geithner, Chairman of the Board of Governors of the Federal Reserve System Ben S. Bernanke, Chairman of the Federal Deposit Insurance Corporation Sheila Bair, February 10, 2009.

[30] If private capital markets were inaccessible, the February 10, 2009 Joint Statement said that these banks would receive a preferred security investment from Treasury in convertible securities that they can convert into common equity if needed to preserve lending in a worse-than-expected economic environment. The announcement indicated that this convertible preferred security would carry a to-be-determined dividend and a conversion price set at "a modest discount" from the prevailing level of the institution's stock price as of the close of the day before the announcement (February 9, 2009).

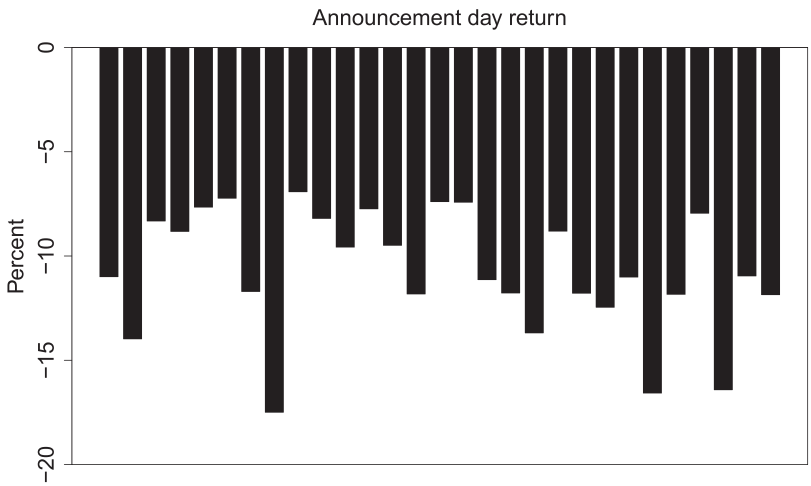

Fig. 6. Dealer stock returns on the announcement date of the SCAP Stress Test Program.
This figure plots the inventory-weighted average dealer stock return on the February 10, 2009 announcement date of the SCAP Stress Test Program for each of the bonds in the sample at the end of January 2009.

tions that were not initially subject to the new capital requirements. Their stock prices declined only modestly on the day.

We use the stock price reaction on the announcement date to measure the magnitude of the capital shock to dealers that followed the announcement of the stress tests. This approach resembles Hanson and Stein (2015) and Gertler and Karadi (2015) who use monetary policy announcements to identify the exogenous effect of monetary policy shocks. For each bond, we compute the inventory-weighted announcement day stock return of the primary dealers that held the bond as of January 31, 2009. We then examine the relation between the dealers' stock price reaction to the announcement and the change in mispricing of individual bonds between January 31, 2009 and February 28, 2009. Fig. 6 plots the inventory-weighted dealer stock returns for the announcement date of the stress tests for each of the bonds in the sample as of the end of January 2009. As shown, there is considerable cross-sectional variation in the shocks to dealer capital for the guaranteed bonds.

To test the implications of the intermediary-constraints literature, we follow an approach similar to that in the previous section. In particular, we regress the changes in mispricing during the announcement month for the individual bonds on the corresponding ex ante values of the dealer CDS spread, dealer haircut, and liquidity measures. To capture the cross-sectional impact of the announcement on dealer capital, we include the inventory-weighted average stock return for the primary dealers on February 10, 2009 for each of the bonds in the regression. We again note that we are implicitly making the exclusion restriction assumption that the SCAP announcement only affected TLGP bond mispricing through its effect on dealer capital costs. We are not aware of any other channel through which the announcement could have had a differential impact on the bonds intermediated by the respective primary dealers, other than perhaps through preexisting differences in bond characteristics such as liquidity between the bonds. Therefore, we control for preexisting bond characteristics such as bid-ask spreads and issue size in the regression. Table 8 reports the regression results.

Table 8
Cross-sectional regression of the change in mispricing following the stress test announcement event.

This table reports the results from the regression of the change in mispricing during the month of February 2009 on the dealer capital shock resulting from the announcement of the stress tests on February 10, 2009, as well as on the indicated equity, leverage, and liquidity variables measured at the end of January 2009. Mispricing is denoted in basis points. Dealer capital shock denotes the inventory-weighted average dealer stock return for each bond on the announcement date of February 10, 2009. Dealer CDS spreads are measured in basis points. Dealer haircuts are measured as percentages. Bid-ask spreads are measured in cents per 100 par amount. Number of dealers denotes the number of dealers that execute trades in a bond. Issue size denotes the logarithm of the total par amount of the bond outstanding measured in billions of dollars. The *t*-statistics are based on robust standard errors. The superscripts * and ** denote significance at the 10% and 5% levels, respectively.

Variable	Coeff.	*t*-stat
Intercept	−20.5362	−2.59**
Feb. 10, 2009 Dealer capital shock	−1.0115	−2.28**
Dealer CDS spread	−0.0188	−1.55
Dealer haircut	0.6056	0.74
Bid-ask spread	−0.0890	−0.66
Number of Dealers	−0.0678	−0.49
Issue size	1.6109	0.84
Adjusted R^2		0.165
Number of observations		29

As shown, the cross-sectional regression provides strong support for the empirical implications of the intermediary-constraints literature. In particular, the dealer capital shock on the announcement date is significantly negatively related to the change in mispricing of the sample bonds during the month of February. These results show that bonds held by dealers with larger expected capital shortfalls as a result of the stress tests become significantly more mispriced during this period. Once we account for the equity effect using the single-day price change, other explanatory variables are not significantly related to the change in mispricing. Our results are also consistent with those in a recent paper by Morelli et al. (2019) who find that the decline in the prices of emerging market debt around the Lehman default was larger for bonds held by the financial institutions that suffered the largest capital shocks.

9. Mispricing and search times

We turn our attention next to testing the implications of the literature on search frictions for asset mispricing in more depth. Recall from the previous discussion that models such as Duffie et al. (2005, 2007), Vayanos and Wang (2007), Weill (2007), Vayanos and Weill (2008), Duffie (2010), Duffie and Strulovici (2012), and Duffie et al. (2015a) suggest that deviations of market prices from economic fundamentals are more likely to occur in thinner markets in which it may take longer to search for trading counterparties. In particular, this literature implies that mispricing should be directly related to the average meeting rate of participants in a search network.

To test these empirical implications of the search literature, our approach will be to examine the cross-sectional relation between the mispricing of the guaranteed bonds and the frequency at which these bonds trade. The intuition for this approach is simply that we would expect networks with higher average meeting rates to result in a higher trading frequency. Thus, trading frequency should serve as a direct proxy for average meeting rates.

In adopting this approach, however, it is important to recognize that there is a potential endogeneity issue. In particular, while search theory implies that search times/trading frequency may be related to mispricing, it is also possible that mispricing itself generates additional trading activity as market participants attempt to exploit potentially profitable trading opportunities. As before, we need to take into account the fact that pricing and trading activity are jointly determined in equilibrium. To address this endogeneity issue, we again use an IV framework in studying the cross-sectional relation between mispricing and trading frequency.

Specifically, we begin with the number of trades during the month for each of the guaranteed bonds and instrument this measure using trading volumes for nonguaranteed corporate bonds of the same dealers. Intuitively, this approach makes sense because the instrument for trading activity of the guaranteed bonds is a measure of trading activity of the dealers that are holding the guaranteed bonds, but it is trading activity in securities not directly linked to the guaranteed bonds in our sample. For example, the approach is able to capture the fact that while one TLGP bond is intermediated by dealers that are large corporate bond intermediaries with very active trading books, another TLGP bond may be intermediated primarily by less active or smaller dealers. Non-TLGP volumes appear to be a relevant instrument for TLGP trading activity—the first-stage F statistic is 33.56—so if a dealer is an important counterparty in the corporate bond network, it is also likely to be an important counterparty in the network for guaranteed corporate bonds. Because TLGP bond mispricing is unlikely to be affected by non-TLGP bond trading volumes except through channels related to the dealers' overall trading behavior, instrumenting TLGP bond trade counts with non-TLGP bond volumes appears to also satisfy the exclusion restriction.

Table 9
Instrumental variables regression of changes in mispricing on trading frequency.

This table reports the estimates from the second stage of a two-stage least squares regression of changes in mispricing on instrumented trading frequency. Trading frequency is instrumented with dealer trading volume for non-TLGP corporate bonds. Mispricing is measured in basis points. Trading frequency is measured in terms of the number of trades during a month. The *t*-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively.

Variable	Coeff.	*t*-stat
Intercept	3.4822	2.68**
Instrumented trading frequency	−0.0987	−4.39**
Number of observations		1,646

Table 9 reports the results from the IV regression of changes in mispricing on instrumented trading frequency. As shown, there is a strong and significant negative relation between changes in mispricing and trading frequency. In particular, the coefficient for trading frequency is highly significant with a *t*-statistic of - 4.39. These results provide strong support for the empirical implications of the search literature.[31]

10. A combined analysis

The panel regression reported in Section 6 tests the cross-sectional implications of the various theoretical literatures. In Sections 7 through 9, we examine the cross-sectional implications of the individual literatures in more depth, typically using either an exogenous shock as an identification vehicle or an IV approach for endogenous variables such as inventory or trading activity. In this section, we conduct a joint analysis in which we include the key variables used in the individual tests of the Treasuries-as-money, intermediary-constraints, and search-friction literatures (reported in Tables 4, 6, and 9) in a single all-inclusive specification. In doing this, one of our objectives is to explore whether any of the various theoretical frameworks in the literature appears to be subsumed by the others.

Table 10 reports the results from the IV regression of changes in mispricing on the following variables: duration times the change in the repo spread, duration times the change in the AAA spread, the instrumented change in dealer inventory, the change in the dealer CDS spread, the change in the dealer haircut, and the instrumented trading frequency.

Table 10 shows that all three streams of the literature included in the analysis are supported by the data—

[31] The results of the regression in Table 9 are basically the same if we use TLGP trading volumes instead of the number of trades as an alternative measure of trading activity. The instrument in this case is also non-TLGP trading volume.

Table 10
Combined instrumental variables regression of changes in mispricing on changes in near-money premium variables, changes in dealer inventory, CDS spreads, and haircuts, and trading frequency.

This table reports the estimates from the second stage of a two-stage least squares regression of changes in mispricing on the interaction between duration and changes in the repo and AAA spreads, instrumented changes in dealer inventory, changes in dealer CDS spreads and haircuts, and on instrumented trading frequency. Changes in dealer inventory are instrumented with changes in dealer inventory holdings of non-TLGP corporate bonds and three lags of TLGP inventory changes. Trading frequency is instrumented with dealer trading volumes for non-TLGP corporate bonds. Mispricing is measured in basis points. Dealer CDS spreads, repo spreads, and AAA spreads are measured in basis points. Dealer haircut is expressed as a percentage. Dealer inventory is expressed as a percentage of total outstanding amount of the bond issue. Trading frequency is measured in terms of the number of trades during a month. The t-statistics are based on robust standard errors clustered by bond. The superscripts * and ** denote significance at the 10% and 5% levels, respectively. The sample is monthly from December 2008 to June 2012.

Variable	Coeff.	t-stat
Intercept	4.7999	2.32**
Duration × Change in Repo spread	0.2577	4.85**
Duration × Change in AAA spread	0.0514	6.45**
Instrumented change in Dealer inventory	−0.5722	−2.45**
Change in Dealer CDS	0.0018	0.16
Change in Dealer haircut	1.7037	3.07**
Instrumented trading frequency	−0.1186	−2.97**
Number of observations		1,451

none of the individual theoretical frameworks appears to be subsumed by the others. In particular, the two variables for the interaction between price risk and changes in near-money premia are both positive and highly significant. Thus, the Treasuries-as-money hypothesis continues to receive strong support even when the other variables are included.

Similarly, the results provide support for the cross-sectional implications of the intermediary-constraints literature. In particular, the coefficient for the instrumented change in dealer inventory is negative and significant, which is again consistent with the role of the inventory channel in this literature. Interestingly, the change in the dealer CDS spread is no longer significant in the combined specification. On the other hand, the change in dealer haircut is positive and significant, which again poses a challenge for the hypothesis that intermediary constraints impact asset pricing only through the inventory channel.

Finally, the results in Table 10 show that the cross-sectional implications of the search-friction literature are also supported by the data. The coefficient for the instrumented trading frequency is negative and significant. Again, this result is consistent with the earlier results.

11. Conclusion

Recent research shows a number of cases in which securities with essentially identical cash flows trade at different prices. A growing number of theories have been proposed to explain these apparent violations of the law of one price.

This paper studies the determinants of mispricing using an extensive cross-sectional data set of the spreads of guaranteed corporate bonds relative to Treasury bonds as well as proprietary data on the CDS spreads, haircuts, inventory positions, and trading activity of the primary dealers providing intermediation for the individual bonds.

The results provide strong support for the key implications of models that focus on the near-money role of Treasury securities. The results also provide support for the intermediary-constraints literature in that we find strong evidence that shocks to dealer CDS spreads and haircuts impact the cross-section of mispricing. However, while the results indicate that these shocks operate through an inventory channel as hypothesized in this literature, they also indicate that they may impact mispricing through other channels as well. Finally, the results provide support for the implications of the search-frictions/network-structure literatures in that we find the cross-section of mispricing is related to average search times or trading frequencies as well as to various network structure measures.

It is important to provide the caveat, however, that our results are based only on the TLGP bond market. Thus, the external validity of our results can probably only be ultimately established through additional empirical work in other markets with different characteristics. Our results, however, provide at least some support for the possibility that they may apply more broadly. For example, finding that changes in non-TLGP inventory provide a strong IV for changes in dealer TLGP inventory suggests that the intermediary constraints/mispricing mechanisms at play in the TLGP market may also apply in the broader corporate bond markets in which these intermediaries participate. These considerations indicate the need for additional research on the sources of cross-sectional dispersion in mispricing across assets in other markets.

Appendix A. The full faith and credit guarantee

As discussed in Section 3, the timely payment of principal and interest on bonds issued under the TLGP administered by the FDIC is guaranteed by the full faith and credit of the US Government. In this section, we provide additional legislative background about the source of this guarantee.

Specifically, the FDIC has the ability to make guarantee programs subject to the full faith and credit of the United States government pursuant to Section 15(d) of the FDI Act (12 USC 1825(d)). Section 15(d) states that:

> (d) FULL FAITH AND CREDIT.–The full faith and credit of the United States is pledged to the payment of any obligation issued after [August 9, 1989], the date of the enactment of the Financial Institutions Reform, Recovery, and Enforcement Act of 1989 by the Corporation, with respect to both principal and interest, if–
>
> (1) the principal amount of such obligation is stated in the obligation; and
>
> (2) the term to maturity or the date of maturity of such obligation is stated in the obligation.

The term obligation is also formally defined within Section 15:

> the term 'obligation' includes-(i) any guarantee issued by the Corporation, other than deposit guarantees;

Thus, there is a clear legislative path by which the full faith and credit pledge for the TLGP can be established and that path existed prior to the onset of the 2008 financial crisis. The TLGP clearly meets both the test of being an obligation under the formal definition of that term as well as having the principal amount and date of maturity stated within the obligation itself given that each bond had a defined principal amount and date of maturity.

The Final Rule issued by the FDIC also makes clear that the guarantee provides that the promised coupon payments and principal amount of bonds issued under this program are paid as scheduled even if the underlying issuer defaults. From the Final Rule:

> However, after considering the comments relevant to the payment of claims under the Debt Guarantee Program, the FDIC has significantly altered the Amended Interim Rule with respect to the method by which the FDIC will satisfy its guarantee obligation on debt issued by institutions and holding companies. These changes are designed to provide assurances to the holders of guaranteed debt that they will continue to receive timely payments following payment default...

Furthermore, in the definition section of the document (specifically, Section 370.12), the Final Rule states in the "Method of Payment" subsection that

> Upon the occurrence of a payment default, the FDIC shall satisfy its guarantee obligation by making scheduled payments of principal and interest pursuant to the terms of the debt instrument through maturity (without regard to default or penalty provisions).

This sentence in the Final Rule is followed by a qualifying statement that following the scheduled end date of the program (ultimately, December 31, 2012), the FDIC could decide to make a simple lump sum payment of remaining principal without prepayment penalty. However, in practice this was never an issue. Despite being permitted, no entity issued guaranteed debt that was scheduled to mature after the end date of the program.

Appendix B. Estimating dealer inventory holdings

We use TRACE to estimate dealer inventory. Our version of TRACE contains dealer identifiers, allowing us to estimate inventory holdings for each dealer and bond issue. We estimate the inventory of the jth dealer in the ith bond on day t as the cumulative difference between its buys and sells following Eq. (B.1):

$$INV_{i,j,t} = \max(0, INV_{i,j,t-1} + BUYs_{i,j,t} - SELLs_{i,j,t}). \tag{B.1}$$

Dealer inventory is constrained to be nonnegative. Most negative inventory observations occur in the period following a bond's issuance and are an artifact of primary market transactions not being recorded in TRACE. We use the dealer inventory estimates to identify the primary dealer for each bond. Specifically, the dealer with the largest average inventory position in a bond during the previous month is considered as the primary dealer for the bond.

As a robustness test, we also repeat the analysis when inventories are allowed to be negative to accommodate the possibility of short sales. The results are not significantly different because negative inventories tend to be small and occur predominantly during the period immediately following bond issuance.

As a further robustness test and as an alternative to using dealer inventory, we identify the primary dealer as the dealer that handles most of the trading volume in a bond over the previous month. The two alternative procedures identify the same dealer as the primary dealer 65% of the time, and the main results are not sensitive to the procedure.

Appendix C. Estimating interdealer and customer trading activity

We also use the TRACE data to compute two measures of a bond's trading activity in each month: total customer trading volume and total interdealer trading volume. The customer trading volume reflects all trades in which a dealer buys or sells from a nondealer counterparty. The interdealer trading volume reflects trading activity in the interdealer market.

Appendix D. State income tax effects

Appendix C of Elton et al. (2001) shows that the effect of state income taxes on the yield of a one-period coupon bond is proportional to $c\ \tau_s\ (1-\tau)$ (using our notation). To extend their analysis to longer maturity bonds, consider a N-year Treasury bond with coupon rate c that trades at par. Recall that the yield to maturity on a coupon bond trading at par is the coupon rate of the bond. Now consider a N-year guaranteed corporate bond with the same coupon rate c but is subject to state income taxes. From an investor's after-tax perspective, the corporate bond is equivalent to a Treasury bond that pays a coupon of only $c\ (1-\tau_s\ (1-\tau))$. Thus, for small values of the marginal state income tax rate, the difference in yields between the bonds can be closely approximated by $c\ \tau_s\ (1-\tau)$.

Given this representation of the state income tax effect, we can now estimate the value of $\tau_s\ (1-\tau)$ directly from a simple cross-sectional regression. Specifically, we regress the yield spreads described in Section 5 on the coupon rate for the bonds in a simple time series panel regression. The coefficient on the coupon rate provides a direct estimate of the marginal state income tax rate $\tau_s\ (1-\tau)$. The regression results are reported in the Internet Appendix. The estimated regression coefficient is 1.655%, which is statistically significant with a t-statistic of 3.95.

We note, however, that 98.44% of the price observations in the sample are premium prices. As discussed by Liu et al. (2007), premium amortization may mitigate the impact of state income taxes on bond prices. There are several reasons, however, why premium amortization may not have a material effect on the estimated state income tax effect on yield spreads. First of all, while Section 171 of the Internal Revenue Code allows taxpayers to amortize the premium on bonds acquired at a price above par, this is actually an optional election rather than a mandatory requirement. Industry sources suggest that relatively few taxpayers have elected to make this election historically. This is particularly likely in the case of the guaranteed TLGP bonds we study in light of the relatively small size of the average premium for these bonds (and the discounted status of many other bonds in the market).

Second, even if the amortization election were to be made by investors, it is clear that the impact of state income taxes on corporate bonds would generally be smaller when the premium is amortized than when it is not. Intuitively, this is because the amortization election allows the bondholder to deduct the premium amortization amount and reduce the taxable coupon income. Because of this, our estimates of the magnitude of state income tax effects on the yield of the TLGP bonds will typically represent upper bounds on the size of the actual tax effects. Using our methodology, we estimate that impact of state income taxes on TLGP bonds is 3.8 basis points on average. In contrast, if the premium is amortized, the actual effect could be significantly less. Thus, our results about the magnitude of mispricing are likely on the conservative side.

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