Commonality in Credit Spread Changes: Dealer Inventory and Intermediary Distress*

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September 27, 2019

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First, the effect of intermediary factors remains the same across bonds with characteristics not tied with margin requirement. Second, dealer inventory affects prices of assets within the corporate credit market only, whereas intermediary distress affects even the non-corporate-credit market. Third, an important component of dealers' inventory change is tied with supply shock of (severely) downgraded bonds by institutional investors, e.g., insurance companies. Instrumenting the effect of dealer inventory on bond prices using institutional sales of "fallen angels", as well as insured losses due to natural disasters, supports this interpretation.

Keywords: Corporate Bonds, Credit, Dealer, Inventory, Bond Market Liquidity
JEL classification: G12, G18, G21, E58

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1 Introduction

The commonality in excess variation of credit spread changes beyond credit risk factors, as documented in Collin-Dufresne, Goldstein, and Martin (2001) (hereafter CGM), is one of the canonical puzzles in asset pricing of credit risk. A key feature of U.S. corporate bond market is that broker-dealers serve as intermediaries of almost all transactions and use their balance sheets to take inventory and absorb bond supply from clients. Meanwhile, the recent intermediary asset pricing literature has argued that intermediary constraints are important determinants of asset prices (see He and Krishnamurthy (2018) for a survey). In this paper, we provide novel evidence that two intermediary factors account for about half of the puzzling common variation in credit spread changes. These factors are (1) a distress measure that captures constraints of the entire intermediary sector and (2) an inventory factor that captures the inventory held by dealers specializing in corporate bonds.

To construct the dealer inventory factor, we use the enhanced TRACE database of corporate bond transactions with untruncated trade size and anonymous dealer codes. Our measure of dealer inventory is computed using cumulative order flows of transactions between customers and dealers. Using records of transactions to construct measures of inventory poses several practical difficulties, such as the unobservable level of dealers' bond inventory even at the beginning of our sample period (2005:Q1), changes of dealer inventory unrelated to transactions (such as bond expiration), and missing of primary market transactions from issuing firms to underwriting dealers. We address these issues carefully, and then construct a quarterly measure of inventory by aggregating cumulative order flows (in par value) of all dealers.

Our measure of intermediary distress combines two existing factors that have be shown to capture the severity of broad intermediation frictions. The first is a balance sheet leverage measure proposed by He, Kelly, and Manela (2017) (hereafter HKM) for bank holding companies of primary dealers recognized by the Federal Reserve Bank of New York (FRBNY); and the second is market-price-based "noise" measure proposed by Hu, Pan, and Wang (2013) (hereafter HPW), i.e., the root mean squared distance between the market yields of Treasury securities and the hypothetical yields implied from yield curve models. Our measure of intermediary distress is computed as the first principal component of these two measures, meant as a parsimonious measure of the capital constraint of the aggregate intermediary sector.

Our analysis starts with individual-bond time series regressions of credit spread changes on seven structural factors and extract the residuals, following CGM. We assign each of the residual series into one of 15 cohorts based on time-to-maturity and rating, compute an average residual for each cohort, and extract the principal components of the *covariance* matrix of these residuals. Similar to CGM, but with a comprehensive data set of corporate bond transactions in recent years, we find that about 80 percent of the variation can be explained by the first PC, indicating a large systematic component that is not captured by structural credit factors.

As one of the main contributions of this paper, we link the two intermediary factors–the intermediary distress and dealer inventory factors–to this common variation of credit spread changes. We find that the two intermediary factors explain 53% of the variation of the first PC. Both intermediary distress and dealer inventory co-move positively with credit spread residuals in a statistically significant way. Economically, a one-standard-deviation increase of dealer inventory and intermediary distress is associated with a quarterly increase of about 3-30 and 5-60 basis points, respectively. We further show that the effect is monotonically decreasing in bond ratings for both intermediary factors, an important empirical pattern that is relevant to our later theoretical modeling.

Furthermore, intermediary distress and dealer inventory factors explain 38%, 55%, and 50% of the total variation of residuals of credit spread changes for short, medium, and long term bonds, respectively, and about 48% for all bonds. About 2/3 of this explanatory power can be attributed to intermediary distress and 1/3 to dealer inventory. Given the low correlation between distress and inventory, the results indicate a two-factor structure, associated with intermediary constraints, of the common unexplained credit spread variation. These effects are robust to many alternative specifications, e.g., controlling for the liquidity factors of Dick-Nielsen, Feldhütter, and Lando (2012) and Bao, Pan, and Wang (2011). [1]

To interpret these results, we present a simple two-agent equilibrium model with hedgers and intermediaries trading multiple assets. Hedgers should be thought of as an agglomeration of institutional investors that face liquidity shocks, e.g., insurance companies and pension funds. Intermediaries absorb supply of bonds coming from hedgers, but are limited in their liquidity provision by a balance sheet constraint due to margin or capital requirements. This model features a single dominant factor, the Lagrange multiplier on the balance sheet constraint, that governs all non-fundamental movements in equilibrium asset prices, consistent with our empirical evidence and that of CGM.

This single factor is endogenously driven by two types of shocks – hedger liquidity shocks

[1] Specifically, our results are also robust to using cohorts based on maturity and leverage; excluding the 2008 financial crisis period; measuring dealer inventory by market value; using only large dealers' inventory; doing all analysis at the monthly frequency; matching the horizon of credit spread changes and innovations of intermediary factors; and controlling for the Adrian, Etula, and Muir (2014) measure, TED spread (difference between three-month Libor and T-bill rates), and Pástor and Stambaugh (2003) stock liquidity factor.

and intermediary wealth shocks. Hedger liquidity shocks are like "supply shocks" in the sense that more bonds arrive onto intermediaries' balance sheets, lowering bond prices. Of course, hedger liquidity shocks are unobservable, so we use the model to argue that dealer inventory effectively captures these supply shocks. Intermediary wealth shocks are like "demand shocks" in the sense that balance sheet frictions are alleviated, which shifts out intermediaries' demand schedules. Intermediary wealth shocks are effectively captured by leverage, one of the building blocks for our intermediary distress factor. Thus, through the lens of our model, our empirical exercise amounts to estimating a supply-demand system with two types of non-fundamental shocks. Model-based regressions with dealer inventory and leverage reproduce the qualitative patterns of our time series regressions in empirical analysis, in particular the monotonic pattern of sensitivities for bonds grouped by rating, which is a key determinant in a bond's margin/capital requirement.

Guided by the model, we develop three sets of empirical tests to further understand the economic channel behind the strong effects of intermediary factors on credit spread changes. First, sorting bonds by any characteristic unrelated to margin/capital requirements should not produce any pattern associated with our two intermediary factors. Indeed, sorting by two such variables, maturity and trading intensity (measured by the total dollar trading volume), produces no detectible pattern in the economic magnitude or statistical significance of regression coefficients on our intermediary factors, controlling for bond rating.

Second, we enlarge our tests to other assets. An extended model with heterogeneous, imperfectly-integrated intermediary trading desks (e.g., a corporate credit desk, a Treasury desk, a securitized product desk, and an equity options desk), each with their own margin constraint, suggests the following testable predictions regarding co-movement across asset classes. Corporate-credit assets should be sensitive to dealers' corporate bond inventory, or even inventory computed from a subset of corporate bonds ("spillover effects"); non-corporate-credit assets should be insensitive to such inventory ("segmentation effects"); and both types of assets should be sensitive to aggregate intermediary distress. Intuitively, inventory coming from different asset classes exacerbates desk-specific constraints independently, whereas aggregate distress shocks affect all desks' constraints.

We find empirical support for this line of reasoning. Results of two tests support the spillover effect within corporate-credit markets: the first using dealer inventory of high-yield bonds and investment-grade bonds separately to explain credit spreads of all bonds, and the second using dealer inventory of bonds to explain CDS spreads. In contrast, agency mortgage-backed securities (MBS), commercial mortgage-backed securities (CMBS), asset-backed securities (ABS), and S&P 500 index options are insensitive to corporate bond inventory, reflecting potential segmentation effects. Despite these differential sensitivities to bond inventory, all non-corporate-credit assets, as well as CDS, are sensitive to our intermediary distress factor, consistent with HKM who show empirically that primary dealers sector behave as the common marginal investor across many asset classes.

Third, we seek to establish the link between dealer inventory and liquidity shocks hitting other investors, as posited by the model. We provide corroborating evidence for this channel using bond-level dealer inventories and institutional holdings of bonds that experience downgrading. More specifically, for each bond at each quarter, we compute the inventory change of all dealers using TRACE, and compute the aggregate change of holdings by each of the three groups of institutional investors – insurance companies, mutual funds, and pension funds – using the eMAXX data. Based on both summary statistics and formal regressions controlling for various bond characteristics, we find that insurance companies decrease their holdings of downgraded bonds, especially those downgraded from investment-grade to high-yield, denoted as "fallen angels" (Ambrose, Cai, and Helwege, 2008), by about \$0.33-0.67 million, relative to the average of those that experience no rating change and that are downgraded from IG rating to IG rating. Mutual funds and pension funds take some of bonds downgraded from IG rating to IG rating, but not "fallen angels". Instead, dealers' inventories of "fallen angels" increase substantially in the quarter when bonds are downgraded, about \$1.61 million. Given the premise that rating downgrades lead to large sell-offs from insurance companies (Ellul, Jotikasthira, and Lundblad, 2011), these results show that a significant amount of sell-offs are absorbed into dealers' inventories, supporting the interpretation of dealer inventory as reflecting bond supply shocks.

We then push this idea further to construct two Instrumental Variables (IV) for the supply shocks to dealer inventory. As the first IV, we take the fallen angels sold off by institutional investors, motivated by the exogenous regulatory constraints that insurance companies face in holding high-yield bonds. To (partially) address the potential confounding effect that fundamental changes trigger sell-offs and simultaneously lower bond prices, we include the sell-offs of all downgraded bonds as an additional control. Second, we obtain unexpected insured losses due to natural disasters to proxy for forced sell-offs of insurance companies. This second IV has a clearer-cut exogeneity than fallen angel liquidations, but it can be statistically weak because selling corporate bonds may only be one of the options for insurance companies to fund large insurance payments.

First-stage regressions show that a one-standard-deviation decrease in institutional holdings of fallen angels and increase in insured loss is associated with a 0.20-0.37 standard deviation increase in dealer inventory, with strong statistical significance for the former but weak for the latter. In second-stage regressions, we hence use regular robust standard errors for evaluating the significance of fallen angel sell-offs but the Anderson and Rubin (1949) Wald-test and Stock and Wright (2000) S-statistic (which are weak-instrument robust) for insured losses. The results show that dealer inventory increases, instrumented by fallen angel sell-offs, are highly significant in increasing credit spreads. When instrumented by insured losses, the p-values on dealer inventory range from 10% to 15% across bond groups, also consistent with the positive effect of dealer inventory on credit spread changes. We also find that the effect of dealer inventory using IVs is larger than that in the baseline analysis, potentially because our IVs mitigate the downward bias caused by unobserved demand shocks driving dealer inventory.

Related literature. This paper contributes primarily to the empirical literatures on corporate credit risk and intermediary asset pricing. In the credit risk literature, the unexplained common variation of credit spread changes, as first documented in Collin-Dufresne, Goldstein, and Martin (2001) (CGM), is a canonical puzzle in the context of structural models like Merton (1974) and Leland (1994). Related is the "credit spread puzzle" of Huang and Huang (2012). In view of these puzzles, attention has been paid to the role of market liquidity, e.g., due to search frictions (a la Duffie, Gârleanu, and Pedersen (2005)). For example, Longstaff, Mithal, and Neis (2005), Bao, Pan, and Wang (2011), and Bao and Pan (2013) among others show that illiquidity measures affect credit spreads and corporate bond returns. He and Milbradt (2014) develop a theory where credit risk in Leland and Toft (1996) and He and Xiong (2012) interacts with the over-the-counter search liquidity, with satisfactory quantitative performance over business cycles shown in Cui, Chen, He, and Milbradt (2017).[2]

In the broad intermediary asset pricing literature, Adrian, Etula, and Muir (2014) and He, Kelly, and Manela (2017) are the first to show that financial intermediary balance sheets have pricing power for large cross-sections of assets. Recent contributions include Du, Tepper, and Verdelhan (2017), Chen, Joslin, and Ni (2018), Siriwardane (2019), Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel (2018), and Fleckenstein and Longstaff (2019), among others. We connect these intermediary-centric literatures to the corporate credit literature by arguing that particular intermediation frictions govern the puzzling commonality across bond price variation.

Our study is also related to the microstructure studies of corporate bond liquidity that

[2]Relatedly, Lin, Wang, and Wu (2011) and Bai, Bali, and Wen (2019) study how liquidity risk beta affects cross-sectional corporate bond returns.

focus on the liquidity provision by dealers. For example, Bao, O'Hara, and Zhou (2018) and Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018) show that dealers face higher regulatory constraints post 2008 crisis, which impairs their liquidity provision. Schultz (2017) and Dick-Nielsen and Rossi (2018) both study the inventory behavior of dealers and show that their inventory capacity is constrained recently. Our study also employs the corporate bond inventory held by dealers, but differs by focusing on asset pricing effects of dealer inventory.

A closely related study, Friewald and Nagler (2019) (FN), conducts a comprehensive analysis of how OTC trading frictions - inventory, search, and bargaining frictions - affect credit spread changes, showing that twelve measures of such frictions jointly explain 23% of the CGM PC1. Besides the magnitude difference that we explain 53% of the CGM PC1, there are several important distinctions. First, in terms of the economic framework, their focus is microstructure-level trading frictions, whereas ours is on dealers' aggregate balance sheet, with a new intermediary distress factor. Accordingly, we conduct analysis at the quarterly frequency, a time-horizon that microstructure frictions are less likely to dominate (for example, Schultz (2017) and Goldstein and Hotchkiss (2019) show that half lives of temporary dealer inventory, potentially due to search friction, are up to several months). Second, we espouse a parsimonious two-factor model that has a clear supply-demand interpretation attached to inventory and distress factors and empirically test further predictions from the model. In particular, we consider various asset classes including CDS, MBS, CMBS, ABS, and options to study imperfectly integrated trading desks within a bank, and use bond-level holdings of insurance companies, mutual funds, and pension funds to provide refined evidence on the supply-demand channels. Finally, there are some differences in the data sample. As explained in details in Section 2.1.2, the 10-year *monthly* sample of FN is much smaller than those used in many studies, e.g., the 10-year monthly sample of Bao and Hou (2017), and even smaller than our *quarterly* sample. Their calculated PC1 accounts for only 53% of the CGM residual variation, much smaller than the 76% in CGM also using a monthly sample. Our calculation matches CGM closely, 82% (76%) in our quarterly (monthly) sample.

Our two-factor empirical framework is motivated by a simple intermediary-based model with margin constraints. See Brunnermeier and Pedersen (2008) and Garleanu and Pedersen (2011) for dynamic asset pricing models with exogenous margin/capital constraints and Biais, Hombert, and Weill (2017) for equilibrium under endogenous versions of such constraints. The innovation of our static model is to focus in detail on two types of shocks: (1) asset supply shocks in the vein of Ho and Stoll (1981) or Kondor and Vayanos (2019); and (2) intermediary wealth shocks in the vein of many standard intermediary asset pricing models a la He and Krishnamurthy (2012) and He and Krishnamurthy (2013). In addition, to study non-bond asset classes empirically, we also extend the model in a way that incorporates some market segmentation on the intermediary side, differently than classic frameworks like Gromb and Vayanos (2002). Such an extension has asset-class-specific intermediaries, as discussed in the slow-moving-capital stories of Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010).

The rest of the paper is organized as follows. Section 2 explains our data and measure. Section 3 presents our main findings. Section 4 presents a simple intermediary-based model that rationalizes the main finding and delivers further implications we test in Section 5. Section 6 concludes.

2 Data and Measure

In this section, we introduce the data sample of U.S. corporate bond transactions and construct the empirical measures used in our main analysis. We also introduce the data sample of institutional holdings and other asset classes used in further tests.

2.1 Data of Corporate Bond Transactions

Our sample of corporate bond transactions are from the enhanced Trade Reporting and Compliance Engine (TRACE) maintained by the Financial Industry Regulatory Authority (FINRA).[3] The FINRA started to collect data of corporate bond transactions in July 2002 and disseminated them to the public in three phrases through early 2005. We choose the starting of our sample period to be 2005:Q1 when the last phase was finished, similar to Schultz (2017) and Dick-Nielsen, Feldhütter, and Lando (2012), and end the sample at 2015:Q2. Each transaction record contains the trade date, time, (untruncated) principal amount, CUSIP, price, an indictor of whether the trade is either between a customer and a dealer or between two dealers, trading capacity of dealers (principal or agent), trade direction, and an anonymous dealer identifier, among many other variables.

[3]The TRACE database covers all corporate bond transactions executed by broker dealers registered with the FINRA. The missing trades from the TRACE database are those executed on all-to-all trading platforms or exchanges such as the New York Stock Exchange's Automated Bond System. These trades account for a very small portion of total corporate bond trading volume, less than 1% in 1990 and 5% in 2014 according to reports of U.S. SEC (1992) and Bank for International Settlements (2016).

2.1.1 Data Filtering

We first apply a number of filters to account for reporting errors and to assign each trade to the actual trading counterparties. In particular, we adjust the sample for trade corrections and cancelations within the same day as well as across days (usually known as trade reversals). We also account for the duplicated reports of inter-dealer trades. Furthermore, we assign a trade to the dealer who executed this trade rather than the reporting dealer for give-up trades in which one respective reporting firm reports on behalf of one actual trading counterparty (e.g., a clearing firm reports on behalf of a correspondent firm) and for locked-in trades in which one reporting firm reports on behalf of both actual trading counterparties. The data sample after these basic adjustments will be used to construct our measures of dealer inventory, hence we denote it "bond inventory sample".

To construct the baseline sample for studying variation of credit spreads, we merge the TRACE database with the Mergent Fixed Income Securities Database (FISD) that provides bond characteristics including the age, maturity, amount outstanding, credit rating, issuance amount, coupon information, and various bond features such as whether a bond is convertible, puttable, callable, and so on. We further merge the data with CRSP for equity price information and with Compustat for accounting information. We exclude those that cannot be matched and restrict our sample to bonds that are denominated in U.S. dollars, without embedded options, with a fixed coupon rate, senior unsecured, and with available credit rating.[4] We further exclude bonds issued by financial firms or utility firms, as we shall consider leverage as an important structural model factor that has different implications for these firms. We also exclude bonds with issue size less than $10 million. In addition, we keep only the secondary market trades by removing the trades with P1 flag (primary market trades; see more explanation in Section 2.2.1) and those with the trading date before and at the bond offering date. We exclude trades of bonds with time-to-maturity less than 1 year and keep only the institutional-sized trades, i.e., those with $100,000 or greater trading volume.

Our main sample frequency is quarterly. For each bond i, we take the price $p_{i,t}$ of the last trade in a quarter t to compute the standard yield-to-maturity, and then calculate its credit spread $cs_{i,t}$ by subtracting off the yield of the corresponding Treasury security.[5] The quarterly changes of credit spreads are then $\Delta cs_{i,t} = cs_{i,t} - cs_{i,t-1}$. However, many corporate bonds do not trade every day, so that the calculated $\Delta cs_{i,t}$ is not necessarily based on

[4]Similar to Bao and Hou (2017), we keep the bonds with a make whole call provision.

[5]The Treasury yields is calculated based on the Gurkaynak, Sack, and Wright (2007) database of Treasury yields with linear interpolations between provided maturities whenever necessary.

two actual quarter-end prices. To avoid large deviations from actual quarterly changes, we exclude a $\Delta cs_{i,t}$ observation if the actual number of days between the trade dates in quarter t and $t-1$ is lower than 45 days or larger than 120 days. We also match the Treasury yield to the exact day of the trade used in each quarter in computing credit spread to eliminate any nonsynchronization issues and scale $\Delta cs_{i,t}$ to make it a 90-day change (see Bao and Hou (2017) for similar adjustments at the monthly frequencies). Finally, we remove upper 1% and lower 1% tails of the credit spread levels to avoid the influence of outliers and require a bond to have at least 4 years of consecutive quarterly observations of $\Delta cs_{i,t}$ to ensure an enough number of observations for regressions on structural model factors.

2.1.2 Summary Statistics

Table 1 reports the summary statistics of our baseline sample of credit spreads. We have 2584 distinct bonds issued by 653 firms, with a total of 55,938 observations at the bond-quarter level. Around 35% of the observations are on high-yield bonds, defined as the Moody's crediting rating lower than BBB.[6] The mean credit spread is 1.52% and 5.27% for investment-grade and high-yield bonds, with a standard deviation of 1.17% and 3.65%, respectively. The average time-to-maturity is 9.78 years, with a higher mean for investment-grade bonds at 10.85 years than for high-yield bonds at 6.78 years. The average issuance size is about \$600 millions for investment-grade bonds, significantly larger than that of high-yield bonds only about \$400 millions. That is, lower rated firms tend to be smaller. The average coupon rates are lower for investment-grade (5.87%) than high-yield bonds (7.6%). For comparison, Bao and Hou (2017) use a sample of about 10 years from July 2002 to December 2013. Because Bao and Hou (2017) focus on monthly frequency, they have a larger sample size with more than 230,000 month-bond observations and around 7000-9000 distinct bonds. FN also focus on monthly frequency from January 2003 to December 2013. However, their sample includes only 974 bonds with 45,000 month-bond observations, which is substantially smaller than that of Bao and Hou (2017), and even smaller than our quarterly sample (55,938 bond-quarter observations).

2.2 Intermediary Factors

This section explains how we construct the two intermediary factors in our paper: dealer corporate bond inventory, and intermediary distress.

[6]The sample and results remain little changed when we use the average of available Moody's, Standard & Poor's, and Fitch ratings.

2.2.1 Dealer Inventory

Our measure of dealer inventory is computed using cumulative order flows between customers and dealers from the data of corporate bond transactions. As our objective is to study the balance sheet pressure imposed by aggregate dealer inventory rather than bond-specific characteristics, we use the "bond inventory sample" as defined in Section 2.1 that includes the whole set of corporate bond transactions. Part of transactions in this sample are not in the baseline sample of individual-bond credit spreads as discussed above.

Using records of transactions to construct measures of inventory poses several practical difficulties, which we address carefully in a few steps. First, we have no data on the actual level of dealers' bond inventory at the beginning of our sample period (2005:Q1 - 2015:Q2).Accordingly, we construct the dealer inventory measure starting from 2002:Q3 when the TRACE data of corporate bond transactions first became available, but only use the inventory measure after 2005:Q1. With this "buffer" period of two and half years, the mismeasurement of dealer inventory starting from 2005:Q1 should be mitigated, in light of the evidence on half lives of dealer inventory being up to several months (e.g., Schultz (2017), Goldstein and Hotchkiss (2019)). The initial holdings should have matured and/or been unwound by dealers.

Second, we do not observe changes of dealer inventory unrelated to market transactions. If dealers hold a bond till its maturity, there is no transaction record indicating the expiration of the bond position. To deal with this issue, we calculate cumulative positions of all dealers for each bond, and from the date of the last transaction of a bond, we assume dealers' inventory of this bond turns zero at its maturity date and hence take the amount of inventory out on that date. And we still miss bonds that are called using our procedure.

Third, dealers who are active in the primary market are "selling" bonds around the issuance date, which should be excluded as we ignore the newly issued corporate bonds in our calculation. Starting March 1, 2010, the FINRA started to require member firms to report trades executed in the primary market, and an identifier is assigned on these trades. Hence we use the provided identifier to take out primary market trades executed after March 1, 2010. For the sample before March 1, 2010, we remove trades of a bond executed before and on its offering date obtained from the Mergent FISD. This procedure should remove most of the primary market trades as underwriting dealers are expected to finish delivering bonds within a short period of time.[7]

[7] Before March 1, 2010, market participants were facing ambiguity regarding the definition of primary vs secondary market trades. This procedure may eliminates some secondary market trades on the issuance day as well as keep some primary market trades after the issuance day.

After making these adjustments, we construct a quarterly measure of dealer inventory by aggregating cumulative order flows of all dealers as a whole with customers. We use the par value rather than market value to avoid the potential confounding effect of price change when studying the effect of dealer inventory on bond prices. The quarterly log change of this measure, denoted as $\Delta Inventory^A$, is the baseline factor of dealer inventory in our analysis of credit spread changes. We also construct measures of dealer inventory of high-yield and investment-grade bonds separately and inventory of large and small dealers separately for some specific tests, which will be discussed in details later.

2.2.2 Intermediary Distress

To construct the intermediary distress factor, we combine the balance-sheet-based leverage ratio measure of the aggregate intermediary sector proposed by HKM and the market-price-based "noise" measure proposed in HPW. The HKM leverage ratio is computed as the aggregate market equity plus aggregate book debt divided by aggregate market equity using CRSP/Compustat and Datastream data, denoted as $\mathrm{Lev}_t^{\mathrm{HKM}}$ for quarter t, of the holding companies of primary dealers recognized by the Federal Reserve Bank of New York.

In measuring the change or innovation of the leverage ratio, we create the variable $\Delta\mathrm{NLev}_t^{\mathrm{HKM}} := \left(\mathrm{Lev}_t^{\mathrm{HKM}} - \mathrm{Lev}_{t-1}^{\mathrm{HKM}}\right) \times \mathrm{Lev}_{t-1}^{\mathrm{HKM}}$, motivated by the nonlinear affect of intermediary constraints on asset prices implied from intermediary-based asset pricing models like He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014). Note that $\Delta\mathrm{NLev}_t^{\mathrm{HKM}}$ weights the change of leverage ratio higher when its level is high.

The HPW noise measure is computed as the root mean squared distance between the market yields of Treasury securities and the hypothetic yields implied from yield curve models like that of Svensson (1994).[8] Besides its obvious connection to our paper as corporate bonds are part of fixed-income securities, the "noise" is widely used a measure of "severe shortage of arbitrage capital" across various markets in the literature. The rationale is that relative value trading dedicated to arbitrage across various habitats on the yield curve is widely conducted at most investment banks and fixe-income hedge funds. Hence, a significant deviation of market yields from model-implied yields is a symptom of a lack of arbitrage capital, and importantly, "to the extent that capital is allocated across markets for major

[8]The Svensson (1994) model is an extension of the yield curve model initially proposed in Nelson and Siegel (1987). These yield curve models are widely used in the academic literature and in practice o compute benchmark yield curves. For example, Gurkaynak, Sack, and Wright (2007) use them to construct Treasury yield curves that are regular inputs of the Federal Reserve's policy discussions and publications. Song and Zhu (2018) discuss the use of these models by the Federal Reserve in evaluating offers submitted in auctions that executed the purchases of Treasury securities for quantitative easing.

marginal players in the market, this symptom applies not only to the Treasury market, but also more broadly to the overall financial market" (see HPW). We denote the quarterly change of the HPW noise measure (in basis points) as $\Delta Noise$.

Our measure of intermediary distress, denoted as $\Delta Distress$, is defined as the first principal component of $\Delta \text{NLev}_t^{\text{HKM}}$ and $\Delta Noise$. Note that the former is constructed mainly using balance sheet information of financial intermediaries, while the latter is based on prices. Hence, combining the two leads to a parsimonious measure of the capital constraint of the aggregate intermediary sector. In fact, as shown later in Section 3.3, both $\Delta \text{NLev}_t^{\text{HKM}}$ and $\Delta Noise$ contribute to a nontrivial fraction of the explanatory power of $\Delta Distress$ for credit spread changes.

To gauge the variation of the two intermediary factors, Figure 1 plots the quarterly time series of $\Delta Inventory^A$ and $\Delta Distress$ (both scaled to have zero mean and unit variance) in the top and middle panels, respectively. Dealer inventory has comparable frequent variation across different sub-periods of the sample, whereas intermediary distress exhibit extreme variation in the 2008 crisis but mild variation otherwise. Importantly, although $\Delta Inventory^A$ does show large negative values in the 2008 crisis, similar to $\Delta Distress$, the two factors exhibit variation orthogonal to each other to a large extent. In fact, from Table 2, the correlation between $\Delta Inventory^A$ and $\Delta Distress$ is only -0.16, with an intuitive negative sign because deleveraging should lead to a lower inventory, though statistically insignificant.

The bottom panel of Figure 1 plots the quarterly time series of $\Delta \text{NLev}^{\text{HKM}}$ and $\Delta Noise$ that are used to construct our measure of intermediary distress. These two series line up with each other well, though $\Delta Noise$ led $\Delta \text{NLev}^{\text{HKM}}$ by a quarter in plummeting during the 2008 crisis. The correlation between them, from Table 2, is 0.83. Our measure $\Delta Distress$, as the first principal component of them, captures 70% of the total variation.

Table 2 also reports the correlation of our intermediary factors with the change of VIX that is widely used as an indicator of financial market stress. We find that $\Delta Distress$ has a significant positive correlation with ΔVIX, about 0.36. In contrast, the correlation of $\Delta Inventory^A$ with ΔVIX (and $\Delta Distress$), though with an intuitive negative sign, is less than 10% and statistically insignificant, implying that dealer inventory is largely orthogonal to these popular measures of market stress. In addition, both of our intermediary factors have low correlations with the illiquidity factor ΔILiq of corporate bond trading of Dick-Nielsen, Feldhütter, and Lando (2012). We shall control for ΔVIX and ΔILiq in studying the effects of intermediary factors on credit spread changes. We now turn to introduce additional measures and controls variables.

2.2.3 Structural Factors and Control Variables

Following CGM, we consider seven determinants, motivated from the Merton (1974) model, of credit spread changes: the firm leverage $lev_{i,t}$, 10-year Treasury interest rate r_t^{10y}, square of 10-year Treasury interest rate $\left(r_t^{10y}\right)^2$, slope of the term structure $slope_t$ measured as the difference between 10-year and 2-year Treasury interest rates, S&P 500 return ret_t^{SP}, jump factor based on S&P 500 index options $jump_t$, and VIX_t. The firm leverage $lev_{i,t}$ is computed as the book debt over the sum of the book debt and market value of equity. The book debt is defined as the sum of "Long-Term Debt - Total" and "Debt in Current Liabilities - Total" from Compustat, whereas the market value of equity is equal to the number of common shares outstanding times the share price from CRSP. The debt data from Compustat are available at the quarterly frequency, and we follow the literature to assume that such balance sheet information becomes available with a lag of one quarter (Bao and Hou (2017)).

The interest rate factors r_t^{10y}, $\left(r_t^{10y}\right)^2$, and $slope_t$ are calculated based on the Gurkaynak, Sack, and Wright (2007) database of Treasury yields (in percent). The S&P 500 return ret_t^{SP} is from CRSP, while the VIX_t is from CBOE. The jump factor $jump_t$ is computed based on at-the-money and out-of-the-money options on the S&P 500 index, from OptionMetrics (see CGM for details on the procedure).

2.3 Institutional Holdings of Corporate Bonds

We obtain data on institutional investors' holdings of corporate bonds from the survivorship-bias free Lipper eMAXX database of Thomson Reuters. This data set contains quarter-end security-level North American (based on where the holder is located) corporate bond holdings of insurance companies, mutual funds, and pension funds. Data on insurance companies' holdings are based on National Association of Insurance Commissioners (NAIC) annual holdings files and quarterly transaction reports to the state insurance commissioners. Data on mutual fund holdings are obtained from Lipper, which is owned by Thomson Reuters, covering over 90% of the mutual fund universe. Data on pension fund holdings are from state and local municipal pension funds and large private pension funds who voluntarily submit data to Thomson Reuters (see Cai, Han, Li, and Li (2019), Bo and Victoria (2015)), and Manconi, Massa, and Yasuda (2012) among others for further details). We use the eMAXX holdings over 2005:Q1 - 2015:Q2, with information on bond characteristics such as historical outstanding balance and credit rating by matching to FISD based on the CUSIP number.

Figure 2 provides a summary of the eMAXX institutional holdings, as well as dealer inventories. In particular, the top panel plots quarterly time series of the holding amount by institutional investors (including mutual funds, pension funds, and insurance companies) based on eMAXX data and by dealers based on TRACE data, as well as the aggregate outstanding balance of U.S. corporate debt based on the "Financial Accounts of the United States" (Z.1) data release by the Federal Reserve, in $trillions of principal value.[9] We observe that the dollar (par) value of holdings has seen a significant increase from $1.3 trillion to $2.7 trillion, mainly after the notable plummeting in the 2008 crisis. The rise of holdings is strongest from mutual funds, amid a sizable expansion of the whole corporate bond market over this period when the total outstanding balance increased from less than $5 trillion to more than $8 trillion. The bottom panel plots quarterly time series of the fraction of U.S. corporate debt held by institutional investors, by dealers, and by both, respectively, in percent. The fraction steadily accounts for 30-35% of the aggregate outstanding balance, except a brief drop during the 2008 crisis.[10]

2.4 Yield Spreads and Returns of Other Asset Classes

Our analysis also uses yield spreads and returns of a host of other asset classes including CDS, agency MBS, CMBS, ABS, and equity options. We obtain CDS quotes on individual U.S. corporations denominated in U.S. dollars from Markit. We use 1-year, 5-year, and 10-year CDS contracts with modified restructuring (MR) clauses, among which 5-year CDS are probably the most popularly traded in the U.S. market. We match the CDS data with equity information from CRSP and accounting information from Compustat. For each entity, we construct quarterly series of CDS spreads using the last quotation in every quarter.

[9] Specifically, the aggregate outstanding balance is the sum of the outstanding debt by nonfinancial corporate business, U.S.-chartered depository institutions, foreign banking offices in the U.S., finance companies, security brokers and dealers, and holding companies in the "L.208 Debt Securities" series.

[10] The level of dealer inventory we compute from TRACE data shares a similar trend with the total holding of corporate bonds of primary dealers reported by the FRBNY (https://www.newyorkfed.org/markets/gsds/search.html), increasing substantially from early 2003 up to mid-2007 and then declined sharply until after 2012. Yet, we observe two differences. First, our level series of dealer inventory indicates an expansion starting from early 2013. Second, the magnitudes often deviate from each other. For example, the total holding of primary dealers is about $250 and $28 billion at the end of 2007Q1 and 2014Q4, respectively, while about $91 and $107 billion from our series. There are several potential reasons for the discrepancies. First, the FRBNY began collecting primary dealers' holdings of corporate bonds as a separate asset class on April 3, 2013, before which only aggregate holdings that do not separating corporate bonds from securities issued by non-federal agencies (e.g., government-supported enterprises) are available. The FRBNY extrapolates corporate bond positions prior to April 3, 2013 using the composition of corporate bond holdings on that date. Second, we include all dealers but only about 20 primary dealers are included in the FRBNY report. Importantly, our analysis only relies on the flows that are accurately measured rather than the levels. In fact, we find that the inventory measure based on the primary dealers' holdings reported by the FRBNY has no explanatory power for credit spread changes at all.

We obtain series of yield spreads of agency MBS, CMBS and ABS from major Wall Street dealers. Specifically, we use (option-adjusted) yield spreads of agency MBS based on the liquid "to-be-announced" (TBA) contracts of 15-year and 30-year production-coupon Fannie Mae and Freddie Mac MBS (see Gabaix, Krishnamurthy, and Vigneron (2007) and Gao, Schultz, and Song (2017) among others for details of TBA contracts and option-adjusted spreads). We use the Barclays yield spreads of non-agency 10-year CMBS of three AAA-rating groups, Super Duper Senior (Duper), mezzanine (AM), and junior (AJ).[11] We also use yield spreads of 5-year AAA-rated ABS on fixed-rate credit card loans and 3-year ABS on fixed-rate prime auto loans of AAA, A, and BBB ratings.

In addition, we use monthly returns of portfolios of S&P 500 index options sorted on moneyness and maturity from Constantinides, Jackwerth, and Savov (2013). These portfolios are leverage-adjusted in that each option portfolio is combined with risk-free account to achieve a targeted market beta of one. In consequence, a leverage-adjusted call option portfolio consists of long positions in calls and some investment in the risk-free account, while a leverage-adjusted put portfolio consists of short positions in puts and more than 100% investment in the risk-free account. For the convenience of interpretation, we take the negative of the put portfolio return. The holding period of these option portfolios is a month regardless of the target maturity that is 30, 60, or 90 days. We use the 30-day maturity to match the holding period precisely, but results are similar using 60-day and 90-day maturities.

3 Main Empirical Results

We discuss the main empirical results in this section. We first replicate the exercise in CGM and show that the strong commonality persists in the U.S. corporate bond market in the past decade. We then show that the two intermediary-based variables, intermediary distress and dealer inventory, can explain more than half of the latent factor. More relevant to our paper, we show that the sensitivities to these intermediary-based factors are monotone in credit risk (i.e., ratings), a pattern that is robust to many other alternative specifications.

[11] These different groups differ in terms of credit enhancement. Moreover, since CMBS usually have restrictions on prepayment and are different from residential-loans backed agency MBS, we use the yield spreads for CMBS but option-adjusted spreads for agency MBS. See Manzi, Berezina, and Adelson (2016) for further details.

3.1 Baseline Analysis

3.1.1 Commonality of Credit Spread Changes

To study the effects of intermediary constraints on corporate bond pricing, we follow CGM and run a time series regression for each bond i:

$$\begin{aligned}\Delta cs_{i,t} &= \alpha_i + \beta_{1,i} \times \Delta Lev_t^i + \beta_{2,i} \times \Delta VIX_t + \beta_{3,i} \times \Delta Jump_t \\ &\quad + \beta_{4,i} \times \Delta r_t^{10y} + \beta_{5,i} \times (\Delta r_t^{10y})^2 + \beta_{6,i} \times \Delta slope_t + \beta_{7,i} \times ret_t^{SP} + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

by which an estimate of each regression coefficient for each bond is obtained. Similar to the empirical procedure of CGM, we assign each bond into one of 15 cohorts based on time-to-maturity and rating, and then report the regression results at the cohort-level. Panel A of Table 3 shows that the sample size is fairly homogenous across maturity groups but heterogeneous across rating groups.

Also reported in panel A are the average regression coefficients across bonds within each cohort, with associated t-statistics computed as the average coefficient divided by the standard error of the coefficient estimates across bonds, again following CGM. We find that the significant dependence of credit spread changes on the factors is as expected based on a structural framework. For example, credit spreads significantly increase with firm leverage and volatility, and decrease with the risk-free rate and the stock market return. The effects of convexity and slope of the term structure are less consistently significant: convexity shows some negative significance for long-maturity bonds and slope of the term structure shows some positive significance for short-maturity bonds, but the coefficients on both switch signs in certain cohorts. The jump factor shows negative significance for most of the medium and long term bonds. Finally, in terms of overall explanatory power, the mean adjusted R^2 is about 30-40% for bonds rated equal to or above BBB and about 55% for bonds rated as equal to or below BB.

Most importantly, there is a strong common factor structure of the regression residuals, as pointed out by CGM. Panel B of Table 3 reports the principal component analysis of the 15 series of regression residuals based on the covariance matrix. The residual series $\varepsilon_{g,t}$ of each cohort g are computed as the average of regression residuals $\varepsilon_{i,t}$ across bonds i in the cohort g. Over 80% of the variation can be explained by the first PC, whereas the second PC explains an additional 6% (the third PC only explains less than 2% and other PCs explain even less, so we only report the first two PCs). Credit spread changes contain a large systematic component that is not captured by structural models factors.

Moreover, the last column of Panel A reports the variation of residuals for each cohort g, ε_g^{var} $(= \sum_t (\varepsilon_{gt} - \bar{\varepsilon}_g)^2)$ with $\bar{\varepsilon}_g$ being the time series mean of ε_{gt}, as a fraction of the total variation of the 15 cohorts $\sum_{g=1}^{15} \varepsilon_g^{var}$. We observe that the BB and B cohorts account for the majority of the total variation, about 86%. That is, although the structure factors can explain more than 50% of the raw credit spread changes in these two cohorts, what remains to be explained is still dominated by credit spread variations in the BB and B cohorts.

It is worth comparing our data sample and results with those of two closely related studies, CGM and FN. In term of data sample, CGM use a 10-year monthly sample from July 1988 to December 1997 with a total of 688 bonds and dealer *quote* prices, while FN also use a 10-year monthly sample but from January 2003 to December 2013 with a total of 974 bonds and actual *transaction* prices. We use a 10-year quarterly sample from 2005:Q1 to 2015:Q3 with a total of 2584 bonds and actual *transaction* prices.

In terms of the overall explanatory power, the average adjusted R^2 is about 25% and 22% in CGM and FN , respectively, but about 45% in our study. The much higher adjusted R^2 is likely because we use a 10-year quarterly sample as opposed to the 10-year monthly sample in the other two studies. Most importantly, the fraction of the total unexplained variance of regression residuals that can be accounted for by the first PC is 76% in CGM and 82% in our study, but only 48% in FN. Overall, all three studies confirm a strong common factor structure for the credit spread changes beyond those driven structural factors, though our paper and CGM document a much stronger commonality than FN.[12]

A possible explanation for this discrepancy, as proposed by FN, is that CGM's use of dealer quotes instead of actual transaction prices "potentially works against their conclusion regarding the magnitude of the latent factor" (page 8 in FN). Our results cast doubt on this conjecture given that actual transaction prices are also used in our analysis. What is more, the same strong comovement persists in our monthly sample: the PC1 accounts for 76% of the variation of the 15 portfolios of corporate bonds, as shown in Table 7 in the next section, exactly matching the finding of CGM.

[12]In terms of individual explanatory variables, leverage, volatility, risk-free rate, and stock market return exhibit uniformly consistent explanatory power, across all three studies, while the significance of convexity, slope of the term structure, and jump factor is weaker and exhibits different patterns. For example, the coefficient on slope of the term structure is significantly positive in FN, contradictory with the overall negative significance documented in CGM in line with structural framework and also in our study especially for short-term bonds. The coefficient on jump factor is significantly positive in CGM, weakly positive in FN, but significantly negative for medium to long term bonds in our study.

3.1.2 Effect of Intermediary Factors on Common Credit Spread Changes

We study the effect of intermediary factors on common credit spread changes based on the following time series regressions:

$$\varepsilon_{g,t} = \alpha_g + \beta_{1,g}\Delta Inventory_t^A + \beta_{2,g}\Delta Distress_t + u_{g,t}, \quad (2)$$

where $\varepsilon_{g,t}$ is the average residual of cohort g $(= 1, \ldots, 15)$. Panels A and B of Table 4 report univariate regressions on dealer inventory and intermediary distress, respectively, and Panel C reports bivariate regressions on both. Both dealer inventory and intermediary distress drive residuals of credit spread changes positively. The statistical significance of dealer inventory is weak in univariate regressions,[13] but strong in joint regressions, whereas intermediary distress shows strong statistical significance in both univariate and joint regressions.

Importantly, the economic significance is large. Since we have standardized the intermediary factors in regressions, the joint regression in Panel C of Table 4 implies that a one-standard-deviation increase of dealer inventory is associated with a quarterly increase of about 3-30 basis points in bond yields. For intermediary distress, this number is about 5-60 basis points.

The effect of both intermediary factors is stronger for lower quality bonds. For example, the coefficients on dealer inventory (intermediary distress) monotonically increase from 0.011 to 0.278 (from 0.048 to 0.499) for medium-term bonds, when the rating goes from AA and above down to B and below. This monotonic pattern is reminiscent of the positive correlation between intermediary factors and the PC1, which has an increasing loading on groups of decreasing rating in Table 3. Given the low (but slightly negative) correlation between dealer inventory and intermediary distress, the results indicate a two-factor structure of the common unexplained credit spread variation, associated with intermediary constraints.

Finally, to evaluate the overall explanatory power of the intermediary factors on credit spread changes, we compute the fraction of the total variation of residuals that is accounted for by $\Delta Inventory^A$ and $\Delta Noise$. In particular, for each of the 15 time series regressions, we can compute the total variation of credit spread residuals ε_g^{var} as above and also the variation $u_g^{var} \equiv \sum_t (u_{g,t})^2$ that cannot be explained by the two intermediary factors. For each of the three maturity groups and all 15 groups, we compute the fraction of variation explained by

[13] This is likely due to the unbalanced number of bonds assigned into different cohorts. Indeed, for cohorts based on firm leverage with a much more balanced number of observations in different cohorts, as used in Table 6 of next section, the statistical significance of both intermediary factors is strong in univariate regressions.

the two intermediary factors as

$$\text{FVE} = 1 - \frac{\sum_{g \in G} u_g^{var}}{\sum_{g \in G} \varepsilon_g^{var}}, \tag{3}$$

where $G \in \{\text{short, medium, long, all}\}$. As reported in the last column of Table 4, the two intermediary factors explain 38%, 55%, and 50% of the total variation of residuals of credit spread changes for short, medium, and long term bonds, respectively, and about 48% for all bonds. Similar calculations for dealer inventory and intermediary distress separately show that 2/3 of this explanatory power can be attributed to intermediary distress and 1/3 to dealer inventory, which is consistent with the correlations of these two factors and the PC1 reported in the last row of Table 3.

In sum, our baseline analysis shows that dealer inventory and intermediary distress have significant positive effects on common credit spread changes. The effects monotonically decrease with bond ratings. The two factors together account for about half of the unexplained total variation of credit spread changes, with one third and two thirds attributable to dealer inventory and intermediary distress, respectively.

3.2 Trading-Based Liquidity Factor and Credit Spread Changes

Since CGM, numerous studies have focused on transaction-cost-based liquidity (e.g., bid-spreads) as a major driver of credit spreads. It is hence instructive to understand how much of credit spread changes at the quarterly frequency can be explained by these microstructure liquidity factors in comparison with our intermediary factors. We use the illiquidity measure of Dick-Nielsen, Feldhütter, and Lando (2012).[14]

Table 5 report quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes similar to (2), but on ΔILiq in univariate regressions (in panel A) and in multivariate regressions along with our two intermediary factors $\Delta Inventory^A$ and $\Delta Distress$ (in panel B), respectively. The results show that ΔILiq mainly adds to the explanatory power (adjusted R^2) of high-rating cohorts but not low-rating cohorts, consistent with Bao, Pan, and Wang (2011), but its explanatory power is quite small. In particular,

[14] Another influential measure of corporate bond market illiquidity is proposed by Bao, Pan, and Wang (2011), which is available at the monthly frequency but only up to 2009. Over 2003 - 2009, its correlation with the Dick-Nielsen, Feldhütter, and Lando (2012) measure is larger than 90%, so we do not expect any material difference using either measure in our analysis. Indeed, Panel B of Table A.5, based on monthly regressions, shows that the change of illiquidity measure of Bao, Pan, and Wang (2011) mainly affects credit spread changes of high-rating bonds, similar to using the change of the illiquidity measure of Dick-Nielsen, Feldhütter, and Lando (2012) as reported in Table 5.

Panel A shows that ΔILiq accounts for about 3% of the total variation of residuals of credit spread changes (and significantly positive only for high-rating cohorts). In panel B, we observe that relative to our baseline with two intermediary factors, ΔILiq only increases the explained fraction by 0.6% (from 48.2% to 48.8%).[15]

3.3 Robustness Check

In this section, we provide further results that either elaborate on the explanatory power of intermediary factors for credit spread changes or confirm the robustness (additional robustness results are in Appendix A).

First, Table 6 reports the results using 15 cohorts based on time-to-maturity and firm leverage. Similar to CGM, we set the breakpoints of leverage to obtain a relatively homogeneous distribution of bonds across cohorts.[16] Panel B reports a PC analysis on the 15 residual series, showing a similar strong common variation with the PC1 accounting for 78% of the total unexplained variation of credit spread changes. Panel C reports the quarterly bivariate series regressions of each of the 15 residuals on dealer inventory and intermediary distress. Intermediary factors have significant positive effects on common credit spread changes, with the effects monotonically increasing with leverage. Compared with the baseline results in Table 4, the statistical significance is stronger (especially for univariate regressions on dealer inventory not reported here) probably because of the balanced number of observations, while the economic significance is similar. The two factors together account for about 42% of the unexplained total variation of credit spread changes.

Second, Table 7 reports results following the baseline procedure except using series of monthly credit spread changes (in percentage). As mentioned before in Section 3.1.1, the PC analysis in panel B shows that the first PC still accounts for 76% of the total unexplained variation of credit spread changes, similar to that in CGM but higher than in FN also using monthly series. Panel C shows bivariate regressions on the intermediary factors for this monthly sample; similar to Table 4, intermediary factors have significant positive effects that monotonically decrease with ratings, with similar economic significance. The statistical significance is stronger, especially for dealer inventory, probably because of the large number

[15] In an alternative approach, we add ΔILiq as an explanatory variable to the individual-bond regression (1). Consistent with the pattern in Table 5, it mainly adds to the explanatory power (adjusted R^2) of high-rating cohorts but not low-rating cohorts. And, two intermediary factors explain 45% of the total variation of residuals, only slightly lower than the 48% in the baseline analysis. In fact, this 3% difference is consistent with 3% of explanatory power of ΔILiq alone reported in Panel A in Table 5.

[16] As seen from Panel A, the range of the number of bonds is 210-300, 250-450, and 170-500 in short, medium, and long term cohorts, much more homogeneous than rating-based cohorts.

of time series observations for each bond. The two factors together account for 20% of the unexplained total variation of credit spread changes, lower than that in the baseline analysis, not surprisingly because of a larger number of observations and higher level of variation at the monthly frequency. But the overall significant explanatory power of intermediary factors for common credit spread changes remains the same.

Finally, recall that we have constructed the intermediary distress factor $\Delta Distress$ as the first PC of both $\Delta Noise$ and $\Delta \text{NLev}^{\text{HKM}}$; this is partly for parsimony and partly for developing our model in the next section. We could have "let data speak" by regressing the credit spread residuals on these two factors separately and jointly, and see the explanatory power of each distress factor. The results of this exercise is reported in Table 8. Similar to $\Delta Distress$, both measures have significant positive effects that monotonically decrease with bond ratings. $\Delta Noise$ accounts for 32% of the unexplained total variation of credit spread changes, higher than the 17% of $\Delta \text{NLev}^{\text{HKM}}$; but jointly both can explain 38%. Therefore, $\Delta Noise$ and $\Delta \text{NLev}^{\text{HKM}}$ have overlapping but nontrivial explanatory power relative to each other, lending support to our construction of the intermediary distress measure as a combination of the two.

4 An Economic Framework

We present a simple intermediary-based setting that is consistent with our main results above, which allows us to provide an interpretation to our data. First, we set up the model and describe its equilibrium. Beyond fundamental shocks, we propose two types of shocks driving asset prices – shocks to bond supply and shocks to intermediary wealth. Second, we use the model to rationalize and interpret our empirical results of Section 3. As a preliminary, we argue dealer inventory is a good proxy for bond supply shocks, whereas intermediary leverage is naturally a good proxy for intermediary wealth shocks. Then, we show how model-based regressions with dealer inventory and leverage reproduce the qualitative patterns of our bond-level regressions. Finally, we derive further tests guided by the model.

4.1 Setting and Equilibrium

Assets. There are many risky assets numbered $a = 1, \dots, A$. Asset cash flows are given by δ, which is normally distributed, $\delta \sim \text{Normal}(\bar{\delta}, \Sigma)$. Let p be the equilibrium asset price vector. There is also a riskless asset that pays 1 per unit of investment, as a normalization.

For simplicity, the risky assets are in zero net supply, i.e.,

$$\theta_H + \theta_I = 0, \tag{4}$$

where θ_H and θ_I are the asset demand vectors from hedgers and intermediaries, respectively.

Hedgers. As in Kondor and Vayanos (2019), hedgers inherit a random endowment $h'\delta$, with $h \geq 0$, and have a mean-variance objective:

$$\max_{\theta_H} \mathbb{E}[W_H] - \frac{\alpha}{2}\mathrm{Var}[W_H] \tag{5}$$

$$W_H := 1 - w + h'\delta + \theta_H \cdot (\delta - p - \mathbf{1}_A), \tag{6}$$

where W_H is ex-post hedger wealth, and $1 - w$ is initial hedger wealth.

Intermediaries. Competitive, risk-neutral intermediaries maximize expected wealth, subject to a margin-type constraint:

$$\max_{\theta_I} \mathbb{E}[w + \theta_I \cdot (\delta - p - \mathbf{1}_A)] \quad \text{s.t.} \quad \theta_I \cdot m \leq w, \tag{7}$$

where w is initial intermediary wealth. The constraint $\theta_I \cdot m \leq w$ is interpretable as a margin, or capital-adequacy, constraint, and m is a vector of margin requirements or risk-weights. While this constraint is sufficient to generate most of our empirical results, we also discuss other types of constraints in Appendix B.1. For example, one could argue that market prices should be in the constraint, or that long and short positions should both incur margin costs.

Equilibrium. Because of the linearity of the intermediary problem, optimization implies a condition on prices

$$p = \bar{\delta} - \mathbf{1}_A - \mu m, \tag{8}$$

where μ is the Lagrange multiplier on the margin constraint. The optimal hedger portfolio is given by the standard mean-variance optimization:

$$\theta_H = (\alpha\Sigma)^{-1}(\bar{\delta} - p - \mathbf{1}_A) - h. \tag{9}$$

Using (8) in (9), and aggregating using (4), we obtain the intermediary portfolio:

$$\theta_I = h - \frac{\mu}{\alpha}\Sigma^{-1} m. \tag{10}$$

Plugging this into the margin constraint, we have

$$\mu = \alpha \frac{(m'h - w)^+}{m'\Sigma^{-1}m}. \tag{11}$$

Thus, the constraint binds (and $\mu > 0$) if and only if $w < m'h$, i.e., if the intermediary wealth is below the required margin from holding all the hedging demands h.

Corporate bond pricing. We are interested in the pricing of a subset of assets in the model. This mirrors our empirical exercise, which zooms in on the corporate bond market. Let $\mathbf{1}_{\text{bond}}$ denote the logical vector of indicators corresponding to corporate bond assets. For instance, if the first two assets are bonds and the others are not, then $\mathbf{1}_{\text{bond}} = (1, 1, 0, 0, \dots)'$.

Below, we perform comparative statics on the supply of corporate bonds and on the level of dealer liquidity-provision. The proxy for dealer liquidity-provision is intermediary wealth w. To proxy bond supply, write total hedging demand as $h = s\bar{h}_{\text{bond}} + \bar{h}_{\text{other}}$ for a scalar s and weakly positive vectors $\bar{h}_{\text{bond}}$ and $\bar{h}_{\text{other}}$, where $\bar{h}_{\text{bond}}$ is only positive for the corporate bond assets, and the reverse for $\bar{h}_{\text{other}}$, i.e., $\bar{h}_{\text{bond}} \cdot \bar{h}_{\text{other}} = 0$. We will refer to changes in s a *supply shock* and changes in w a *demand shock*.

Proposition 1. *If the intermediary margin constraint is binding, i.e., $w < m'h$,*

$$\begin{aligned} (\text{“Supply Shock”}) \quad \frac{\partial p}{\partial s} &= -\Big(\frac{m'\bar{h}_{bond}}{m'\Sigma^{-1}m}\Big)\alpha m \\ (\text{“Demand Shock”}) \quad \frac{\partial p}{\partial w} &= \Big(\frac{1}{m'\Sigma^{-1}m}\Big)\alpha m. \end{aligned}$$

Otherwise, $\frac{\partial p}{\partial s} = \frac{\partial p}{\partial w} = 0$.

Proposition 1 says that increases in bond supply reduce asset prices, moreso for higher-margin assets. Similarly, decreases in intermediary demand reduce asset prices, moreso for higher-margin assets. Notice that bond supply s affects all asset prices, not just bond prices, which occurs through the impact of bond supply on the tightness of intermediaries' constraint. Finally, since margin constraints bind when intermediaries' risk-bearing capacity (w) is low, bond prices become more sensitive to s-shocks when w is low.

4.2 Empirical Implementation

Shock proxies. Recall in Section 2.2 our empirical pricing factors are “bond inventory” and “intermediary distress.” Whereas we take as given that the second factor is closely related to w^{-1}, we would like to use the model to argue that the bond inventory factor is closely related to s. Define our inventory and distress factors as

$$\xi := \log(\theta_I \cdot \mathbf{1}_{\text{bond}}) \tag{12}$$

$$\lambda := w^{-1}. \tag{13}$$

In equilibrium, assuming the intermediary margin constraint binds, the bond inventory measure is related to shocks (s, w) as follows:

$$(\text{“Supply Shock”}) \quad \frac{\partial \xi}{\partial s} = \exp(-\xi)\bar{h}_{\text{bond}} \cdot \mathbf{1}_{\text{bond}} - \left(\frac{\partial \xi}{\partial w}\right)\bar{h}_{\text{bond}} \cdot m \tag{14}$$

$$(\text{“Demand Shock”}) \quad \frac{\partial \xi}{\partial w} = \exp(-\xi)\frac{m'\Sigma^{-1}\mathbf{1}_{\text{bond}}}{m'\Sigma^{-1}m}. \tag{15}$$

Whatever features make inventory less sensitive to demand shocks (w) make inventory more sensitive to supply shocks (s), as $\partial\xi/\partial w$ enters $\partial\xi/\partial s$ negatively. This happens because higher bond supply tightens intermediary margin constraints, reducing intermediation capacity, just as lower intermediary wealth does. Practically speaking, we may argue that inventory is insensitive to w-shocks, and in doing so, we are also arguing it is a good proxy for s-shocks.[17]

Bond inventory is insensitive to w for two basic reasons. First, higher-margin bonds tend to be riskier. Intuitively, intermediaries try to sell high-margin assets in response to a negative wealth shocks, but risk-averse hedgers are somewhat unwilling to purchase those assets. Another way for intermediaries to reduce their bond inventory is by selling low-margin assets, but intermediaries value these highly when their constraints bind. As a result, intermediaries simply retain high bond inventories. Mathematically, consider the following simple $A = 2$ example, with $\mathbf{1}_{\text{bond}} = (1, 1)'$, and

$$\Sigma = \begin{bmatrix} \phi & \rho \\ \rho & \phi^{-1} \end{bmatrix} \quad \text{and} \quad m = \bar{m} \times (\phi, \phi^{-1})', \quad \phi > 1.$$

Then, with binding margin constraints,

$$\frac{\partial \xi}{\partial w} = \exp(-\xi)\frac{m'\Sigma^{-1}\mathbf{1}_{\text{bond}}}{m'\Sigma^{-1}m} = \exp\left[\frac{1}{\bar{m}}\frac{2-(\phi+\phi^{-1})\rho}{\phi+\phi^{-1}-2\rho}(m'h - w) - h \cdot \mathbf{1}_2\right]\frac{1}{\bar{m}}\frac{2-(\phi+\phi^{-1})\rho}{\phi+\phi^{-1}-2\rho},$$

[17] Separately, these expressions help us make sense of our empirical result that “intermediary distress” (and as well as its two ingredients “noise” and “intermediary leverage”) have small *negative* correlations with inventory. Indeed, $\text{corr}(\mathrm{d}\xi, \mathrm{d}\lambda) = -\text{corr}(\mathrm{d}\xi, \mathrm{d}w) < 0$.

which is strictly decreasing in ϕ.[18]

Second, constraints are likely to be occasionally-binding in reality. When the margin constraint is slack, inventory becomes completely insensitive to w, whereas its sensitivity to s increases.[19] Hence, occasionally-binding constraints makes ξ an even purer proxy for s.

Bond regressions. Supposing changes to s and w are the only shocks, we can write

$$\mathrm{d}p = \frac{\partial p}{\partial s}\mathrm{d}s + \frac{\partial p}{\partial w}\mathrm{d}w \quad \text{and} \quad \mathrm{d}\xi = \frac{\partial \xi}{\partial s}\mathrm{d}s + \frac{\partial \xi}{\partial w}\mathrm{d}w \quad \text{and} \quad \mathrm{d}\lambda = -(\lambda/w)\mathrm{d}w.$$

Substituting results above, we obtain an exact regression-like characterization.

Proposition 2. *If s and w are the only non-fundamental shocks, and margin constraints bind, then*

$$\begin{aligned}
&\mathrm{d}p = \beta_\xi \mathrm{d}\xi + \beta_\lambda \mathrm{d}\lambda \\
&\beta_\xi := -\exp(\xi) m'\bar{h}_{bond}\Big[\bar{h}_{bond}\cdot \mathbf{1}_{bond} - \frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m}\bar{h}_{bond}\cdot m\Big]^{-1}\frac{\alpha m}{m'\Sigma^{-1}m} \\
&\beta_\lambda := -\frac{w}{\lambda}\Big(m'\bar{h}_{bond}\Big[\bar{h}_{bond}\cdot \mathbf{1}_{bond} - \frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m}\bar{h}_{bond}\cdot m\Big]^{-1}\frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m} + 1\Big)\frac{\alpha m}{m'\Sigma^{-1}m}.
\end{aligned}$$

If margin constraints are slack, then $\mathrm{d}p = 0$.

Proposition 2 allows us to relate our model to the data. First, the model is able to reproduce our measured pattern of regression coefficients. In Proposition 2, coefficients β_ξ and β_λ reflect the margin vector m, up to proportionality. Thus, the ratio of the regression betas of assets i and j are given by their relative margin requirements:

$$\beta_\xi^{(i)}/\beta_\xi^{(j)} = \beta_\lambda^{(i)}/\beta_\lambda^{(j)} = m_i/m_j. \tag{16}$$

Lower-rated bonds and higher-leverage bonds are likely to have larger margin and/or capital requirements and thus should display larger loadings on both inventory and distress changes. For example, under the Basel II agreement, implemented during our sample period in many non-US jurisdictions, corporate bond holdings incur capital charges that decrease with ratings: under the so-called standardized approach, there is a 20% risk weight applied to securities rated between AAA to AA-; 50% for A+ to A-; 100% for BBB+ to BB-; and

[18] The same point holds in levels, i.e., replace ϕ with $1+\epsilon$ and ϕ^{-1} with $1-\epsilon$ for some small $\epsilon > 0$. In that case, $\frac{\partial \xi}{\partial w} = \exp\left[\frac{(1-\epsilon)(1+\epsilon)-\rho}{(1-\epsilon)(1+\epsilon)(1-\rho)}(m'h - w) - h\cdot \mathbf{1}_2\right]\frac{(1-\epsilon)(1+\epsilon)-\rho}{(1-\epsilon)(1+\epsilon)(1-\rho)}$, which is decreasing in ϵ.

[19] Mathematically, under $\mu = 0$, we have $\frac{\partial \xi}{\partial w} = 0$ and $\frac{\partial \xi}{\partial s} = \bar{h}_{\text{bond}}\cdot \mathbf{1}_{\text{bond}}/\exp[s\bar{h}_{\text{bond}}\cdot \mathbf{1}_{\text{bond}}]$.

150% for those below BB-.[20] Relatedly, under the SEC's "net capital rule," US broker-dealers' capital requirements are tied to the riskiness of securities in their portfolios (e.g., using a VaR approach), and lower-rated corporate bonds tend to be riskier. In line with this discussion and with formula (16), our empirical results show inventory and dealer distress betas share a similar pattern, both rising with proxies of margin requirements (in Table 4, we measure $\hat{\beta}_\xi^{\mathrm{AA}}/\hat{\beta}_\xi^{\mathrm{B}} \approx 10 - 20$ and $\hat{\beta}_\lambda^{\mathrm{AA}}/\hat{\beta}_\lambda^{\mathrm{B}} \approx 7 - 15$, which are a bit above the capital-requirement-implied sensitivity ratios, i.e., $m_{\mathrm{B}}/m_{\mathrm{AA}} = 150\%/20\% = 7.5$ in Basel II).[21]

Second, although this model has two factors (inventory and distress), it is also consistent with a single dominant principal component, as documented in CGM and our Table 3. All non-fundamental shocks - supply and demand - alter asset prices by affecting the multiplier μ of the intermediary margin constraint (see equation (8)), thus both show up as part of the "single" pricing factor in an intuitive way. Here, margin m represents the asset price loadings on this single factor μ, analogous to bonds' eigenvector loadings on their first principal component.

Unfortunately, the "single factor" μ is not directly measurable. Faced with this challenge, we have instead opted to measure the shocks that drive μ (e.g., s-shocks and w-shocks). The primary empirical difficulty is that bond supply s is not easily measurable, and our model hence is useful in helping design our inventory proxy ξ.

Developing new tests. Besides clarifying the results of Section 3, the model also allows us to design new tests. Below, we develop Predictions 1-3, which we shall take to data in Section 5.

First, although assets have many other features besides their margin requirements and capital charges, the model says that *only* the asset's margin matters for pricing by intermediary constraints; see equation (16). If two assets differ on some characteristic $x_i \neq x_j$, but they have the same margin $m_i = m_j$, then they will have the same sensitivities to the intermediary factors (ξ, λ), i.e., $\beta_\xi^{(i)} = \beta_\xi^{(j)}$ and $\beta_\lambda^{(i)} = \beta_\lambda^{(j)}$. This produces the following empirical prediction.

[20] See page 23, paragraph 66 of `https://www.bis.org/publ/bcbs128b.pdf`. There is also an alternative to the standardized approach, the so-called internal ratings-based (IRB) approach, which assigns capital charges according to self-assessed default probabilities and loss-given-defaults for the underlying securities. Using the IRB approach generates qualitatively similar patterns of capital charges, because lower-rated securities have higher default probabilities and default losses.

[21] Although we have only included corporate bonds inventory in our regression for parsimony, this proportionality test is robust to omission of other non-corporate-bond inventories whose supply shock might be correlated with s. Under this model, one can show the slope coefficient for the omitted inventory variable inherits the same proportionality to vector m as the included variables ξ and λ. Accounting for any such omitted variable bias will modify the magnitude of β_ξ and β_λ but not their patterns. Said differently, equation (16) still holds for the biased estimates.

Prediction 1. *Sorting bonds by any characteristic unrelated to margin or capital requirements should not produce any pattern in sensitivities on dealer inventory or intermediary distress.*

Second, the model features the following "spillover effect": when dealers take into inventory any asset carrying margin requirements, their margin constraint is tightened, and they will demand a higher premium on all other margin-carrying assets they trade. Of course, there are intuitive limitations, which are absent from our baseline model, on the extent of this spillover effect. One leading economic mechanism for such limitations is potential market segmentation across assets/dealers.

To develop a formal prediction on the extent of any spillover effects, we modify the model slightly as follows. Rather than a single margin constraint as in (7), suppose that dealers face asset-class-specific margin constraints, modeled as different constraints on non-overlapping sets of assets $\mathcal{A}_1$ and $\mathcal{A}_2$:

$$\sum_{a \in \mathcal{A}_1} \theta_{I,a} m_a \leq w_1 \quad \text{and} \quad \sum_{a \in \mathcal{A}_2} \theta_{I,a} m_a \leq w_2.$$

There are two Lagrange multipliers, μ_1 and μ_2, associated with each constraint, and the pricing condition is modified to be $p = \bar{\delta} - \mathbf{1}_A - \text{diag}(m)(\mu_1 \mathbf{1}_{\mathcal{A}_1} + \mu_2 \mathbf{1}_{\mathcal{A}_2})$.

One interpretation of this modified constraint is that assets in $\mathcal{A}_1$ and $\mathcal{A}_2$ are being traded by imperfectly integrated trading desks within a bank, each with independent portfolio limits. In practice, the bank's lead portfolio manager passes on capital charges to the subsidiary trading desks, according to their individual trading positions, in the form of costs against their profit book or even trading restrictions. Under this type of model, $\mathcal{A}_2$ traders have little incentive to care about the inventory of $\mathcal{A}_1$ assets. Mathematically, we can show that μ_1 is sensitive to $\mathcal{A}_1$ inventory, whereas μ_2 is not (see Appendix B.2). But when the bank is in distress globally, in the sense that $w_1 + w_2 = w$ is reduced, all subsidiary trading desks become restricted, in the sense that both μ_1 and μ_2 rise. This model extension leads to the following prediction.

Prediction 2. *Assets traded by corporate bond dealers (or within-dealer trading desks focused on corporate bonds) will be sensitive to bond inventory, in proportion to their margin requirements; other assets will not. All margin-carrying assets will be sensitive to aggregate intermediary distress.*

Lastly, we have used the model to argue bond inventory is a good proxy for bond supply. For example, we measure $\beta_\xi < 0$ in our regressions; see Table 4, which shows positive regression coefficients for bond yields on inventory, implying negative coefficients for bond prices. The model then implies that $\partial\xi/\partial s > 0$ (see Proposition 2 and compare with equation (14)). But this line of reasoning depends on the model structure. A more direct test would be to extract plausibly exogenous supply shocks $\mathrm{d}s$ and observe how inventory ξ changes.

Prediction 3. *If investors liquidate some bond positions for reasons plausibly unrelated to aggregate intermediary wealth, economic conditions, or firm fundamentals, then (i) dealer bond inventory should increase; and (ii) bond prices should fall.*

5 Empirical Support to the Economic Framework

In this section, we provide additional supporting evidence, corresponding to Predictions 1-3 above, that corroborates the key economic mechanism of dealer margin constraints. First, sorting bonds based on variables that are unlikely related to margin and capital charges does not reproduce similar regression patterns as the main findings in Section 3. Second, dealer inventory has spillover effects within the corporate credit market but not outside, while intermediary distress affects various asset classes universally. Third, dealer inventory changes are negatively associated with changes of institutional holdings of substantially downgraded bonds, lending support to the interpretation of dealer inventory factor as representing supply shocks. We further provide IV estimates for the effect of dealer inventory on credit spread changes via the supply channel.

5.1 Sorts on Variables Unrelated to Margin

Our margin-based model suggests a placebo test: sorting bonds based on variables unrelated to margin should produce no pattern in price sensitivities to intermediary factors (see Prediction 1). A result of this type can be observed in Table 4, where the regression coefficients of both $\Delta Inventory^A$ and $\Delta Distress$ are roughly similar across maturity groups, a sorting variable unlikely to be tied to margin requirements.

To present further evidence along this direction, we sort bonds into cohorts based on rating and trading volume, the latter of which is plausibly unrelated to a bond's margin requirements. Specifically, for each bond in each quarter, we compute the total trading volume (in dollar market value) in the last month of the quarter. Then for each quarter, we sort bonds independently into one of 15 groups based on quintiles of ratings and terciles of total trading volume. Panel A of Table 9 reports summary statistics, including the number of bonds, number of bond-quarter observations, and average total trading volume across all bonds and quarters, in each group. Within each rating category, the average total trading volume differs substantially across the tercile groups, about \$2, \$17, and \$100 million respectively.

Panel B of Table 9 reports time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage) on $\Delta Inventory^A$ and $\Delta Distress$. The magnitude and statistical significance of coefficients on both intermediary factors increase from high-rating groups to low-rating groups, consistent with the results in Section 3, but remain roughly the same across the terciles by trading volume.

5.2 Spillover and Segmentation

Closely-related assets are likely to be intermediated by the same dealers, or traded by the same desks within a dealer firm, and should feature a spillover effect with respect to the bond inventory factor (see Prediction 2). We provide two tests of this prediction – the first splits bond inventory into high-yield and investment-grade inventories; the second considers CDS responses to bond inventory. We expect high-yield bonds to be sensitive to investment-grade inventory (and vice versa) and CDS spreads to be sensitive to bond inventory, because these are all closely-related assets. Lastly, there seems no spillover effect from corporate bond inventory to other non-corporate-credit asset classes, indicating market segmentation on this front.

5.2.1 High-Yield and Investment-Grade Bonds

Similar to the aggregate inventory measure, we construct dealer inventory of high-yield (HY) and investment-grade (IG) bonds separately, denoted as $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$. Table 10 reports time series regressions of each of the 15 residuals of credit spread changes, on $\Delta Inventory^{IG}$ and $\Delta Inventory^{HY}$ separately, as well as the intermediary distress factor.

Both $\Delta Inventory^{IG}$ and $\Delta Inventory^{HY}$ demonstrate explanatory power for credit spread changes of the bonds that are not in the rating categories used to compute the inventory measures, consistent with the spillover effect. As the model predicts, $\Delta Inventory^{HY}$ has overall stronger effects than $\Delta Inventory^{IG}$ because an increase in the former tightens dealers' margin constraints more than a similar increase in the latter. Both inventory measures also show a similar monotone effect from high-rating to low-rating bonds as the aggregate inventory $\Delta Inventory^A$ in Table 4.

One concern with the interpretation of these results as evidence of spillover effect is that HY and IG grade inventories may be simply correlated or driven by an unobserved common factor. Table A.8 reports correlations of the inventory measures inconsistent with this alternative interpretation. In particular, $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$ are negatively correlated in raw changes and near zero in percentage changes.

5.2.2 CDS Spreads

The second test considers CDS spreads, which are tightly-linked to corporate bonds by arbitrage, and so likely to be traded by corporate bond desks. Moreover, CDS carry capital charges requirements, and CDS of riskier, lower-rated firms tend to have higher capital requirements. Agreements such as Basel II treat CDS as "credit risk mitigation" and, ignoring counterparty risk, tie CDS capital charges directly to the capital charges of the underlying bond (Shan, Tang, and Yan (2016)).[22] Similarly, through its VaR approach, the SEC's "net capital rule" would require CDS of higher-risk firms to be held with higher capital charges.

Panel A of Table 11 reports summary statistics of our sample of quarterly CDS spread changes (in percentage). We have 1038 distinct entities, with a total of 55,744 observations at the firm-quarter level. The fraction of observations across the five rating categories remains roughly the same for different CDS maturities, about 80% with a crediting rating equal to and above BBB.

We conduct quarterly time series regressions of CDS spread changes on the same set of variables as for bond yield spreads, and compute the quarterly series of residuals. For each quarter and each maturity, we sort firms into one of the five groups of credit rating and take an average of the residuals within each group and in each quarter. Panel B of Table 11 reports the principal component analysis of the CDS spread change residuals. Similar to the baseline evidence in Table 3, the first PC accounts for over 80% of the common variation in CDS spread changes. Panel C reports regressions of these residuals on dealers' bond inventory and intermediary distress. The patterns of regression coefficients mirror those for bonds themselves, i.e., positive and monotonically decreasing with bond rating. The total explanatory power is lower than the 48% in the baseline evidence, but still reaches 37%.[23]

[22] See page 46, section 5, paragraph 196 of `https://www.bis.org/publ/bcbs128b.pdf`. If the long bond position is completely hedged by a long CDS position, then the net capital charge is only related to counterparty risk. Thus, for our argument to hold, some banks trading in both bonds and CDS must not be completely hedged.

[23] One may concern that the sensitivity of CDS spreads to bond inventory reflects some latent unobservable common credit risk factor. We provide two results to mitigate this concern. First, time series credit risk controls are included in regressions to obtain CDS spread change residuals. Second, results remain the same using the sample of CDS for which the underlying entities are not matched to the firms in the sample of TRACE transactions of corporate bonds used to construct the dealer inventory measure.

5.2.3 Non-Corporate-Credit Asset Classes

These spillover effects may be limited by the presence of some market segmentation. To investigate this, we perform a similar analysis on a host of non-corporate-credit asset classes, which are less likely to be traded by corporate bond dealers or corporate credit trading desks within a dealer firm. Specifically, we regress quarterly changes of yield spreads (relative to Treasury) of agency MBS, CMBS, ABS, and monthly returns of S&P 500 index options on the time series variables to extract the residuals. We then run time series regressions of these residuals on $\Delta Inventory^A$ and $\Delta Distress$. According to Prediction 2, these assets should be insensitive to bond inventory changes, but should still respond to aggregate intermediary distress. Consistent with this prediction, Table 12 shows statistically insignificant co-movement of these assets with bond inventory, but non-trivial co-movement with intermediary distress.

5.3 Bond-Level Evidence of Supply Shocks and IV Regressions

In this section, by delving into bond-level dealer inventories and institutional holdings, we provide evidence that the change of dealer inventory is driven by the supply of bonds from investors who experience liquidity shocks. Based on such micro-level evidence, we then construct instruments for the dealer inventory factor at the aggregate level and conduct IV analysis of the effect of dealer inventory on credit spread changes.

A word of caution: bond downgrades clearly contain information about firm fundamentals and economic conditions, so we cannot argue that investor sell-offs are truly exogenous "supply shocks" (as in Prediction 3). But recall that when constructing the residuals of credit spread changes we have controlled the firm and market level structural factors. What is more, severely downgrades–from IG rating to HY rating which are also called "fallen angels"–are more likely to serve as pure supply shocks, thanks to the regulatory constraint imposed on financial institutions. Our later IV analysis uses "fallen angels" (controlling normal downgrades) together with the insured losses due to natural disasters to instrument the supply shock.

5.3.1 Bond-Level Evidence of Supply Shocks

Our bond-level analysis makes use of rating downgrades of bonds that can lead to large sell-offs from institutional investors. We provide evidence that a significant amount of such sell-offs are absorbed into dealers' balance sheet as inventories.

Holding Changes in Downgrades and Fallen Angels: Raw Data We proceed with the data as follows. From Mergent FISD, we obtain the dates and reasons of all bonds' historical rating changes. From TRACE, we compute the total inventory change of all dealers for each bond i in each quarter t, denoted as $\Delta Inventory_{i,t}$. From eMAXX, we compute the change of total holdings for each bond i and in each quarter t, denoted as $\Delta Holding_{i,t}$, by each of the three groups of institutional investors – insurance companies, mutual funds, and pension funds. We identify observations of $\Delta Inventory_{i,t}$ and $\Delta Holding_{i,t}$ as "downgrade" observations if bond i is downgraded from IG rating to IG or HY rating in quarter t and as "no rating change" observations if the credit rating remains unchanged. Among "downgrade" observations, we further identify "fallen angels" that have been downgraded from IG rating to HY rating (Ambrose, Cai, and Helwege (2008), Ellul, Jotikasthira, and Lundblad (2011)) and "downgrade (IG)" observations with bonds downgraded from IG rating to IG rating. Our analysis relies on the sell-offs induced by bond downgrading, so we exclude the "upgrade" observations with bonds upgraded.[24] We also exclude observations with bonds downgraded from HY rating to HY rating as the different initial rating category makes it hard to compare with "downgrade" observations.

Table 13 reports the average quarterly change of holdings by insurance companies, mutual funds, and pension funds, in panels A, B, and C, respectively, and the average quarterly change of dealers' inventories in panel D. In particular, for each of these four groups of investors, we report the average of $\Delta Holding_{i,t}$ or $\Delta Inventory_{i,t}$ across "downgrade (IG)", "fallen angels", and "no rating change" observations. Both the number of observations and average holdings change (in $millions) are reported. We also include the average of changes in quarter $t+1$, i.e., one quarter following the rating change, because it may take time for investors to adjust their positions. To put the magnitudes in context, we report the average level of institutional holding $Holding_{i,t-1}$ and dealer inventory $Inventory_{i,t-1}$ as of quarter $t-1$ in the last row of each panel.

For the set of "downgrade (IG)" bonds, both at the quarter (t) of downgrade and the following quarter ($t+1$), insurance companies decreased their holdings by about $0.92-1.01 million, while mutual funds and pension funds increased their holdings by about $0.29-0.38 million at quarter t but sold about $0.16-0.25 million at quarter $t+1$. Similar patterns are found for "fallen angels". In particular, insurance companies sold off "fallen angels" in both quarters, about $1.27-1.35 million, while mutual funds and pension funds bought about $0.12-0.20 million at quarter t and sold about $0.24-0.47 million at quarter $t+1$. That

[24] Including "upgrade" observations as a comparison group leads to stronger results in quantifying the sell-offs of downgraded bonds by institutional investors, not surprisingly.

is, the sell-offs by insurance companies are larger for “fallen angels” than for “downgraded (IG)” bonds, but the purchases of mutual funds and pension funds are larger for the latter than for the former bonds, even using the bonds that maintained the same rating as a benchmark. This is consistent with insurance companies being forced to sell downgraded bonds, especially “fallen angels”, due to regulatory constraints, and mutual funds and pension funds purchasing these bonds to take advantage of “fire-sale” discounts (Cai, Han, Li, and Li (2019), Anand, Jotikasthira, and Venkataraman (2018)).

Importantly, panel D of Table 13 shows that dealers buy a similar amount of “downgrade (IG)” bonds in quarter t to mutual funds and pension funds, about \$0.34 million, but a much larger amount of “fallen angels”, about \$1.31 million. Dealers also buy “downgrade (IG)” bonds and sell “fallen angels” in quarter $t+1$, but with a much smaller amount. Compared with the level of inventory as of quarter $t-1$, dealers’ purchase amount of “fallen angles” is strikingly large, an increase of about 78%, substantially larger than those of mutual funds and pension funds that are below 1%.

Holding Changes in Downgrades and Fallen Angels: Regression Next, we conduct regression analysis–which allows us to control bond characteristics–to formally test the relation between institutional investors’ sell-offs and dealers’ inventory changes. The first three columns of Table 14 report results based on the following regression:

$$\begin{aligned} & \Delta Holding_{i,t+\tau} \\ = \; & Intercept + \beta_1 \times \text{Fallen}_{i,t} + \beta_2 \times \text{Downgrade}_{i,t} + \beta_3 \times log(\text{Amt}_{i,t+\tau}) + \beta_4 \times log(\text{Size}_i) \\ & + \beta_5 \times \text{Age}_{i,t+\tau} + \beta_6 \times \text{Time-to-Mature}_{i,t+\tau} + \sum_t \text{FE}_t + \varepsilon_{i,t+\tau}, \end{aligned} \tag{17}$$

where $\tau = 0$ for the change in quarter t (reported in panel A) and $\tau = 1$ for the change in quarter $t+1$ (reported in Panel B). The indicator variable $\text{Downgrade}_{i,t}$ equals 1 if bond i is downgraded in quarter t and 0 otherwise, whereas $\text{Fallen}_{i,t}$ equals 1 if bond i is a “fallen angel” in quarter t and 0 otherwise.

The sample includes “downgrade (IG)”, “fallen angels”, and “no rating change” observations. Thus, the coefficient on $\text{Downgrade}_{i,t}$ captures the $(t+\tau)$ change of institutional investors’ holdings of a average downgraded bond in quarter t, relative to that of a bond that has no rating change contemporaneously. Similarly, the coefficient on $\text{Fallen}_{i,t}$ captures the $(t+\tau)$ change of institutional investors’ holdings of a bond downgraded from IG rating to HY rating in quarter t, relative to the average of those that have no rating change and that are downgraded from IG rating to IG rating contemporaneously. We control for various bond characteristics including the log of outstanding balance ($log(\text{Amt}_{i,t+\tau})$), the log of issue size ($log(\text{Size}_i)$), bond age ($\text{Age}_{i,t+\tau}$), and time-to-maturity ($\text{Time-to-Mature}_{i,t+\tau}$), and also include time fixed effects. Panel regressions of changes in dealers' inventories $\Delta Inventory_{i,t+\tau}$, similar to (17) are reported in the last column.

Consistent with summary statistics in Table 13, we observe that insurance companies decrease their holdings of downgraded bonds in both quarters, about \$0.48-0.80 million, relative to the bonds with no rating changes. Mutual funds and pension funds seem to take some of the downgraded bonds sold by insurance companies in quarter t, about \$0.51 and \$0.36 million respectively, but no detectable patterns in the following quarter. Insurance companies sell "fallen angels" even more aggressively, about \$0.67 million in quarter t and \$0.33 million in quarter $t+1$, relative to average bonds that experience no rating changes and that are downgraded from IG rating to IG rating. Mutual funds and pension funds do not conduct significant purchases of "fallen angles". In contrast, dealers' inventories of "fallen angels" increase substantially in quarter t (about \$1.61 million) and then decrease somewhat in quarter $t+1$ (about \$0.45 million). That is, dealers first take inventories of "fallen angels" in providing liquidity to insurance companies, and then unwind (part of) these inventories at a later time, consistent with standard inventory control behavior (Ho and Stoll, 1981). Interestingly, dealers' inventories of average downgraded bonds do not seem to be significantly different from those with no rating change.

In sum, insurance companies dump a large amount of "fallen angels", and dealers take them into their inventories. Taking as a premise that insurance companies face constraints due to regulations for holding low-rating bonds (Ellul, Jotikasthira, and Lundblad, 2011), we interpret downgrade-induced sell-offs by insurance companies as a supply shock to increase dealers' inventories, independent of their balance sheet condition (wealth or leverage). In the following, we construct an IV for the dealer inventory factor based on institutional investors' holdings of "fallen angels".

5.3.2 IV Regressions

To construct a time series IV for the dealer inventory factor $\Delta Inventory_t^A$, we aggregate the changes of institutional holdings of downgraded bonds in each quarter. In particular, we use the sell-offs of "fallen angels" $\Delta Holding_t^{FA}$ as the IV and the sell-offs of all downgraded bonds $\Delta Holding_t^D$ as a control. Using $\Delta Holding_t^D$ as a control (partially) takes care of the confound that downgrading contains information on the fundamental value of bonds, which then leads to both sell-offs and price effects. In addition, recall that the sell-offs of "fallen angels" come mainly from insurance companies that face clear-cut regulatory constraints, so

$\Delta Holding_t^{FA}$ is likely a purer proxy for bond supply shocks than $\Delta Holding_t^{D}$. Yet, all types of institutional investors are included in computing $\Delta Holding_t^{FA}$ and $\Delta Holding_t^{D}$, rather than only insurance companies, to capture the net selling to dealers given that mutual funds and pension funds seem to take some amount of downgraded bonds sold by insurance companies.[25] We scale $\Delta Holding_t^{FA}$ and $\Delta Holding_t^{D}$ by their respective levels of holdings as of $t-1$, corresponding to constructing $\Delta Inventory_t^{A}$ as a percentage change.

To complement the analysis using $\Delta Holding_t^{FA}$, we also construct a second IV using insured losses due to natural disasters. In particular, we obtain from the Insurance Information Institute an annual series of realized industry-wide losses from catastrophes, capturing the total net insurance payment for personal and commercial property lines of insurance.[26] A linear time series model is fitted to the logarithm of this annual series with the residuals as the payout shocks. As catastrophes mostly happen in the third quarter of the year, we assign each year's payout shock to the third quarter and zero to other quarters. The resulting quarterly series is denoted by InsuredLoss_t.

Our rationale of using InsuredLoss_t as an IV is that the shock or unexpected insured loss is likely to induce sell-offs of corporate bonds by insurance companies to make payments. The advantage of InsuredLoss_t to $\Delta Holding_t^{FA}$ as an IV is its clear-cut exogeneity to bond value shocks. The disadvantage is that selling of corporate bonds may only be one of the strategies for insurance companies to collect payment money, which, for example, can be achieved by selling other fixed-income securities like Treasuries or agency MBS, or by withdrawing their cash lent out in short-term funding markets. Moreover, insured looses are only available at the annual level, and they are only shocks to P&C insurers, leaving life insurers unaffected. These issues may make InsuredLoss_t a statistically-weak IV, which needs to be addressed using proper econometric procedures.

Table 15 reports first-stage regressions of $\Delta Inventory^{A}$ on $\Delta Holding_t^{FA}$ and InsuredLoss_t, separately in the first two columns and jointly in the third column. As mentioned above, we include $\Delta Holding_t^{D}$ as a control, in addition to the intermediary distress factor and six time series variables also used in the baseline bond-level regressions (1). All variables are

[25] Of course, this will overestimate (underestimate) the net selling amount to dealers if other investors like hedge funds also buy (sell) some amount of.

[26] The included catastrophes, following definitions of the Property Claim Services division of Verisk Analytics, are those that caused insured property losses of $25 million or more in 1997 dollars and affected a significant number of policyholders and insurers, excluding losses covered by the federally administered National Flood Insurance Program. The types of catastrophes include, for example, wildfires, heat waves, droughts, tropical cyclones, severe thunderstorms, winter storms, cold waves, floods, and earthquakes. See https://www.iii.org/fact-statistic/facts-statistics-us-catastrophes#Loss%20Events%20in%20the%20U.S.,%201980-2018 for detailed information about natural catastrophes and https://www.iii.org/table-archive/20922 for our data series.

scaled to have zero mean and unit variance except the six time series variable from (1). We observe that a one-standard-deviation decrease in institutional holdings of "fallen angels" is significantly associated with about a 0.37 standard deviation increase in dealer inventory, indicating the relevance of $\Delta Holding_t^{FA}$ for $\Delta Inventory^A$. A one-standard-deviation increase of InsuredLoss_t is associated with a 0.07 standard derivation increase in dealer inventory, but as expected, the statistical significance is weak.

Table 16 reports second-stage regressions of quarterly residuals of credit spread changes (as in the baseline analysis of Table 4) on $\Delta Distress$ and $\Delta Inventory^A$, using $\Delta Holding_t^{FA}$ as an inventory IV in Panel A, using InsuredLoss_t as an inventory IV in Panel B, and using both as IVs in Panel C. The last two rows in each panel reports the test statistic for weak instruments by Montiel-Olea and Pflueger (2013) (MP) and associated critical values (Pflueger and Wang, 2015), which allow for conditionally-heteroskedastic and serially-correlated errors.[27]

From Panel A of Table 16, the value of the MP-statistic is larger than the critical value, so the null hypothesis that $\Delta Holding_t^{FA}$ is a weak investment for $\Delta Inventory_t^A$ is rejected at a significance level of 10% with a worst-case bias greater than 20% of the OLS bias. The regression coefficients and t-statistics reported in parentheses show that the dealer inventory factor instrumented by institutional holdings of "fallen angels" is highly significant in affecting credit spread changes positively, consistent with the baseline results in Section 3.

The MP test reported in Panel B of Table 16 is below the critical value, so we cannot reject the null hypothesis that InsuredLoss_t is a weak instrument. Therefore, we choose to report p-values of the Anderson and Rubin (1949) Wald-test in the left bracket and p-values of the Stock and Wright (2000) S-statistic in the right bracket that are both weak-instrument robust for testing the significance of the instrumented $\Delta Inventory_t^A$. The dealer inventory factor instrumented by InsuredLoss_t affects credit spread changes significantly at the 10% level mainly for groups of short to medium maturities and low ratings based on the Anderson and Rubin (1949) Wald-test, but only at the 15% significance level based on the Stock and Wright (2000) S-test. The value of the MP-statistic in Panel C is larger than the critical value, so weak instrument is less of a concern when we use both $\Delta Holding_t^{FA}$ and InsuredLoss_t as IVs. The regression coefficients and t-statistics further confirm the positive effect of dealer inventory on credit spread changes.

We note that the coefficients in IV regressions, especially on $\Delta Inventory_t^A$, are significantly larger than those in the baseline regressions of Table 4.[28] One potential reason is

[27]The widely used Cragg and Donald (1993) test and associated critical values by Stock and Yogo (2005) are only valid for conditionally-homoskedastic and serially-uncorrelated errors.

[28]Another difference between the IV regressions and baseline regressions (2) is that the former includes

that the change of dealer inventory could be driven by a (unobserved) demand shock, due to more optimistic beliefs of dealers regarding bond fundamentals, higher risk taking of dealers' bond trading desks, or looser regulatory requirements.[29] Such a demand shock leads to higher dealer inventory but lower credit spreads, i.e., a negative relationship between dealer inventory and credit spreads, which biases against the positive supply-driven comovement of dealer inventory and credit spread. Using the two IVs, which we claim are purely about supply, can purge our price-inventory sensitivity of demand effects.

6 Conclusion

It has been almost two decades since CGM raised one of the canonical puzzles in asset pricing of credit risk, i.e., there is a large common variation in credit spread changes beyond canonical structural factors. In this paper, we build on recent developments in intermediary asset pricing (He and Krishnamurthy, 2013; He, Kelly, and Manela, 2017) and demonstrate the importance of intermediary constraints to explain this canonical puzzle.

In particular, we show that two intermediary-based factors, an intermediary distress measure that captures financial constraints of the whole intermediary sector and a dealer inventory measure that captures inventory held by dealers specializing in corporate bonds, explain about 50% of the puzzling common variation documented in CGM. A simple economic framework in which intermediaries face margin constraints and absorb assets sales from customers delivers the robust empirical pattern that both intermediary distress and bond inventory factors are associated with credit spread changes, and these effects are monotone in bond ratings.

As a key contribution to the literature, we construct the aggregate corporate bond inventory for the broker/dealer sector, which can facilitate future research. We also augment this inventory measure with data on corporate bond holdings by other institutional investors (insurance companies, mutual funds, and pension funds). An important component of dealers' inventory change is tied to institutional investors' sales of (severely) downgraded bonds, which we interpret as a supply shock. Instrumental variable regressions using institutional

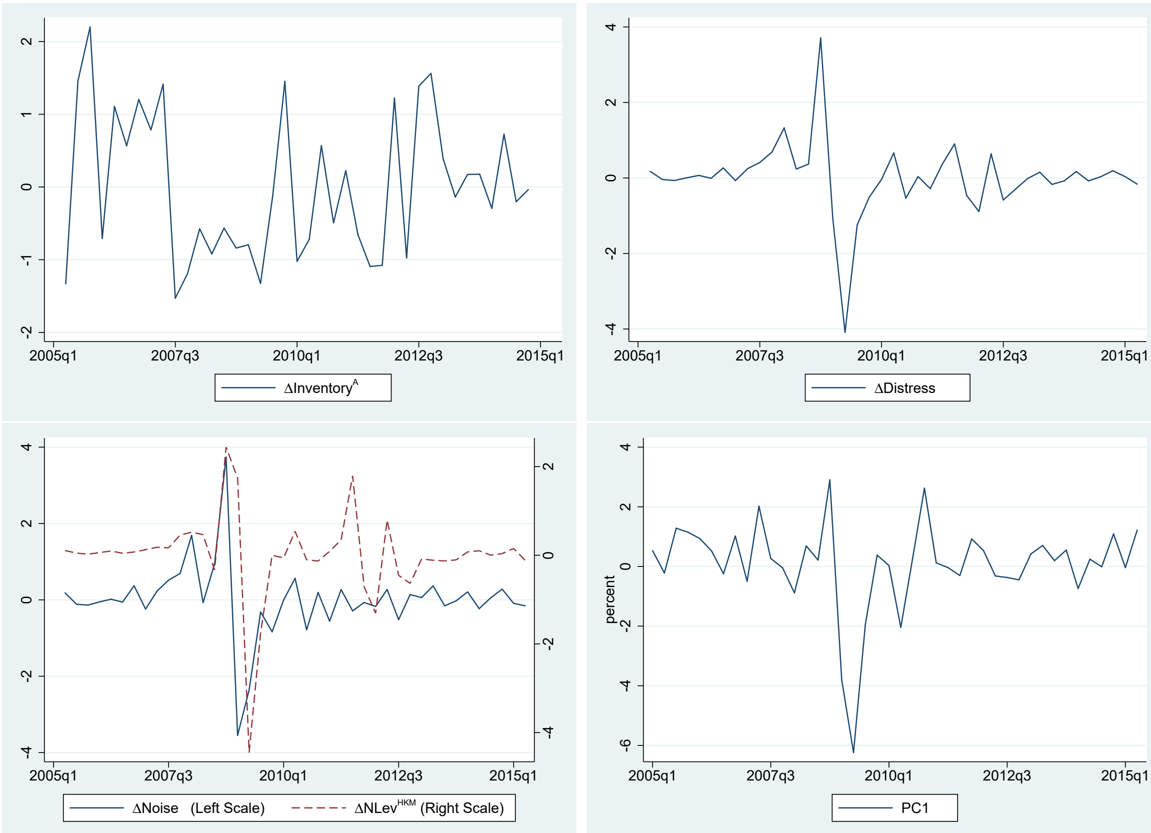
additional time series controls. These controls are not included in the baseline regressions because they have been controlled for in the bond-level regressions (1) used to construct the residuals. We include them in IV regressions to make sure the IV analysis is robust to them, which, however, is not the reason for the larger regression coefficients on $\Delta Inventory_t^A$.

[29] The demand shock could theoretically also be a distress-type shock, which affects bond inventory, as we show in our model. However, we view this possibility as unlikely, given we find the IV-OLS discrepancy in a multivariate setting, with our Distress measure included.

holdings of severely downgraded bonds, as well as insured losses due to natural disasters, support the interpretation of dealer inventory as a proxy for bond supply shocks.

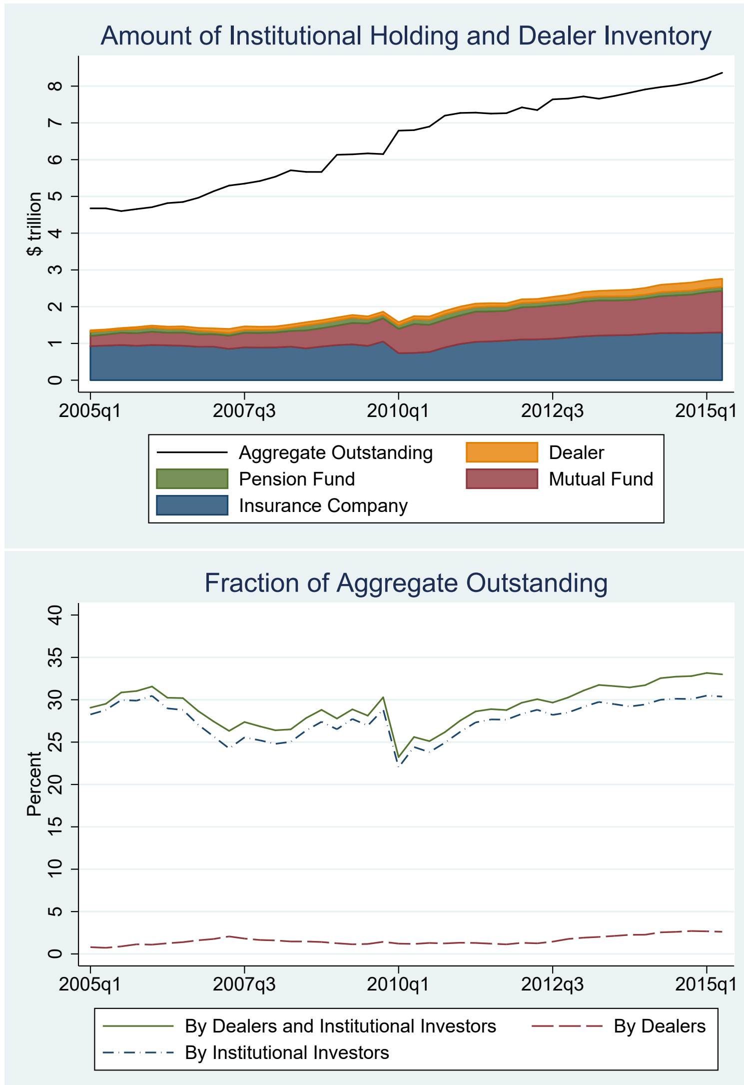
Our analysis has mainly focused on time series variations of credit spreads following CGM. Given both the fact that credit spread changes are inherently tied to returns and our finding that comovements of intermediary factors and credit spread changes differ across bonds (of different credit ratings), a natural question is how intermediary factors affect cross-sectional bond pricing. As an exploratory analysis, Table 17 presents regressions of four bond-return factors, proposed by Bai, Bali, and Wen (2019) recently in studying cross-sectional bond returns, on our two intermediary factors, with all factors orthogonalized against structural factors. We find that intermediary distress comoves with all return factors significantly, but not dealer inventory. Hence, intermediary distress provides a potential balance-sheet foundation for these return-based factors, while dealer inventory adds a potential balance-sheet factor to the set of cross-sectional return predictors. This can be a fertile future research direction.

Figure 1: Quarterly Time Series of Intermediary Factors and CGM PC1



Note: This figure plots quarterly time series of $\Delta Inventory^{A}$, $\Delta Distress$, $\Delta Noise$, $\Delta\text{NLev}^{\text{HKM}}$, and the first principal component of regression residuals of credit spread changes on structure factors (CGM PC1) as reported in Table 3. The sample period is from 2005:Q1 through 2015:Q2. The four intermediary variables are standardized to zero mean and unit standard deviation, and the CGM PC1 is based on 90-day change of credit spreads in percent.

Figure 2: Summary of Amount of Institutional Holdings and Dealer Inventories



Note: The top panel plots quarterly time series of the holding amount by institutional investors (including mutual funds, pension funds, and insurance companies) based on eMAXX data and by dealers based on TRACE data, as well as the aggregate outstanding balance of U.S. corporate debt based on the "Financial Accounts of the United States" (Z.1) data release by the Federal Reserve, in $trillions of principal value. The bottom panel plots quarterly time series of the fraction of U.S. corporate debt held by institutional investors, by dealers, and by both, respectively, in percent. The sample period is from 2005:Q1 through 2015:Q2.

Table 1: Summary of the Credit Spread Sample

All Bonds					
Number of bonds	2,584				
Number of firms	653				
Number of bond-quarters	55,398				
	mean	std	p25	p50	p75
Yield spread	2.51	2.69	0.95	1.60	3.12
Coupon	6.32	1.59	5.38	6.30	7.25
Time-to-Maturity	9.78	8.07	4.19	6.80	11.84
Age	5.12	4.32	2.14	3.86	6.67
Issuance	550.50	471.97	250.00	400.00	650.00
Rating	9.25	3.43	7.00	9.00	11.00
Investment Grade Bonds					
Number of bonds	1,980				
Number of firms	383				
Number of bond-quarters	40,828				
	mean	std	p25	p50	p75
Yield spread	1.52	1.17	0.81	1.22	1.85
Coupon	5.87	1.42	5.00	5.90	6.75
Time-to-Maturity	10.85	8.76	4.21	7.38	17.56
Age	5.34	4.46	2.21	4.01	7.06
Issuance	605.62	505.64	300.00	500.00	750.00
Rating	7.58	1.90	6.00	8.00	9.00
High Yield Bonds					
Number of bonds	900				
Number of firms	373				
Number of bond-quarters	14,570				
	mean	std	p25	p50	p75
Yield spread	5.27	3.65	3.15	4.46	6.12
Coupon	7.60	1.33	6.75	7.50	8.25
Time-to-Maturity	6.78	4.50	4.14	5.92	7.80
Age	4.53	3.87	1.97	3.49	5.69
Issuance	396.04	313.28	200.00	300.00	500.00
Rating	13.96	2.15	12.00	14.00	16.00

Note: This table reports bond characteristics for our baseline sample of credit spreads. We report the mean, standard deviation (sd), median (p50), 25th percentile (p25), and 75th percentile (p75) for the whole sample, investment grade subsample, and high yield subsample. The total number of bonds is smaller than the sum of the number of bonds in the investment grade and high yield subsamples because rating change make some bonds of investment grade in one part of the sample period but of high yield in the other part. Credit spread (in percentage) is the difference between the annualized yield-to-maturity of a corporate bond and a Treasury with the same maturity calculated with linear interpolations whenever necessary. Coupon is the coupon rate in percent. Time-to-maturity is in units of years. Age is the number of years since issuance. Issuance size is in $millions of face value. Rating is the Moody's credit rating of a bond coded numerically so that a higher number means lower rating, e.g., Aaa=1 and C=21. The overall sample period is 2005:Q1 - 2015:Q2

Table 2: Correlations of Empirical Measures

	$\Delta Inventory^A$	$\Delta Distress$	$\Delta Noise$	$\Delta\text{NLev}^{\text{HKM}}$	ΔVIX	ΔILiq
$\Delta Inventory^A$	1.000					
$\Delta Distress$	-0.116	1.000				
$\Delta Noise$	-0.094	0.833***	1.000			
$\Delta\text{NLev}^{\text{HKM}}$	-0.099	0.833***	0.388**	1.000		
ΔVIX	-0.094	0.357***	0.167	0.427***	1.000	
ΔILiq	-0.106	0.228	0.192	0.188	0.381**	1.000

Note: This table reports correlations of quarterly time series of $\Delta Inventory^A$, $\Delta Distress$, $\Delta\text{NLev}^{\text{HKM}}$, $\Delta Noise$, ΔVIX, and ΔILiq. The sample period is from 2005:Q1 through 2015:Q2. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value.

Table 3: Individual-Bond Regressions of Credit Spread Changes on Structural Factors

Groups		A: Individual Bond Regressions											B: PC	
Maturity	Rating	ΔLev^i	ΔVIX	$\Delta Jump$	Δr^{10y}	$(\Delta r^{10y})^2$	$\Delta slope$	ret^{SP}	R^2_{adj}	Bond#	Obs	$\varepsilon_g^{var} / \sum_{g=1}^{15} \varepsilon_g^{var}$	PC1	PC2
Short	AA	1.321	0.018	1.150	-0.164	-0.137	0.234	0.121	0.273	60	628	0.53%	0.056	-0.035
		1.306	2.223	1.502	-3.475	-1.597	3.864	2.007						
Short	A	-0.550	0.022	-0.094	-0.229	-0.115	0.163	-0.823	0.320	446	4717	0.77%	0.086	-0.028
		-0.737	7.244	-0.203	-7.503	-2.388	4.871	-24.599						
Short	BBB	2.303	0.021	-0.435	-0.398	-0.063	0.222	-2.413	0.429	751	7645	1.58%	0.128	-0.038
		6.178	7.302	-0.974	-11.257	-1.206	6.113	-66.34						
Short	BB	5.412	0.044	-2.498	-1.043	0.362	0.585	-2.282	0.562	319	2358	4.79%	0.237	-0.136
		7.911	6.257	-2.343	-13.821	3.705	7.564	-29.493						
Short	B	10.609	0.090	2.986	-1.474	0.09	0.449	-5.495	0.560	369	2953	18.25%	0.443	-0.517
		10.791	5.105	1.152	-10.613	0.373	2.433	-29.758						
Medium	AA	0.912	0.01	-0.457	-0.148	-0.204	0.049	-0.797	0.296	56	493	0.58%	0.055	-0.073
		1.266	3.703	-0.992	-2.808	-5.760	0.945	-15.408						
Medium	A	0.481	0.011	-0.929	-0.125	-0.138	-0.010	-1.404	0.331	382	3161	1.01%	0.089	-0.026
		1.455	6.079	-2.534	-4.556	-4.097	-0.35	-48.926						
Medium	BBB	2.211	0.012	-2.690	-0.278	-0.013	0.024	-2.361	0.444	720	5736	2.09%	0.143	-0.038
		7.590	4.379	-7.246	-7.395	-0.325	0.616	-59.832						
Medium	BB	4.659	0.022	-3.541	-0.969	0.169	0.517	-3.299	0.607	376	2564	6.10%	0.237	0.101
		9.057	4.401	-4.018	-10.449	2.412	4.317	-27.551						
Medium	B	8.758	0.07	-2.517	-1.362	0.039	0.250	-3.489	0.617	417	3307	15.93%	0.431	0.061
		9.767	4.614	-0.951	-7.651	0.148	1.178	-16.451						
Long	AA	0.746	0.011	-1.475	-0.058	-0.119	-0.145	-0.895	0.441	95	1289	0.36%	0.047	-0.013
		1.539	5.901	-4.667	-1.575	-5.048	-3.782	-23.341						
Long	A	0.969	0.011	-1.939	-0.102	-0.102	-0.150	-1.239	0.428	534	7269	0.64%	0.075	-0.017
		4.469	8.261	-7.822	-4.420	-4.722	-6.467	-53.45						
Long	BBB	5.472	0.032	-2.914	0.008	-0.249	0.095	-1.256	0.492	855	9890	6.36%	0.103	0.797
		3.056	2.493	-9.741	0.071	-2.384	0.701	-9.263						
Long	BB	5.322	0.013	-4.821	-0.834	-0.047	0.252	-3.346	0.550	268	1789	5.89%	0.220	0.090
		8.434	2.172	-4.675	-5.695	-0.588	1.159	-15.412						
Long	B	6.359	0.048	-4.522	-1.219	-0.850	-0.180	-6.229	0.579	218	1599	35.12%	0.617	0.214
		8.823	3.704	-1.360	-6.925	-3.470	-0.908	-31.39						
Pct Explained													0.817	0.056
Corr($\Delta Inventory^A$, PC)													0.286	-0.253
Corr($\Delta Distress$, PC)													0.625	0.321

Notes: Panel A reports individual-bond quarterly time series regressions of credit spread changes (scaled as 90-day change in percentage) on seven structural factors as in (1). We assign each bond into one of 15 cohorts based on maturity and rating. Bonds with short, medium, and long maturities are those with maturity less than 5 years, between 5 and 8 years, and larger than 8 years. Bonds in the AA cohort are those with a rating of AAA or above, whereas bonds in the B cohort are those with a rating of B or below. The reported regression coefficient is the average of regression coefficients across bonds within each cohort, with associated t-statistics (in the row below that of the regression coefficient) computed as the average coefficient divided by the standard error of the coefficient estimates across bonds. The last column reports the variation of residuals for each cohort i, ε_g^{var} $(= \sum_t (\varepsilon_{gt} - \bar{\varepsilon}_g)^2)$, as a fraction of the total variation of the 15 cohorts $\sum_{g=1}^{15} \varepsilon_g^{var}$. Panel B reports the total number of bonds and number of bond×quarter observations for each cohort. Panel C reports the first two components of the covariance matrix of the 15 residual series, each computed as the average of regression residuals across bonds in a cohort. The last three row report the fraction of the total variation of the 15 residuals explained by the first two PCs and the correlations of $\Delta Inventory^A$ and $\Delta Distress$ with the two PCs. The sample period is from 2005:Q1 through 2015:Q2.

Table 4: Regressions of Credit Spread Change Residuals on Intermediary Factors

Groups		A: $\Delta Inventory^A$		B: $\Delta Distress$		C: $\Delta Inventory^A + \Delta Distress$			
Maturity	Rating	$\Delta Inventory^A$	R^2_{adj}	$\Delta Distress$	R^2_{adj}	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	0.023	0.040	0.039*	0.114	0.026	0.053***	0.212	0.378
		(1.275)		(1.946)		(1.341)	(3.302)		
Short	A	0.019	0.018	0.059***	0.167	0.033*	0.078***	0.297	
		(0.916)		(2.669)		(1.935)	(4.688)		
Short	BBB	0.025	0.015	0.105***	0.260	0.046**	0.133***	0.411	
		(0.944)		(3.209)		(2.204)	(4.825)		
Short	BB	0.062	0.017	0.161***	0.153	0.095**	0.203***	0.337	
		(0.860)		(3.002)		(2.143)	(5.384)		
Short	B	0.198**	0.078	0.298*	0.170	0.294***	0.370***	0.383	
		(2.269)		(1.929)		(3.909)	(3.740)		
Medium	AA	0.022	0.032	0.046***	0.130	0.011	0.048***	0.140	0.550
		(1.105)		(3.436)		(0.591)	(3.956)		
Medium	A	0.041*	0.060	0.087***	0.264	0.048**	0.093***	0.342	
		(1.733)		(2.588)		(2.132)	(3.661)		
Medium	BBB	0.064**	0.071	0.137***	0.317	0.075**	0.146***	0.410	
		(2.097)		(2.730)		(2.543)	(4.030)		
Medium	BB	0.130*	0.098	0.235***	0.321	0.129***	0.251***	0.414	
		(1.902)		(4.230)		(3.050)	(5.934)		
Medium	B	0.172**	0.067	0.465***	0.465	0.278***	0.499***	0.647	
		(2.041)		(3.444)		(5.455)	(6.477)		
Long	AA	0.018	0.030	0.040*	0.151	0.017	0.042**	0.184	0.503
		(1.025)		(1.852)		(1.302)	(2.274)		
Long	A	0.022	0.027	0.065**	0.231	0.034*	0.069***	0.295	
		(1.118)		(2.194)		(1.936)	(2.909)		
Long	BBB	-0.074	0.031	0.157***	0.136	-0.045	0.153***	0.149	
		(-1.243)		(5.208)		(-0.896)	(5.493)		
Long	BB	0.103	0.066	0.226***	0.302	0.124***	0.240***	0.394	
		(1.550)		(4.321)		(2.910)	(5.855)		
Long	B	0.211*	0.046	0.676***	0.448	0.362***	0.722***	0.591	
		(1.771)		(2.819)		(3.662)	(4.303)		
Total									0.482

Notes: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on $\Delta Inventory^A$ (in panel A), on $\Delta Distress$ (in panel B), and on both (in panel C). Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column reports the fraction of the total variation of residuals that is accounted for by $\Delta Inventory^A$ and ΔDistress, denoted as E and computed as in (3) for short, medium, and long term bonds, as well as all bonds. The sample period is from 2005:Q1 through 2015:Q2.

Table 5: Regressions of Credit Spread Changes Residuals on Liquidity Factor

Groups		A: ΔILiq			B: $\Delta Inventory^A + \Delta Distress + \Delta$ILiq				
Maturity	Rating	ΔILiq	R^2_{adj}	FVE	$\Delta Inventory^A$	$\Delta Distress$	ΔILiq	R^2_{adj}	FVE
Short	AA	0.053***	0.181	0.028	0.027	0.041***	0.041***	0.318	0.385
		(3.299)			(1.466)	(4.686)	(3.872)		
Short	A	0.032	0.044		0.034**	0.074***	0.011	0.302	
		(1.083)			(1.993)	(4.978)	(1.037)		
Short	BBB	0.042	0.039		0.046**	0.131***	0.005	0.411	
		(0.795)			(2.231)	(5.044)	(0.394)		
Short	BB	0.056	0.023		0.095**	0.203***	0.002	0.337	
		(0.960)			(2.164)	(5.021)	(0.061)		
Short	B	0.037	0.003		0.292***	0.387***	-0.060	0.390	
		(0.207)			(3.801)	(3.747)	(-1.290)		
Medium	AA	0.034***	0.070	0.023	0.011	0.042***	0.022	0.167	0.555
		(2.769)			(0.626)	(3.381)	(1.628)		
Medium	A	0.048	0.080		0.048**	0.085***	0.025*	0.363	
		(1.346)			(2.235)	(4.157)	(1.850)		
Medium	BBB	0.045	0.034		0.075**	0.144***	0.006	0.411	
		(0.705)			(2.558)	(4.320)	(0.356)		
Medium	BB	0.027	0.004		0.128***	0.263***	-0.043	0.424	
		(0.393)			(3.000)	(5.804)	(-0.764)		
Medium	B	0.101	0.022		0.277***	0.509***	-0.036	0.650	
		(0.475)			(5.322)	(6.817)	(-0.854)		
Long	AA	0.042**	0.168	0.039	0.017	0.033***	0.033***	0.280	0.508
		(2.543)			(1.448)	(2.784)	(4.728)		
Long	A	0.049*	0.130		0.034**	0.059***	0.033**	0.349	
		(1.827)			(2.139)	(3.366)	(2.562)		
Long	BBB	0.065	0.023		-0.044	0.147***	0.018	0.151	
		(1.478)			(-0.896)	(5.882)	(0.670)		
Long	BB	-0.002	0.000		0.122***	0.261***	-0.072*	0.422	
		(-0.032)			(2.829)	(6.263)	(-1.775)		
Long	B	0.214	0.045		0.362***	0.716***	0.020	0.592	
		(0.687)			(3.671)	(4.461)	(0.236)		
Total				0.032					0.488

Notes: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on ΔILiq in univariate regressions (in panel A) and in multivariate regressions along with $\Delta Inventory^A$ and $\Delta Distress$ (in panel B), respectively. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column in each panel reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3) for short, medium, and long term bonds, as well as all bonds. The sample period is from 2005:Q1 through 2015:Q2.

Table 6: Quarterly Series by Leverage Cohort

Groups		A: Sample		B: PC		C: Regressions of Residuals			
Maturity	Leverage	Bond #	Obs	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
Short	<15%	295	3434	0.095	-0.004	0.048***	0.087***	0.322	0.324
						(2.773)	(3.579)		
Short	15-25%	476	5714	0.137	-0.0002	0.064**	0.119***	0.259	
						(2.271)	(4.030)		
Short	25-35%	414	4691	0.177	-0.035	0.109***	0.151***	0.323	
						(3.322)	(3.870)		
Short	35-45%	212	2112	0.271	-0.025	0.144**	0.238***	0.293	
						(2.515)	(3.962)		
Short	>45%	249	2350	0.442	-0.163	0.273***	0.393***	0.342	
						(3.296)	(3.446)		
Medium	<15%	276	2687	0.105	-0.018	0.056**	0.099***	0.336	0.547
						(2.575)	(3.091)		
Medium	15-25%	453	4055	0.188	0.029	0.103***	0.237***	0.563	
						(3.108)	(6.545)		
Medium	25-35%	436	3919	0.217	0.001	0.127***	0.252***	0.526	
						(3.436)	(5.382)		
Medium	35-45%	255	2331	0.269	0.062	0.150***	0.279***	0.385	
						(2.881)	(5.288)		
Medium	>45%	263	2269	0.441	-0.028	0.356***	0.544***	0.623	
						(4.793)	(4.474)		
Long	<15%	361	5059	0.079	0.004	0.036**	0.078**	0.322	0.392
						(2.008)	(2.360)		
Long	15-25%	506	7063	0.102	0.978	-0.047	0.191***	0.112	
						(-0.739)	(4.370)		
Long	25-35%	418	6038	0.129	0.029	0.074**	0.136***	0.405	
						(2.459)	(3.485)		
Long	35-45%	174	1885	0.190	0.051	0.139***	0.227***	0.523	
						(4.231)	(6.776)		
Long	>45%	166	1791	0.493	-0.075	0.322***	0.554***	0.513	
						(3.169)	(3.220)		
Pct Explained				0.781	0.102				0.422

Notes: This table reports results using 15 cohorts based on time-to-maturity and firm leverage. Panel A reports the number of bonds and observations for each cohort. Panel B reports the loadings of the first two PCs on the 15 regression residuals and the fraction of total variation these two PCs account for. Panel C reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage) on $\Delta Inventory^A$ (in panel A) and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of Panel C reports the fraction of the total variation of residuals that is accounted for by the two intermediary factors, denoted as FVE and computed as in (3) for short, medium, and long term bonds, as well as all bonds. The sample period is from 2005:Q1 through 2015:Q2.

Table 7: Monthly Series by Rating Group

Groups		A: Sample		B: PC		C: Regression of Residuals			
Maturity	Rating	Bond #	Obs	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	87	2611	0.065	0.124	0.016*	0.014	0.045	0.192
						(1.801)	(1.285)		
Short	A	525	15871	0.093	0.142	0.012	0.037***	0.129	
						(1.494)	(3.131)		
Short	BBB	881	25114	0.15	0.16	0.009	0.053**	0.131	
						(0.797)	(2.206)		
Short	BB	401	7835	0.291	0.251	0.042**	0.127***	0.195	
						(2.095)	(3.818)		
Short	B	485	10061	0.48	0.065	0.077**	0.172***	0.191	
						(2.097)	(4.422)		
Medium	AA	73	1680	0.061	0.106	0.013	0.022**	0.077	0.138
						(1.530)	(2.338)		
Medium	A	448	9885	0.087	0.153	0.016**	0.016	0.043	
						(2.022)	(1.029)		
Medium	BBB	880	18088	0.146	0.21	0.023*	0.046**	0.104	
						(1.893)	(2.038)		
Medium	BB	491	8989	0.274	0.218	0.061***	0.122***	0.246	
						(3.482)	(2.875)		
Medium	B	593	13111	0.402	0.163	0.047	0.106*	0.091	
						(1.353)	(1.828)		
Long	AA	119	4495	0.058	0.117	0.014**	0.011	0.046	0.235
						(1.966)	(0.965)		
Long	A	638	24132	0.082	0.131	0.015**	0.024*	0.092	
						(2.082)	(1.731)		
Long	BBB	1049	33504	0.114	0.262	0.015	0.033*	0.032	
						(1.422)	(1.946)		
Long	BB	352	6768	0.232	0.204	0.029	0.070***	0.101	
						(1.450)	(2.935)		
Long	B	277	5715	0.551	-0.761	0.098**	0.261***	0.264	
						(1.986)	(3.070)		
Pct Explained				0.757	0.092				0.196

Notes: This table reports results at the monthly frequency using 15 cohorts based on time-to-maturity and credit rating. Panel A reports the number of bonds and observations for each cohort. Panel B reports the loadings of the first two PCs on the 15 regression residuals and the fraction of total variation these two PCs account for. Panel C reports monthly time series regressions of each of the 15 residuals of monthly credit spread changes (in percentage) on $\Delta Inventory^A$ and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of Panel C reports the fraction of the total variation of residuals that is accounted for by the two intermediary factors, denoted as FVE and computed as in (3) for short, medium, and long term bonds, as well as all bonds. The sample period is from 2005:Q1 through 2015:Q2.

Table 8: Measures of Intermediary Distress

Groups		A: $\Delta Noise$		B: $\Delta \text{NLev}^{\text{HKM}}$		C: $\Delta Noise + \Delta \text{NLev}^{\text{HKM}}$		
Maturity	Rating	$\Delta Noise$	R^2_{adj}	$\Delta \text{NLev}^{\text{HKM}}$	R^2_{adj}	$\Delta Noise$	$\Delta \text{NLev}^{\text{HKM}}$	R^2_{adj}
Short	AA	0.043*	0.113	0.021	0.026	0.042*	0.005	0.114
		(1.683)		(0.845)		(1.883)	(0.199)	
Short	A	0.082**	0.225	0.029	0.028	0.083**	-0.004	0.226
		(2.429)		(1.026)		(2.494)	(-0.141)	
Short	BBB	0.132***	0.306	0.069*	0.083	0.124***	0.021	0.312
		(3.368)		(1.682)		(2.973)	(0.619)	
Short	BB	0.320***	0.399	0.010	0.000	0.373***	-0.135*	0.459
		(2.804)		(0.097)		(3.610)	(-1.958)	
Short	B	0.389***	0.221	0.206	0.062	0.363***	0.065	0.226
		(2.762)		(1.115)		(2.668)	(0.399)	
Medium	AA	0.058***	0.188	0.023	0.029	0.058**	0.001	0.188
		(2.614)		(1.363)		(2.358)	(0.030)	
Medium	A	0.077**	0.182	0.070**	0.152	0.058	0.047	0.241
		(1.980)		(2.180)		(1.431)	(1.601)	
Medium	BBB	0.127**	0.224	0.115**	0.184	0.097*	0.077*	0.295
		(2.376)		(2.284)		(1.868)	(1.771)	
Medium	BB	0.310***	0.448	0.107	0.053	0.316***	-0.016	0.449
		(3.550)		(1.224)		(2.951)	(-0.286)	
Medium	B	0.432***	0.304	0.422***	0.290	0.316**	0.300***	0.429
		(2.669)		(3.070)		(2.352)	(2.700)	
Long	AA	0.034	0.076	0.021	0.030	0.030	0.010	0.081
		(1.102)		(0.734)		(1.425)	(0.367)	
Long	A	0.066*	0.186	0.043	0.079	0.058*	0.021	0.202
		(1.815)		(1.354)		(1.715)	(0.711)	
Long	BBB	0.177***	0.155	0.114***	0.064	0.156***	0.054*	0.167
		(3.037)		(4.169)		(2.762)	(1.806)	
Long	BB	0.291***	0.457	0.114	0.071	0.290***	0.002	0.457
		(4.632)		(1.423)		(3.664)	(0.047)	
Long	B	0.672***	0.374	0.566**	0.265	0.533**	0.359*	0.465
		(2.851)		(2.412)		(2.282)	(1.769)	
FVE			0.321		0.168			0.380

Notes: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on $\Delta Noise$ (in panel A), on $\Delta \text{NLev}^{\text{HKM}}$ (in panel B), and on both (in panel C). Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last row reports the fraction of the total variation of residuals that is accounted for by $\Delta Noise$, $\Delta \text{NLev}^{\text{HKM}}$ and both, respectively, denoted as FVE and computed as in (3) for all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table 9: Groups by Trading Volume

Groups		A: Sample Summary			B: Regressions of Residuals		
Leverage	Trd Volume	TrdVolume ($ million)	Bond#	Obs	$\Delta Distress$	$\Delta Inventory^A$	R^2_{adj}
AA	Low	2.462	92	530	0.036	0.018	0.067
					(1.517)	(0.934)	
AA	Medium	17.779	113	796	0.051***	0.017	0.177
					(3.100)	(1.040)	
AA	High	136.25	129	1084	0.038	0.016	0.098
					(1.161)	(0.938)	
A	Low	1.995	684	6201	0.072***	0.039*	0.260
					(2.892)	(1.803)	
A	Medium	16.882	741	4700	0.086***	0.045*	0.302
					(3.300)	(1.907)	
A	High	110.411	699	4246	0.073*	0.035	0.207
					(1.759)	(1.509)	
BBB	Low	2.011	1199	9465	0.146***	0.023	0.085
					(3.556)	(0.564)	
BBB	Medium	17.056	1209	7401	0.174***	0.057*	0.426
					(5.770)	(1.848)	
BBB	High	106.026	1137	6405	0.150***	0.070**	0.355
					(2.698)	(2.329)	
BB	Low	2.584	431	1973	0.251***	0.160***	0.369
					(4.007)	(2.688)	
BB	Medium	17.777	471	2435	0.262***	0.155**	0.358
					(4.540)	(2.118)	
BB	High	100.298	451	2303	0.227***	0.123*	0.279
					(4.774)	(1.732)	
B	Low	2.36	412	2282	0.450***	0.317***	0.411
					(4.502)	(3.473)	
B	Medium	17.342	468	2973	0.526***	0.270***	0.461
					(3.459)	(2.996)	
B	High	89.654	437	2604	0.586***	0.304***	0.481
					(3.283)	(3.155)	

Note: This table reports results using 15 cohorts based on credit rating and trading volume (dollar value of the total trading volume in the last month of a quarter). Panel A reports the total dollar trading volume in $millions, number of bonds, and number of observations for each cohort. Panel B reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage) on $\Delta Inventory^A$ and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The sample period is from 2005:Q1 through 2015:Q2.

Table 10: Inventories of HY vs IG Bonds

Groups		A: $\Delta Inventory^{HY}$			B: $\Delta Inventory^{IG}$		
Maturity	Rating	$\Delta Distress$	$\Delta Inventory^{HY}$	R^2_{adj}	$\Delta Distress$	$\Delta Inventory^{IG}$	R^2_{adj}
Short	AA	0.041	0.016	0.107	0.042	0.024	0.126
		(1.472)	(0.894)		(1.627)	(1.340)	
Short	A	0.071**	0.042*	0.218	0.070**	0.021	0.174
		(2.492)	(1.748)		(2.439)	(1.073)	
Short	BBB	0.127***	0.062**	0.327	0.126***	0.033	0.282
		(3.294)	(1.979)		(3.327)	(1.160)	
Short	BB	0.210***	0.119	0.207	0.215***	0.121**	0.210
		(2.994)	(1.278)		(3.876)	(2.137)	
Short	B	0.376**	0.191	0.238	0.391***	0.251**	0.276
		(2.097)	(1.373)		(2.735)	(2.231)	
Medium	AA	0.052***	0.030	0.184	0.049***	0.002	0.136
		(3.561)	(1.583)		(3.034)	(0.132)	
Medium	A	0.093**	0.053**	0.325	0.090**	0.016	0.252
		(2.319)	(2.412)		(2.082)	(0.697)	
Medium	BBB	0.154***	0.083**	0.389	0.149**	0.025	0.307
		(2.661)	(2.522)		(2.443)	(0.765)	
Medium	BB	0.264***	0.142**	0.381	0.261***	0.076	0.319
		(4.082)	(1.971)		(4.628)	(1.569)	
Medium	B	0.538***	0.237**	0.529	0.541***	0.197***	0.504
		(3.609)	(2.368)		(4.190)	(2.912)	
Long	AA	0.036	0.029**	0.129	0.034	0.001	0.077
		(1.137)	(2.063)		(0.960)	(0.051)	
Long	A	0.069*	0.033*	0.232	0.070*	0.025	0.215
		(1.816)	(1.703)		(1.829)	(1.335)	
Long	BBB	0.177***	0.012	0.156	0.175***	-0.009	0.155
		(5.107)	(0.280)		(4.966)	(-0.348)	
Long	BB	0.256***	0.129*	0.412	0.255***	0.089*	0.369
		(4.416)	(1.888)		(5.734)	(1.770)	
Long	B	0.772***	0.244*	0.526	0.788***	0.306***	0.554
		(2.991)	(1.748)		(3.446)	(2.693)	
FVE				0.397			0.322

Note: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on $\Delta Inventory^{HY}$ (in panel A), on $\Delta Inventory^{IG}$ (in panel B). Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last row reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3), for all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table 11: Credit Default Swaps

Groups		A: Sample		B: PC		C: Regression of Residuals			
Maturity	Rating	Firm #	Obs	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
1y	AA	20	939	0.039	-0.029	0.007	0.030**	0.121	0.375
						(0.542)	(2.012)		
1y	A	111	5742	0.041	0.042	0.032***	0.040***	0.463	
						(4.218)	(6.210)		
1y	BBB	200	7942	0.067	0.062	0.048***	0.057***	0.414	
						(3.882)	(5.025)		
1y	BB	128	2309	0.149	0.151	0.099***	0.141***	0.367	
						(3.615)	(7.691)		
1y	B	64	1377	0.651	0.686	0.305***	0.492**	0.377	
						(2.721)	(2.521)		
5y	AA	21	1140	0.031	-0.010	0.013*	0.026***	0.185	0.354
						(1.725)	(2.914)		
5y	A	112	5688	0.043	0.035	0.030***	0.042***	0.356	
						(2.950)	(7.351)		
5y	BBB	208	7995	0.067	0.003	0.046***	0.067***	0.379	
						(2.752)	(4.479)		
5y	BB	132	2377	0.127	0.072	0.007	0.112***	0.165	
						(0.176)	(4.294)		
5y	B	71	1601	0.583	-0.643	0.287***	0.440***	0.376	
						(2.666)	(2.912)		
10y	AA	20	1117	0.023	-0.018	0.011	0.012	0.063	0.395
						(1.375)	(1.440)		
10y	A	111	5611	0.036	0.035	0.025**	0.039***	0.314	
						(2.228)	(6.795)		
10y	BBB	198	8071	0.055	-0.001	0.036**	0.058***	0.350	
						(2.263)	(5.811)		
10y	BB	127	2426	0.094	0.039	0.026	0.074***	0.122	
						(0.792)	(4.387)		
10y	B	65	1409	0.413	-0.277	0.206**	0.354***	0.438	
						(2.515)	(2.667)		
Pct Explained				0.830	0.070				0.371

Note: This table reports results using 15 cohorts of CDS based on the CDS maturity and credit rating of the underlying entity. Panel A reports the number of firms and observations for each cohort. Panel B reports the loadings of the first two PCs on the 15 regression residuals (computed from time series regressions of quarterly CDS spread changes in percentage similar to (1)) and the fraction of total variation these two PCs account for. Panel C reports quarterly time series regressions of each of the 15 residuals of quarterly CDS spread changes (in percentage) on $\Delta Inventory^A$ and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * p < 0.1, ** p < 0.05, and *** p < 0.01 with p as the p-value. The last column of Panel C reports the fraction of the total variation of residuals that is accounted for by the two intermediary factors, denoted as FVE and computed as in (3) for 1-year, 5-year, and 10-year CDS cohorts, as well as all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table 12: Non-Corporate-Credit Assets

	A: Agency MBS				
	FN30y	FN15y	FG30y	FG15y	
$\Delta Inventory^A$	3.70**	2.64	3.30	1.05	
	(2.10)	(1.58)	(1.64)	(0.55)	
$\Delta Distress$	5.79***	6.21***	6.55***	5.12***	
	(3.08)	(3.65)	(3.60)	(2.81)	
R^2_{adj}	0.18	0.26	0.17	0.15	
	B: CMBS				
	Duper	AM	AJ		
$\Delta Inventory^A$	15.48*	2.94	4.33		
	(1.89)	(0.16)	(0.21)		
$\Delta Distress$	28.06***	84.50***	87.38***		
	(5.10)	(4.24)	(5.14)		
R^2_{adj}	0.27	0.36	0.31		
	C: ABS				
	Credit Card	Auto AAA	Auto A	Auto BBB	
$\Delta Inventory^A$	1.35	1.86	22.44	7.86	
	(0.40)	(0.44)	(1.39)	(0.34)	
$\Delta Distress$	21.63***	6.58	145.86***	138.35**	
	(4.77)	(1.17)	(3.25)	(2.06)	
R^2_{adj}	0.37	0.02	0.51	0.39	
	D: S&P 500 index options				
	Call: 0.90	Call: 0.95	Call: ATM	Call: 1.05	Call: 1.10
$\Delta Inventory^A$	0.034	0.020	0.007	0.013	-0.148
	(0.320)	(0.183)	(0.064)	(0.100)	(-1.101)
$\Delta Distress$	0.263	0.257	0.314	0.272	0.225
	(0.601)	(0.538)	(0.604)	(0.483)	(0.371)
R^2_{adj}	0.027	0.023	0.028	0.017	0.013
	Put: 0.9	Put: 0.95	Put: ATM	Put: 1.05	Put: 1.10
$\Delta Inventory^A$	0.241	0.165	0.121	0.088	0.078
	(0.823)	(0.746)	(0.723)	(0.674)	(0.675)
$\Delta Distress$	0.503***	0.355***	0.300**	0.277*	0.227
	(3.660)	(3.076)	(2.247)	(1.739)	(1.221)
R^2_{adj}	0.043	0.034	0.034	0.037	0.028

Note: This table reports quarterly time series regressions of residuals of quarterly yield spread changes (in basis points) of agency MBS (in panel A), CMBS (in panel B), and ABS (in panel C) on $\Delta Inventory^A$ and $\Delta Distress$ and monthly series regressions of residuals of one-month unannualized returns (in percentage) of S&P 500 index option portfolios (in panel D). Each residual series is computed from the regression of the yield spread change or return on the six time series factors included in (1). Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses, with significance levels indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$, where p is the p-value. The overall sample period is 2005:Q1 - 2015:Q2 for yield spreads, and January 2005 - January 2012 for options.

Table 13: Average Quarterly Changes of Institutional Investors' Holdings and Dealers' Inventories of Individual Bonds

A: Insurance Companies						
	Downgrade (IG)		Fallen Angels		No Rating Change	
	Obs	mean	Obs	mean	Obs	mean
$\Delta Holding_{i,t}$	9673	-0.916	3261	-1.353	416254	-0.390
$\Delta Holding_{i,t+1}$	9604	-1.008	3185	-1.274	416965	-0.404
$Holding_{i,t-1}$		73.359		71.075		87.087
B: Mutual Funds						
	Downgrade (IG)		Fallen Angel		No Rating Change	
	Obs	mean	Obs	mean	Obs	mean
$\Delta Holding_{i,t}$	5265	0.376	1760	0.116	345154	-0.423
$\Delta Holding_{i,t+1}$	5204	-0.161	1701	-0.237	345385	-0.390
$Holding_{i,t-1}$		76.882		75.998		65.153
C: Pension Funds						
	Downgrade (IG)		Fallen Angel		No Rating Change	
	Obs	mean	Obs	mean	Obs	mean
$\Delta Holding_{i,t}$	4566	0.285	1484	0.204	304541	-0.321
$\Delta Holding_{i,t+1}$	4508	-0.246	1443	-0.474	304883	-0.309
$Holding_{i,t-1}$		19.621		18.110		11.971
D: Dealers						
	Downgrade (IG)		Fallen Angel		No Rating Change	
	Obs	mean	Obs	mean	Obs	mean
$\Delta Inventory_{i,t}$	20254	0.343	6792	1.311	687927	0.254
$\Delta Inventory_{i,t+1}$	18949	0.022	6449	-0.275	614380	0.028
$Inventory_{i,t-1}$		1.949		1.708		1.188

Note: This table reports the average quarterly change of holdings by insurance companies, mutual funds, and pension funds, in panels A, B, and C, respectively, and the average quarterly change of dealers' inventories in panel D. The average quarterly change for three sets of observations is computed separately: "downgrade (IG)" observations (in the first two columns) with bonds downgraded from IG rating to IG rating, "fallen angels" observations (in the second two columns) with bonds downgraded from IG rating to HY rating, and "no rating change" observations (in the last two columns) with bond experiencing no rating change. Both the number of observations and average amount change (in $millions) are reported. Both the change in the current quarter and the change in the subsequent quarter are included. For comparison, the average level of institutional holding and dealer inventory (in $millions) as of the current quarter is reported in the last row of each panel. The sample period is 2005:Q1 - 2015:Q2.

Table 14: Changes in Institutional Holdings and Dealers' Inventories of Downgraded Bonds

A: Changes of Institutional Holdings and Dealer Inventories in quarter t				
	Insurance	Mutual	Pension	Dealer
	(1)	(3)	(5)	(7)
Fallen	-0.665***	-0.219	-0.058	1.607**
	(-3.383)	(-0.574)	(-0.270)	(1.980)
Downgrade	-0.480***	0.509**	0.363***	-0.127
	(-4.007)	(2.310)	(2.811)	(-0.158)
Obs	423,766	348,092	306,971	705,516
R^2_{adj}	0.070	0.013	0.036	0.0004
Bond Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
B: Changes of Institutional Holdings and Dealer Inventories in quarter $t+1$				
	Insurance	Mutual	Pension	Dealer
	(1)	(3)	(5)	(7)
Fallen	-0.326*	-0.010	-0.088	-0.447***
	(-1.654)	(-0.028)	(-0.434)	(-3.187)
Downgrade	-0.795***	-0.073	0.069	0.124
	(-7.125)	(-0.332)	(0.590)	(1.371)
Obs	424,413	348,266	307,265	630,957
R^2_{adj}	0.071	0.013	0.036	0.001
Bond Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Note: The first three columns report panel regressions in (17) of changes in institutional holdings of bond i in quarter $t+\tau$ (τ equals 0 in in panel A and 1 in panel B) on indicator variables $\text{Downgrade}_{i,t}$, which equals 1 if bond i is downgraded from IG rating to either IG or HY rating in quarter t and 0 otherwise and indicator $\text{Fallen}_{i,t}$ that equals 1 if bond i is downgraded from IG rating to HY rating in quarter t and 0 otherwise, for insurance companies, mutual funds, and pension funds, respectively. Similar panel regressions of changes in dealers' inventories $\Delta Inventory_{i,t+\tau}$ are reported in the last column. Bond controls include the log of outstanding balance in \$thousands ($log(\text{Amt}_{i,t+\tau})$), the log of issue size in \$millions ($log(\text{Size}_i)$), bond age in years ($\text{Age}_{i,t+\tau}$), and time-to-maturity in years ($\text{Time-to-Mature}_{i,t+\tau}$). For simplicity, we suppress the coefficients on these controls and the intercept. The sample includes observations of bonds downgraded from investment grade to either investment grade or high yield and of bonds with no rating change. Robust t-statistics based on clustered standard errors at the bond level are reported in parentheses with significance levels represented by * for $p < 0.1$, ** for $p < 0.05$, and *** for $p < 0.01$, where p is the p-value. The sample period is from 2005:Q1 - 2015:Q2.

Table 15: First-Stage Regressions

	$\Delta Inventory_t^A$	$\Delta Inventory_t^A$	$\Delta Inventory_t^A$
$\Delta Holding_t^{FA}$	-0.377***		-0.369***
	(-2.618)		(-3.983)
Insurance Loss_t		0.101	0.073
		(1.188)	(1.413)
$\Delta Distress$	0.552***	0.456***	0.545***
	(4.890)	(3.423)	(5.738)
$\Delta Holding_t^D$	0.045	-0.179*	0.047
	(0.255)	(-1.701)	(0.273)
ΔVIX	0.003	0.005	0.002
	(0.114)	(0.176)	(0.146)
$\Delta Jump$	-15.995***	-13.876**	-15.775***
	(-3.260)	(-2.156)	(-6.003)
Δr^{10y}	0.806*	0.654	0.728***
	(1.934)	(1.547)	(4.242)
$\left(\Delta r^{10y}\right)^2$	-0.294	-0.396	-0.314
	(-1.043)	(-1.270)	(-1.014)
$\Delta slope$	-0.400	-0.359	-0.352**
	(-1.158)	(-0.909)	(-2.302)
ret_t^{SP}	7.591***	7.088***	7.842***
	(4.462)	(3.194)	(9.014)
Intercept	0.041	0.066	0.040
	(0.258)	(0.417)	(0.324)
R^2_{adj}	0.547	0.482	0.552

Note: This table reports the first-stage regressions of $\Delta Inventory^A$ on $\Delta Holding_t^{FA}$ and InsuredLoss_t, separately in the first two columns and jointly in the third column. The change in institutional holdings of all downgraded bonds $\Delta Holding_t^D$ is included as a control, in addition to $\Delta Distress$ and the six time series variables used in the baseline bond-level regression (1). All measures except the six time series variable from (1) are scaled to have zero mean and unit variance. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses, with significance levels indicated by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$, where p is the p-value. The sample period is 2005:Q1 - 2015:Q2.

Table 16: Second-Stage Regressions

Groups		A: $\Delta Holding_t^{FA}$		B: Insurance Loss_t		C: $\Delta Holding_t^{FA}$ + Insurance Loss_t	
Maturity	Rating	$\Delta Inventory_t^A$	$\Delta Distress_t$	$\Delta Inventory_t^A$	$\Delta Distress_t$	$\Delta Inventory_t^A$	$\Delta Distress_t$
Short	AA	0.208**	0.004	0.188	0.014	0.206***	0.005
		(2.375)	(0.057)	[0.254] [0.164]	(0.177)	(2.945)	(0.090)
Short	A	0.208*	0.081	0.214	0.078	0.208**	0.081
		(1.828)	(1.015)	[0.074] [0.157]	(1.041)	(2.459)	(1.383)
Short	BBB	0.188	0.199***	0.191	0.197***	0.188**	0.198***
		(1.642)	(2.662)	[0.089] [0.156]	(3.596)	(2.205)	(3.660)
Short	BB	0.508*	0.311*	0.762	0.185	0.535**	0.298**
		(1.679)	(1.762)	[0.070] [0.145]	(0.916)	(2.541)	(2.262)
Short	B	0.740**	0.630**	1.463	0.270	0.818***	0.591***
		(2.181)	(2.448)	[0.0004] [0.135]	(0.666)	(3.822)	(3.491)
Medium	AA	0.208**	-0.003	0.140	0.031	0.201**	0.001
		(1.973)	(-0.038)	[0.265] [0.157]	(0.603)	(2.249)	(0.012)
Medium	A	0.194*	0.096	0.165	0.110**	0.191**	0.097
		(1.751)	(1.217)	[0.143] [0.147]	(2.199)	(2.075)	(1.544)
Medium	BBB	0.200*	0.223***	0.260	0.193***	0.206**	0.220***
		(1.873)	(2.994)	[0.026] [0.146]	(2.960)	(2.345)	(3.762)
Medium	BB	0.544*	0.294*	0.561	0.285**	0.546**	0.293**
		(1.792)	(1.726)	[0.037] [0.137]	(1.993)	(2.428)	(2.495)
Medium	B	0.671***	0.668***	0.461	0.773***	0.648***	0.679***
		(2.621)	(4.116)	[0.023] [0.174]	(4.419)	(3.492)	(6.637)
Long	AA	0.123***	0.012	-0.030	0.088	0.106**	0.020
		(2.784)	(0.278)	[0.757] [0.642]	(1.553)	(2.553)	(0.542)
Long	A	0.214**	0.035	0.057	0.113**	0.197**	0.043
		(2.225)	(0.472)	[0.533] [0.383]	(2.432)	(2.426)	(0.697)
Long	BBB	0.144	0.213	0.141	0.215*	0.144	0.213*
		(0.848)	(1.214)	[0.598] [0.295]	(1.886)	(1.345)	(1.807)
Long	BB	0.388***	0.362***	0.151	0.481***	0.363***	0.375***
		(2.768)	(4.681)	[0.480] [0.286]	(5.128)	(2.929)	(6.161)
Long	B	0.654***	1.219***	0.759	1.167***	0.666***	1.213***
		(2.795)	(7.768)	[0.002] [0.127]	(4.331)	(3.875)	(12.307)
MP Test		15.815		2.100		9.678	
Critical Value		[12.374]		[12.374]		[7.749]	

Note: This table reports second-stage regressions of quarterly residuals of quarterly credit spread changes (in percentage) on $\Delta Distress$ and $\Delta Inventory^A$, using $\Delta Holding_t^{FA}$ as instrument in panel A, InsuredLoss_t as instrument in panel B, and both as instruments in panel C. Regression coefficients on $\Delta Inventory^A$ and $\Delta Distress$ are reported, but those on control variables ($\Delta Holding_t^D$, $\Delta Distress$, and the six time series variables used in (1)) are omitted for simplicity of reporting. The last two rows in each panel report the test statistic for weak instruments by Montiel-Olea and Pflueger (2013) (MP) and associated critical values (Pflueger and Wang (2015)). An MP-statistic greater than critical values in brackets below rejects the hypothesis of weak instruments (with a worst-case bias greater than 20% of the OLS bias) at a significance level of 10%. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses, with significance levels indicated by * p $<$ 0.1, ** p $<$ 0.05, and *** p $<$ 0.01, where p is the p-value. For the coefficient on $\Delta Inventory^A$ in panel B, p-values of the Anderson and Rubin (1949) Wald-test and the Stock and Wright (2000) S-statistic are reported in the left and right brackets, which are both weak-instrument robust for testing the significance of $\Delta Inventory_t^A$. The sample period is from 2005:Q1 - 2015:Q2.

Table 17: Regressions of Bond-Return Factors on Intermediary Factors

	MKT^{Bond}	DRF	CRF	LRF
A: Regressions on Dealer Inventory				
$\Delta Inventory_t^A$	0.027	-0.008	0.111	-0.149
	(0.280)	(-0.038)	(0.508)	(-0.812)
R^2_{adj}	0.002	0.000	0.009	0.017
B: Regressions on Intermediary Distress				
$\Delta Distress_t$	-0.388***	-0.941***	-0.651***	-1.120***
	(-2.807)	(-5.201)	(-3.635)	(-6.280)
R^2_{adj}	0.235	0.324	0.202	0.586
C: Regressions on Dealer Inventory and Intermediary Distress				
$\Delta Inventory_t^A$	0.103	0.173	0.242	0.058
	(1.341)	(1.064)	(1.304)	(0.485)
$\Delta Distress_t$	-0.418***	-0.995***	-0.721***	-1.136***
	(-3.231)	(-5.558)	(-4.287)	(-6.566)
R^2_{adj}	0.263	0.367	0.244	0.593

Note: This table reports quarterly time series regressions of return-based factors, including corporate bond market return (MKT^{Bond}), downside risk factor (DRF), credit risk factor (CRF), and liquidity risk factor (LRF) of Bai, Bali, and Wen (2019), on $\Delta Inventory^A$ and $\Delta Distress$. The original series of return factors are one-month returns (in percent) of monthly rebalanced portfolios, and we construct quarterly return factors using geometric mean of the three monthly returns for each quarter. We orthogonalize both the return factors and intermediary factors against the six time series structural factors as used in (1). Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The sample period is from 2005:Q1 through 2015:Q2.

Appendices

A Additional Data Summary and Empirical Results

In this appendix, we provide additional data summary statistics and empirical results.

First, Figure A.1 and Table A.1 provide a summary of the eMAXX institutional holdings. The top panel of Figure A.1 shows the quarterly series of the total number of institutions, which increased from about 5000 to more than 6000. This increase is mainly due to the growth of mutual funds, whereas the number of insurance companies remains stable around 2800. As shown in the middle panel, the total number of bonds held by these institutions is about 15000 steadily, and largest by insurance companies. Finally, the bottom panel plots quarterly series of the total holding amount by all institutions and outstanding balance of an average bond, calculated as the respective average of the total holding amount and outstanding balance across all bonds in each quarter. The average holding amount and outstanding have increased roughly in parallel to each other, so the institutional holding steadily accounts for 30-35% of the outstanding except a brief drop during the 2008 crisis.

Panel A of Table A.1 reports the number of institutional investors, panel B reports the number of bonds, and panel C reports the aggregate holding amount in principal value, by insurance companies, mutual funds, pension funds, and all institutions separately. Panel D reports summary statistics of quarterly series of the total holding amount by all institutions and the outstanding balance, of an average bond. Specifically, for each bond in each quarter, we first sum the holding amounts by all institutions to obtain a total holding amount $Holding_{it}$. Then across all the bonds i in each quarter, we compute the mean of $Holding_{it}$ as the total holding amount of an average bond (or average bond's holding amount). Across all the bonds in each quarter, we also compute the mean of outstanding balance as the outstanding balance of an average bond (or average bond's outstanding balance). In each quarter, we compute the ratio of average holding amount to average outstanding balance and obtain a quarter series of average holding/outstanding.

Second, Table A.2 reports summary statistics of quarterly time series of option-adjusted spreads of agency MBS, yield spreads of non-agency CMBS, and yield spreads of ABS all in basis points, in panels A, B, and C, respectively. Panel D reports summary statistics of monthly time series of (unannualized) one-month return of leverage-adjusted S&P 500 index option portfolios in percentage.

Third, panel A of of Table A.3 reports quarterly time series regressions of the baseline residuals on the two intermediary factors, with $\Delta Inventory^A$ based on dollar value of corporate bond transactions, as opposed to par value used in the baseline measure.

Fourth, in the baseline analysis, $\Delta Inventory^A$ and $\Delta Distress$ are both measured using changes between two quarter ends. In contrast, the credit spread change Δcs may not be exactly between two quarter ends, and the time duration of the change ranges from 45 to 120 days. Panel B of Table A.3 reports quarterly time series regressions of the baseline residuals on intermediary factors that are constructed by matching to the horizon of credit spread changes. Specifically, for each observation Δcs_{it}, we compute measures $\Delta Inventory_{it}^{match}$ and $\Delta Distress_{it}^{match}$ as the changes of dealer inventory and intermediary distress measures over the same time horizon. We then take the average of $\Delta Inventory_{it}^{match}$ and $\Delta Distress_{it}^{match}$ across all bonds in each quarter t as the aggregate time series measures of intermediary factors, denoted as $\Delta Inventory_{t}^{match}$ and $\Delta Distress_{t}^{match}$. That is, these alternative measures take into account the distribution of time horizons of credit spread changes across bonds.

Fifth, Table A.4 reports quarterly time series regressions of baseline residuals on baseline intermediary factors, controlling for two other potential measures of intermediary distress, the leverage measure of broker-dealers in Adrian, Etula, and Muir (2014), here constructed in the same nonlinear way as in our baseline HKM measure, i.e., $\Delta \text{NLev}_t^{\text{AEM}} := (\text{Lev}_t^{\text{AEM}} - \text{Lev}_{t-1}^{\text{AEM}}) \times \text{Lev}_{t-1}^{\text{AEM}}$ (in panel A) and TED spread computed as the difference between three-month Libor and T-bill rates (in panel B). We find that the broker-dealer leverage does not have incremental explanatory power relative to our two intermediary factors. TED spread adds certain explanatory power, statistically significant for IG bonds with similar economic significance for different cohorts, different from the monotonic increasing effect of our two intermediary factors with decreasing ratings.

Sixth, Table A.5 reports quarterly time series regressions of baseline residuals on intermediary factors, controlling for the Pástor and Stambaugh (2003) stock liquidity factor (in panel A), and monthly time series regressions controlling for the Bao, Pan, and Wang (2011) corporate bond liquidity factor (in panel B). We find that neither of these two liquidity factors contribute significant incremental explanatory power in explaining common credit spread changes.

Seventh, one may be concerned that the strong explanatory power documented is mainly due to the inclusion of the 2008 financial crisis. Table A.6 reports results following the baseline procedure but excluding the 2008 financial crisis period (defined as 2007:Q3 - 2009:Q1 similar to Bao, O'Hara, and Zhou (2018), Schultz (2017), and others). From Panel A of the PC analysis, we observe a strong common variation with the PC1 accounting for 80% of the total unexplained variation of credit spread changes. From Panel B of the quarterly bivariate series regressions of on dealer inventory and intermediary distress, intermediary factors have significant positive effects that monotonically increase with decreasing ratings, and similar economic significance. The two factors together account for 48% of the unexplained total variation of credit spread changes, slightly higher than that in the baseline Table 4 including the crisis observations.

Eighth, as reported in Di Maggio, Kermani, and Song (2017), Bao, O'Hara, and Zhou (2018), and Schultz (2017), there are both large core dealers and small peripheral dealers in the corporate bond market. It is usually large dealers who take bonds into their inventories and use their balance sheets to provide liquidity ultimately. Instead, small dealers often unwind temporary inventory positions to large dealers. Therefore, we expect the explanatory power of $\Delta Inventory^A$ to be mainly driven by large dealers' inventory. To verify this conjecture, we construct inventory measures of large and small dealers $\Delta Inventory^L$ and $\Delta Inventory^S$, similar to $\Delta Inventory^A$, with large dealers defined as the top 20 dealers based on the total trading volume of all bonds across the whole sample period and small dealers as the rest (the top 20 dealers account for 92% of all trading volume). Table A.7 reports quarterly bivariate series regressions of the baseline residuals on $\Delta Inventory^L$ and $\Delta Inventory^S$ separately, along with $\Delta Distress$. We observe that $\Delta Inventory^L$ has significant positive effects on common credit spread changes, similar to $\Delta Inventory^A$, but $\Delta Inventory^S$ has no significant effects.

Ninth, Table A.8 reports time series correlations of the three different inventory measures, $\Delta Inventory^{A}$, $\Delta Inventory^{HY}$, and $\Delta Inventory^{IG}$. We consider both simple changes and percentage changes. We observe that $\Delta Inventory^{A}$ is positively correlated with both $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$ at a 10% significance level. Importantly, the correlation between $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$ is slightly negative in raw changes and near zero in percentage changes, statistically insignificant.

Finally, Table A.9 reports summary statistics of corporate bond holdings of insurance companies, mutual funds, and pension funds by rating groups. We find that insurance companies have a lower fraction of holdings in HY bonds than mutual funds and pension funds, consistent with strict regulatory constraints on insurance companies (Ellul, Jotikasthira, and Lundblad (2011)).

B Model Extensions

B.1 More Traditional Margin Constraints

The form of our margin-like constraint,

$$\sum_{a=1}^{A} \theta_{I,a} m_a \leq w, \tag{18}$$

is chosen for analytical tractability but differs from reality in two basic ways. First, margin is typically required for both long and short positions. Such a constraint, similar to Garleanu and Pedersen (2011), would be

$$\sum_{a=1}^{A} |\theta_{I,a}| m_a \leq w. \tag{19}$$

Constraint (19) will deliver the additional prediction that the law of one price can fail. Two assets with the same payoffs but different margin requirements can be priced differently, which can be used to discuss empirical phenomena such as the bond-CDS basis or covered-interest-parity deviations. Our empirics do not focus on such situations. Furthermore, since our model focuses on hedgers' demand for insurance (through $h > 0$), intermediaries will typically hold long positions ($\theta_I > 0$), making (19) equivalent to (18).

Second, margin requirements m typically depend on current and future asset prices. For example, if margin is calculated as a fraction of the expenditure on assets, then $m_a = \bar{m}_a p_a$ in (18), i.e.,

$$\sum_{a=1}^{A} \theta_{I,a} \bar{m}_a p_a \leq w. \tag{20}$$

Constraints augmented with price, as in (20), will have an additional mitigating force to (18). Indeed, a positive s-shock decreases asset prices and thus loosens constraint (20) through lower margin requirements. Equilibrium prices fall by less than they would under (18). As another example, exchanges often compute margin based on future prices, through return volatility, in which case $m_a = \bar{m}_a p_a v_a$. As prices and volatilities tend to be negatively correlated, this formulation would tend to amplify our effects: a price decline accompanied by a volatility spike would tighten the margin constraint. Since these forces are qualitatively similar to our baseline model, just mitigated or amplified, we ignore them and focus on (18).

B.2 Asset-Class-Specific Constraints

Rather than a single margin constraint, suppose dealers face asset-class-specific margin constraints. For example, different trading desks within a bank may be given independent portfolio limits. Alternatively, there may be some market segmentation – different intermediaries, each having its own margin constraint, may participate in non-overlapping asset markets. Mathematically, partition the assets $a \in \{1, \ldots, A\}$ into two subsets $\mathcal{A}_1$ and $\mathcal{A}_2$, and impose different constraints on the subsets:

$$\sum_{a \in \mathcal{A}_1} \theta_{I,a} m_a \leq w_1 \quad \text{and} \quad \sum_{a \in \mathcal{A}_2} \theta_{I,a} m_a \leq w_2. \tag{21}$$

If we interpret (21) as desk-specific constraints within a given intermediary, we would set $w_1 = w_2 = w$. Otherwise, there are two types of intermediaries, with wealths w_1 and w_2 that sum to aggregate intermediary wealth w. Under (21), there are two Lagrange multipliers, μ_1 and μ_2 associated with each inequality. The pricing condition (8) is modified to be $p = \bar{\delta} - \mathbf{1}_A - \mathrm{diag}(m)(\mu_1 \mathbf{1}_{\mathcal{A}_1} + \mu_2 \mathbf{1}_{\mathcal{A}_2})$. In this case, shocks affecting one of the Lagrange multipliers disproportionately more than the other, such as asset-specific supply shocks, will have an outsized effect on those assets.

Fully solving the model, one can derive the results of the following Lemma.

Lemma 1. *The Lagrange multipliers are given by*

$$\mu_1 = \begin{cases} \alpha[\mathbf{1}'_{\mathcal{A}_1} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_1}]^{-1} x_1, & \text{if} \quad x_1 \geq 0,\ x_2 < \phi_1 x_1 \\ \alpha[\mathbf{1}'_{\mathcal{A}_1} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_1}]^{-1} [1 - \phi_1 \phi_2]^{-1} \left[x_1 - \phi_2 (x_2)^+\right]^+, & \text{otherwise} \end{cases}$$

$$\mu_2 = \begin{cases} \alpha[\mathbf{1}'_{\mathcal{A}_2} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_2}]^{-1} x_2, & \text{if} \quad x_2 \geq 0,\ x_1 < \phi_2 x_2 \\ \alpha[\mathbf{1}'_{\mathcal{A}_2} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_2}]^{-1} [1 - \phi_1 \phi_2]^{-1} \left[x_2 - \phi_1 (x_1)^+\right]^+, & \text{otherwise} \end{cases}$$

where $M := diag(m)$, and where

$$\phi_1 := \frac{\mathbf{1}'_{\mathcal{A}_1} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_2}}{\mathbf{1}'_{\mathcal{A}_1} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_1}} \quad \textit{and} \quad \phi_2 := \frac{\mathbf{1}'_{\mathcal{A}_1} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_2}}{\mathbf{1}'_{\mathcal{A}_2} M \Sigma^{-1} M \mathbf{1}_{\mathcal{A}_2}}$$
$$x_1 := h' M \mathbf{1}_{\mathcal{A}_1} - w_1 \quad \textit{and} \quad x_2 := h' M \mathbf{1}_{\mathcal{A}_2} - w_2.$$

With Lemma 1, we can study how prices respond to different shocks. Suppose $\mathcal{A}_1$ are corporate bonds and $\mathcal{A}_2$ are other assets. Write $h = s_1 \bar{h}_1 + s_2 \bar{h}_2$ for scalars s_1, s_2 and vectors $\bar{h}_1, \bar{h}_2$ that are independent, i.e., $\bar{h}_1 \cdot \bar{h}_2 = 0$. Then, it is easy to see that $x_1 = s_1 \bar{h}'_1 M \mathbf{1}_{\mathcal{A}_1} - w_1$ and $x_2 = s_2 \bar{h}'_2 M \mathbf{1}_{\mathcal{A}_2} - w_2$. A supply shock to s_1 is a pure shock to x_1. When supply of bonds is sufficiently high such that $x_1 > 0$, then $\mu_1 > 0$, and μ_1 is strictly increasing in s_1, whereas μ_2 is invariant to s_1.[30] In words, pure bond supply shocks only affect prices of bonds and other assets traded on the bond desk, i.e., assets in $\mathcal{A}_1$.

On the other hand, shocks affecting aggregate intermediary wealth w affect all assets in a similar manner to the baseline model. Consider a shock to $w_1 + w_2 = w$ such that w_1/w_2 remains constant. Both x_1 and x_2 unambiguously rise, which one can show weakly increases μ_1 and μ_2. The result is a larger price discount, induced by tightening constraints on all trading desks.

B.3 Risk-Averse Intermediaries

Here, we generalize the model by assuming intermediaries have mean-variance preferences with risk aversion $\gamma(w)$, an exogenously decreasing function of w. The dependence of risk aversion on wealth w captures the wealth-effect mechanism of Kyle and Xiong (2001) and others. The benchmark results are obtained in the appropriate limit $\gamma \to 0$. Specifically, suppose intermediaries solve

$$\begin{aligned} &\max_{\theta_I} \mathbb{E}[W_I] - \frac{\gamma(w)}{2}\mathrm{Var}[W_I] \\ &\text{s.t.} \quad W_I := w + \theta_I \cdot (\delta - p - \mathbf{1}_A) \quad \text{and} \quad \theta_I \cdot m \leq w. \end{aligned} \tag{22}$$

Letting μ denote the Lagrange multiplier on the margin constraint, the optimal intermediary portfolio is given by

$$\theta_I = (\gamma(w)\Sigma)^{-1}[\bar{\delta} - p - \mathbf{1}_A - \mu m].$$

Clearing markets with (4), asset prices satisfy

$$\bar{\delta} - p - \mathbf{1}_A = \Gamma(w)\Big[\Sigma h + \gamma(w)^{-1}\mu m\Big],$$

where $\Gamma(w) := (\alpha^{-1} + \gamma(w)^{-1})^{-1}$. Combining these results with the margin constraint, we have that

$$\mu = \frac{\alpha}{m'\Sigma^{-1}m}\Big[m'h - (1 + \frac{\gamma(w)}{\alpha})w\Big]^+$$

which can be plugged into the expression for prices to solve completely for equilibrium.

[30] Lemma 1 also shows that it is possible to have μ_1 increasing in s_1, while μ_2 is decreasing in s_1. This occurs when $x_1, x_2 < 0$, $x_2 < \phi_1 x_1$, and $x_1 < \phi_2 x_2$. This case helps explain why non-bond assets may be insensitive to bond inventory even if trading desks are sometimes integrated. Indeed, integrated trading desks implies all prices are sensitive to bond inventory, as in Proposition 2. In contrast, segmented trading desks implies there is a region in which non-bond assets are completely insensitive to bond inventory, and a region in which non-bond assets are oppositely sensitive to bond inventory. The existence of these three regions with differing sensitivities thus muddies the observed empirical relationships between non-bond assets and bond inventory.

Proposition 3. *If the intermediary margin constraint is binding, i.e., $w < w^* := \{\tilde{w} : \tilde{w} = (1 + \frac{\gamma(\tilde{w})}{\alpha})^{-1} m'h\}$, then*

$$\text{(“Supply Shock”)} \quad \frac{\partial p}{\partial s} = -\Gamma(w)\Sigma\bar{h}_{bond} + \frac{\Gamma(w)}{\gamma(w)}\Big(\frac{m'\bar{h}_{bond}}{m'\Sigma^{-1}m}\Big)\alpha m$$

$$\text{(“Demand Shock”)} \quad \frac{\partial p}{\partial w} = \frac{\Gamma(w)^2}{w\gamma(w)}\epsilon_\gamma(w)\Sigma h + \Big[1 - \frac{1}{w}\Big(\frac{\gamma(w)-1}{\gamma(w)}\Gamma(w)w - (\Gamma(w)-1)m'h\Big)\frac{\Gamma(w)}{\gamma(w)}\epsilon_\gamma(w)\Big]\frac{\alpha m}{m'\Sigma^{-1}m}.$$

where $\epsilon_\gamma(w) := -\frac{w\gamma'(w)}{\gamma(w)} > 0$ is the risk-aversion-wealth elasticity. Otherwise, if $w > w^*$, then

$$\text{(“Supply Shock”)} \quad \frac{\partial p}{\partial s} = -\Gamma(w)\Sigma\bar{h}_{bond}$$

$$\text{(“Demand Shock”)} \quad \frac{\partial p}{\partial w} = \frac{\Gamma(w)^2}{w\gamma(w)}\epsilon_\gamma(w)\Sigma h.$$

Proposition 3 can help explain why some asset classes may display trivial sensitivity to bond supply s (and its empirical proxy, bond inventory ξ) even when they display large sensitivity to intermediary wealth w (and its empirical proxy, leverage λ). These will be assets with low margin requirements and low covariance to bonds. For example, consider an asset a which has $m_a = 0$ and zero fundamental correlation to any other asset, including bonds. In that case, $\partial p_a/\partial s = 0$ whereas $\partial p_a/\partial w = \frac{\Gamma(w)^2}{w\gamma(w)}\epsilon_\gamma(w)\sigma_a^2 h_a > 0$ (these formulas hold independent of whether the margin constraint binds). Notice that the discrepancy between $\partial p_a/\partial s$ and $\partial p_a/\partial w$ is increasing in the asset's own volatility σ_a and hedger's liquidity demand h_a.

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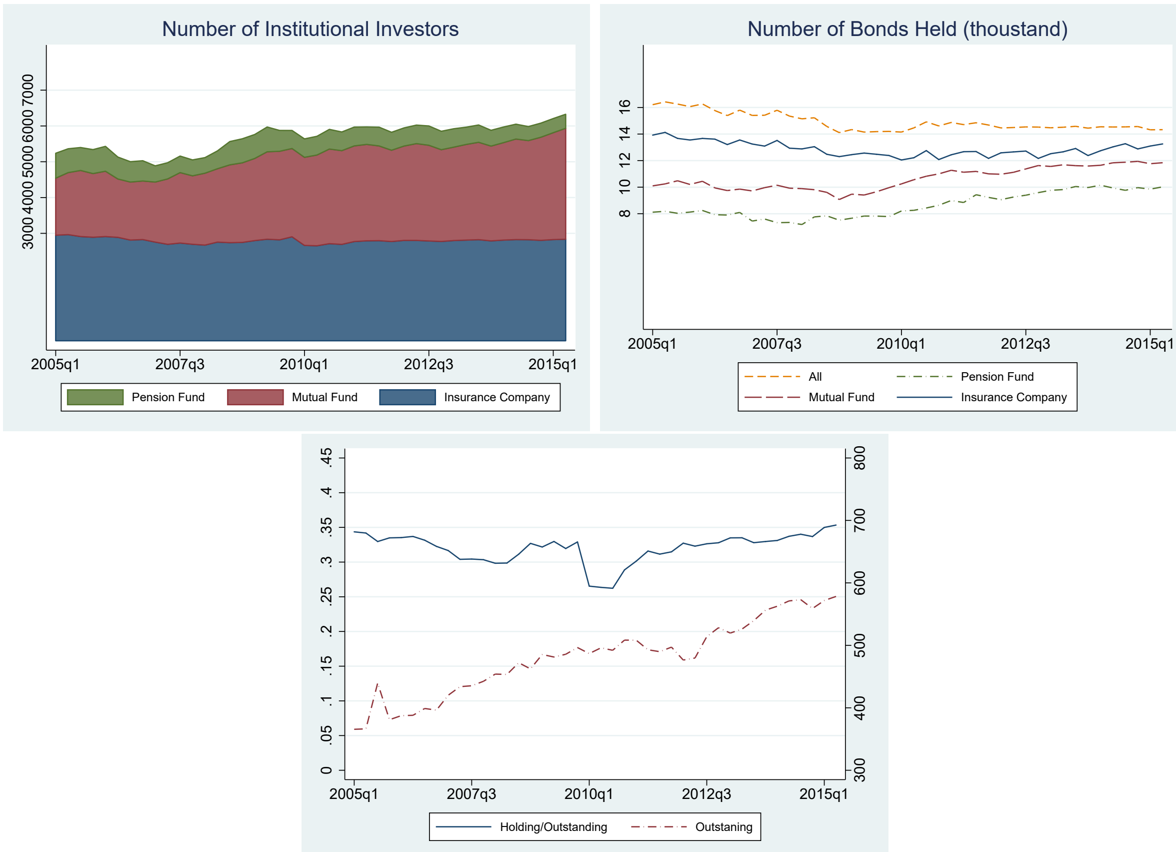
Figure A.1: Summary of Institutional Holdings



Note: This figure plots quarterly time series, based on eMAXX data of institutional holdings, of the number of institutional investors (top left panel) and the number of bonds in thousands (top right panel), by insurance companies, mutual funds, pension funds, and all institutions separately, as well as an average bond's outstanding balance (in $millions) and ratio of total holding amount by all institutions to outstanding balance (bottom panel). The number of bonds held by all institutions is lower than the sum of the number of bonds held by insurance companies, mutual funds, and pension funds because different institutions can hold the same bond. The average bond's total holding amount is calculated by first summing the holding amounts by all institutions for each bond in each quarter and then taking an average across all the bonds in each quarter. The average bonds' outstanding balance is computed by taking the average of outstanding balance across all the bonds in each quarter. The average bond's ratio of holding to outstanding is computed by dividing its total holding amount by outstanding balance in each quarter. The sample period is from 2005:Q1 through 2015:Q2.

Table A.1: Summary of Institutional Holdings

	mean	sd	min	p25	p50	p75	max
A: Number of Institutional Investors							
Insurance Company	2797	74	2653	2756	2801	2826	2965
Mutual Fund	2345	436	1593	1912	2504	2672	3099
Pension Fund	529	92	392	453	515	582	696
All	5670	392	4886	5340	5842	5971	6327
B: Number of Bonds							
Insurance Company	12873	525	12049	12477	12748	13249	14125
Mutual Fund	10652	843	9072	9925	10523	11561	11943
Pension Fund	8629	945	7189	7826	8254	9590	10150
All	14910	673	14109	14465	14579	15392	16424
C: Aggregate Holding Amount ($trillion)							
Insurance Company	1.02	0.16	0.74	0.91	0.96	1.16	1.30
Mutual Fund	0.67	0.27	0.28	0.39	0.70	0.91	1.13
Pension Fund	0.11	0.02	0.07	0.10	0.11	0.12	0.15
All	1.80	0.41	1.28	1.40	1.68	2.18	2.54
D: Average Bond Holding Amount and Outstanding Balance ($million)							
Average Bond Holding Amount	116.54	27.18	80.94	87.99	114.74	143.35	162.04
Average Bond Outstanding Balance	480.32	59.80	365.62	439.65	486.27	519.65	578.31
Average Bond Holding/Outstanding	0.32	0.02	0.26	0.31	0.33	0.33	0.35

Notes: This table reports summary statistics of quarterly time series, based on eMAXX data of institutional holdings, of the number of institutional investors (in panel A), the number of bonds (in panel B), and aggregate holding amount in $trillions of principal value (in panel C), by insurance companies, mutual funds, pension funds, and all institutions separately, as well as an average bond's holding amount (in $millions), outstanding balance (in $millions) and ratio of holding amount by all institutions to outstanding balance (in panel D). The number of bonds held by all institutions is lower than the sum of the number of bonds held by insurance companies, mutual funds, and pension funds because different institutions can hold the same bond. The average bond's total holding amount is calculated by first summing the holding amounts by all institutions for each bond in each quarter and then taking an average across all the bonds in each quarter. The average bonds' outstanding balance is computed by taking the average of outstanding balance across all the bonds in each quarter. The average bond's ratio of holding to outstanding is computed by dividing its total holding amount by outstanding balance in each quarter. The sample period is from 2005:Q1 through 2015:Q2.

Table A.2: Summary of Yield Spreads and Returns of Non-Corporate-Credit Assets

	N	mean	sd	p25	p50	p75
A: Agency MBS (in BPs)						
FN30y	42	15.76	21.17	-4.48	14.96	34.40
FN15y	42	16.07	23.75	-3.65	10.04	31.73
FG30y	42	18.79	22.73	-2.84	17.63	35.30
FG15y	42	22.31	22.92	4.41	17.48	35.59
B: Non-agency CMBS (in BPs)						
Duper	39	153.62	168.56	73.00	99.00	185.00
AM	39	296.38	402.65	63.00	133.00	341.00
AJ	39	439.03	608.24	121.00	210.00	450.00
C: ABS (in BPs)						
Credit Card Loan 5y	40	79.08	67.93	47.00	54.00	63.50
Auto Loan 3y: AAA	37	50.57	67.21	19.00	27.00	36.00
Auto Loan 3y: A	36	121.36	136.64	56.50	74.00	122.50
Auto Loan: 3y BBB	34	154.74	136.71	100.00	121.00	175.00
D: S&P 500 index options (in percentage)						
Call: 0.90	85	0.09	4.41	-2.04	0.51	2.28
Call: 0.95	85	0.02	4.30	-1.84	0.30	2.05
Call: ATM	85	-0.12	4.14	-1.75	0.04	1.65
Call: 1.05	85	-0.26	3.94	-1.77	-0.14	1.71
Call: 1.10	85	-0.49	3.64	-1.78	-0.35	0.81
Put: 0.90	85	-0.89	7.79	-4.56	-1.95	1.63
Put: 0.95	85	-0.74	6.95	-3.96	-1.58	1.37
Put: ATM	85	-0.54	6.28	-3.34	-1.12	1.78
Put: 1.05	85	-0.38	5.71	-3.00	-0.86	1.68
Put: 1.10	85	-0.32	5.37	-2.82	-0.94	1.70

Note: This table reports summary statistics of quarterly time series of option-adjusted spreads of agency MBS, yield spreads of non-agency CMBS, and yield spreads of ABS, all in basis points, in panels A, B, and C, respectively, as well as summary statistics of monthly series of (unannualized) one-month return in percent of leverage-adjusted S&P 500 index option portfolios. The series of yield spreads are provided by major Wall Street dealers, whereas the option returns are those used in Constantinides, Jackwerth, and Savov (2013). The sample period of yield spreads is 2005:Q1 - 2015:Q2 overall, with variation across different series depending on data availability. The sample period is January 2005 - January 2012 for options.

Table A.3: Measuring Inventory by Dollar Value and Matching Horizons

Groups		A: Measuring Inventory by Dollar Value				B: Matching Horizons			
Maturity	Rating	$\Delta Inventory^{Dollar}$	$\Delta Distress$	R^2_{adj}	FVE	$\Delta Inventory^{Match}$	$\Delta Distress^{Match}$	R^2_{adj}	FVE
Short	AA	0.029	0.044***	0.176	0.300	0.039**	0.044***	0.212	0.256
		(1.381)	(2.609)			(2.200)	(2.769)		
Short	A	0.038*	0.065***	0.237		0.030	0.061***	0.191	
		(1.865)	(3.637)			(1.576)	(3.247)		
Short	BBB	0.052*	0.114***	0.321		0.047*	0.112***	0.318	
		(1.893)	(4.196)			(1.953)	(4.328)		
Short	BB	0.119	0.180***	0.233		0.092	0.170***	0.141	
		(1.631)	(3.633)			(1.312)	(3.371)		
Short	B	0.282***	0.344***	0.317		0.258***	0.329***	0.294	
		(3.196)	(2.888)			(2.892)	(2.707)		
Medium	AA	0.027	0.051***	0.172		0.029*	0.049***	0.176	0.546
		(1.404)	(4.512)		0.553	(1.750)	(4.896)		
Medium	A	0.059**	0.096***	0.382		0.056**	0.095***	0.364	
		(2.523)	(3.712)			(2.458)	(3.905)		
Medium	BBB	0.086***	0.151***	0.438		0.096***	0.149***	0.463	
		(2.891)	(3.886)			(3.869)	(4.047)		
Medium	BB	0.162***	0.262***	0.469		0.186***	0.255***	0.492	
		(2.858)	(5.592)			(3.741)	(6.150)		
Medium	B	0.275***	0.509***	0.623		0.247***	0.494***	0.601	
		(5.216)	(5.206)			(3.747)	(5.051)		
Long	AA	0.020	0.043**	0.187	0.484	0.029***	0.043**	0.219	0.477
		(1.641)	(2.250)			(2.654)	(2.435)		
Long	A	0.034*	0.070***	0.292		0.036**	0.068***	0.295	
		(1.800)	(2.716)			(2.169)	(2.719)		
Long	BBB	-0.066	0.146***	0.160		-0.006	0.145***	0.136	
		(-1.024)	(5.443)			(-0.630)	(6.066)		
Long	BB	0.140***	0.249***	0.415		0.140***	0.238***	0.405	
		(2.640)	(5.370)			(2.861)	(5.566)		
Long	B	0.341***	0.731***	0.559		0.320***	0.716***	0.557	
		(3.217)	(3.677)			(3.060)	(3.667)		
Total					0.452				0.432

Notes: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on $\Delta Inventory^{Dollar}$ measured using dollar value of transactions (in panel A) and $\Delta Inventory^{Match}$ matching the horizons of inventory change and credit spread change (in panel B), together with $\Delta Distress$. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of both panels reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3), for short, medium, and long term cohorts, as well as all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table A.4: AEM Leverage Measure and TED Spread

Groups		A: AEM Leverage Measure					B: TED spread				
Maturity	Rating	$\Delta Inventory^A$	$\Delta Distress$	$\Delta \mathrm{NLev}^{\mathrm{AEM}}$	R^2_{adj}	FVE	$\Delta Inventory^A$	$\Delta Distress$	ΔTED	R^2_{adj}	FVE
Short	AA	0.028	0.044***	0.008	0.175	0.301	0.029	0.047***	0.037***	0.273	0.306
		(1.490)	(3.441)	(0.450)			(1.634)	(5.678)	(5.925)		
Short	A	0.036**	0.063***	-0.003	0.241		0.036**	0.066***	0.025**	0.272	
		(2.160)	(3.675)	(-0.159)			(2.330)	(5.388)	(2.572)		
Short	BBB	0.047**	0.109***	-0.016	0.321		0.047**	0.115***	0.030*	0.338	
		(2.134)	(3.550)	(-0.653)			(2.372)	(5.556)	(1.947)		
Short	BB	0.109**	0.171***	-0.022	0.224		0.109**	0.178***	0.034	0.228	
		(2.282)	(3.651)	(-0.719)			(2.386)	(3.950)	(1.078)		
Short	B	0.290***	0.332***	-0.004	0.322		0.290***	0.335***	0.025	0.323	
		(3.834)	(3.171)	(-0.062)			(3.854)	(3.381)	(0.385)		
Medium	AA	0.010	0.050***	0.013	0.150	0.551	0.011	0.052***	0.033***	0.207	0.558
		(0.565)	(4.073)	(1.149)			(0.613)	(3.837)	(3.302)		
Medium	A	0.048**	0.093***	0.003	0.343		0.048**	0.098***	0.043***	0.408	
		(2.129)	(3.674)	(0.137)			(2.349)	(5.655)	(4.192)		
Medium	BBB	0.074**	0.147***	0.005	0.411		0.075***	0.150***	0.034*	0.429	
		(2.554)	(3.950)	(0.159)			(2.705)	(4.939)	(1.722)		
Medium	BB	0.130***	0.247***	-0.029	0.419		0.129***	0.255***	0.038	0.422	
		(3.000)	(5.289)	(-0.618)			(3.152)	(5.556)	(1.326)		
Medium	B	0.278***	0.498***	-0.010	0.647		0.278***	0.502***	0.025	0.649	
		(5.408)	(5.775)	(-0.135)			(5.606)	(6.571)	(0.571)		
Long	AA	0.016	0.044***	0.018	0.213	0.507	0.017	0.047***	0.044***	0.368	0.524
		(1.280)	(3.412)	(1.261)			(1.492)	(5.485)	(5.595)		
Long	A	0.033*	0.069***	0.004	0.296		0.034**	0.074***	0.046***	0.412	
		(1.939)	(2.959)	(0.174)			(2.281)	(5.003)	(5.784)		
Long	BBB	-0.044	0.150***	-0.018	0.151		-0.044	0.159***	0.054*	0.165	
		(-0.885)	(5.197)	(-0.542)			(-0.888)	(4.894)	(1.909)		
Long	BB	0.126***	0.231***	-0.069	0.421		0.124***	0.240***	-0.000	0.394	
		(2.725)	(4.757)	(-1.538)			(2.900)	(5.709)	(-0.014)		
Long	B	0.361***	0.726***	0.034	0.592		0.364***	0.739***	0.150	0.613	
		(3.850)	(4.398)	(0.257)			(4.143)	(5.421)	(1.620)		
Total						0.483					0.494

Note: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on our nonlinear version of the Adrian, Etula, and Muir (2014) measure of broker-dealer leverage $\Delta \mathrm{NLev}^{\mathrm{AEM}}$ (panel A) and the TED spread ΔTED (panel B), together with $\Delta Inventory^A$ and $\Delta Distress$. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of both panels reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3), for short, medium, and long term cohorts, as well as all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table A.5: Stock and Bond Liquidity Factors

Groups		A: PS Liquidity					B: BPW Liquidity				
Maturity	Rating	$\Delta Inventory^A$	$\Delta Distress$	ΔPS	R^2_{adj}	FVE	$\Delta Inventory^A$	$\Delta Distress$	ΔBPW	R^2_{adj}	FVE
Short	AA	0.027	0.044***	0.010	0.179	0.315	0.022*	-0.005	0.041**	0.115	0.315
		(1.456)	(2.960)	(0.912)			(1.657)	(-0.358)	(2.286)		
Short	A	0.034*	0.066***	0.020	0.259		0.016	0.019	0.041*	0.219	
		(1.949)	(4.459)	(1.363)			(1.175)	(1.090)	(1.938)		
Short	BBB	0.044**	0.115***	0.025	0.331		0.013	0.044	0.025	0.166	
		(2.008)	(4.822)	(1.235)			(0.750)	(1.192)	(0.678)		
Short	BB	0.104**	0.180***	0.046	0.234		0.061*	0.153**	-0.074	0.244	
		(2.186)	(4.293)	(1.574)			(1.660)	(2.341)	(-0.950)		
Short	B	0.283***	0.345***	0.095	0.338		0.092**	0.173***	0.022	0.280	
		(3.626)	(3.645)	(1.265)			(2.039)	(2.674)	(0.228)		
Medium	AA	0.010	0.049***	0.007	0.143	0.562	0.013	0.005	0.034**	0.143	0.159
		(0.569)	(4.349)	(0.526)			(1.168)	(0.392)	(2.052)		
Medium	A	0.046**	0.096***	0.024	0.362		0.022*	-0.000	0.039	0.102	
		(2.108)	(3.981)	(1.218)			(1.712)	(-0.019)	(1.453)		
Medium	BBB	0.073**	0.149***	0.020	0.417		0.030*	0.034	0.031	0.142	
		(2.485)	(4.259)	(0.803)			(1.756)	(0.906)	(0.690)		
Medium	BB	0.127***	0.253***	0.020	0.416		0.070**	0.134*	-0.033	0.274	
		(2.965)	(6.262)	(0.619)			(2.071)	(1.819)	(-0.462)		
Medium	B	0.270***	0.511***	0.088	0.664		0.045	0.094	0.037	0.105	
		(5.599)	(7.163)	(1.336)			(0.926)	(1.015)	(0.393)		
Long	AA	0.017	0.042**	0.002	0.184	0.512	0.021***	-0.007	0.035*	0.149	0.338
		(1.292)	(2.323)	(0.186)			(2.639)	(-0.414)	(1.755)		
Long	A	0.032*	0.072***	0.023	0.323		0.019*	0.010	0.036	0.187	
		(1.802)	(3.210)	(1.569)			(1.836)	(0.519)	(1.620)		
Long	BBB	-0.046	0.155***	0.018	0.151		0.015	0.020	0.031	0.133	
		(-0.895)	(5.552)	(0.672)			(1.073)	(0.921)	(1.038)		
Long	BB	0.124***	0.240***	-0.000	0.394		0.058*	0.054	0.023	0.142	
		(2.903)	(5.978)	(-0.005)			(1.695)	(1.193)	(0.432)		
Long	B	0.353***	0.737***	0.113	0.604		0.142**	0.336***	-0.141*	0.375	
		(3.777)	(4.486)	(1.295)			(2.143)	(4.758)	(-1.772)		
Total						0.482					0.263

Note: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on the Pástor and Stambaugh (2003) (PS) stock liquidity factor (in panel A) and monthly time series regressions of monthly credit spread changes (in percentage) on the Bao, Pan, and Wang (2011) (BPW) corporate bond liquidity factor (in panel B), together with $\Delta Inventory^A$ and $\Delta Distress$. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * p < 0.1, ** p < 0.05, and *** p < 0.01 with p as the p-value. The last column of both panels reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3), for short, medium, and long term cohorts, as well as all cohorts. The sample period is 2005:Q1 - 2015:Q2 in panel A, but January 2005 - June 2009 due to the unavailability of the BPW measure.

Table A.6: Excluding the 2008 Crisis

Groups		A: PC		B: Regression of Residuals			
Maturity	Rating	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	0.062	-0.019	0.020	0.042***	0.173	0.268
				(0.918)	(3.399)		
Short	A	0.079	-0.026	0.030	0.051***	0.208	
				(1.560)	(3.641)		
Short	BBB	0.125	-0.022	0.042*	0.92***	0.266	
				(1.744)	(3.573)		
Short	BB	0.154	-0.136	0.092**	0.065	0.142	
				(2.283)	(1.283)		
Short	B	0.459	-0.394	0.264***	0.273**	0.277	
				(3.097)	(2.243)		
Medium	AA	0.05	-0.061	-0.008	0.041***	0.132	0.583
				(-0.476)	(3.234)		
Medium	A	0.1	-0.02	0.035	0.098***	0.396	
				(1.475)	(5.975)		
Medium	BBB	0.159	-0.023	0.059*	0.146***	0.421	
				(1.829)	(5.086)		
Medium	BB	0.172	0.099	0.087**	0.170***	0.463	
				(2.492)	(5.737)		
Medium	B	0.443	0.041	0.249***	0.461***	0.651	
				(4.355)	(6.453)		
Long	AA	0.055	0.006	0.008	0.055***	0.330	0.542
				(0.671)	(6.002)		
Long	A	0.077	-0.009	0.030*	0.73***	0.395	
				(1.792)	(5.351)		
Long	BBB	0.069	0.88	-0.072	0.156***	0.140	
				(-1.343)	(5.183)		
Long	BB	0.181	0.102	0.085**	0.164***	0.366	
				(2.086)	(5.032)		
Long	B	0.656	0.156	0.309***	0.699***	0.650	
				(3.503)	(6.294)		
Pct Explained		0.798	0.082				0.477

Note: This table reports results using 15 cohorts based on time-to-maturity and credit rating excluding the 2008 crisis period, defined as 2007:Q3 - 2009:Q1. Panel A reports the loadings of the first two PCs on the 15 regression residuals and the fraction of total variation these two PCs account for. Panel B reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage) on $\Delta Inventory^A$ and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of panel B reports the fraction of the total variation of residuals that is accounted for by the two intermediary factors, denoted as FVE and computed as in (3) for short, medium, and long term bonds, as well as all bonds.

Table A.7: Inventories of Large vs Small Dealers

Groups		A: $\Delta Inventory^L$			B: $\Delta Inventory^S$		
Maturity	Rating	$\Delta Distress$	$\Delta Inventory^L$	R^2_{adj}	$\Delta Distress$	$\Delta Inventory^S$	R^2_{adj}
Short	AA	0.042*	0.024	0.126	0.039	-0.006	0.094
		(1.676)	(1.341)		(1.413)	(-0.468)	
Short	A	0.073***	0.045*	0.226	0.068**	-0.020	0.172
		(2.998)	(1.959)		(2.392)	(-1.183)	
Short	BBB	0.131***	0.069**	0.341	0.123***	-0.031	0.279
		(4.140)	(2.307)		(3.209)	(-1.287)	
Short	BB	0.223***	0.186**	0.282	0.204***	-0.097*	0.191
		(4.130)	(2.382)		(3.392)	(-1.871)	
Short	B	0.398***	0.300***	0.311	0.364**	-0.120	0.208
		(2.943)	(3.031)		(2.149)	(-1.484)	
Medium	AA	0.050***	0.005	0.137	0.048***	0.017	0.151
		(3.052)	(0.236)		(2.759)	(1.106)	
Medium	A	0.092**	0.031	0.272	0.088*	0.010	0.247
		(2.297)	(1.209)		(1.941)	(0.523)	
Medium	BBB	0.153***	0.052	0.334	0.145**	0.011	0.300
		(2.747)	(1.464)		(2.263)	(0.385)	
Medium	BB	0.266***	0.1114*	0.350	0.251***	-0.003	0.294
		(4.839)	(1.654)		(3.956)	(-0.058)	
Medium	B	0.549***	0.253***	0.542	0.518***	-0.050	0.447
		(4.690)	(3.362)		(3.398)	(-0.743)	
Long	AA	0.036	0.020	0.103	0.034	-0.007	0.081
		(1.145)	(1.333)		(1.009)	(-0.547)	
Long	A	0.072**	0.044**	0.266	0.067*	-0.021	0.206
		(2.120)	(2.017)		(1.759)	(-1.128)	
Long	BBB	0.181***	0.038	0.162	0.179***	-0.064	0.175
		(4.993)	(1.018)		(4.876)	(-1.361)	
Long	BB	0.262***	0.142**	0.432	0.246***	-0.051	0.342
		(5.912)	(2.489)		(4.892)	(-1.180)	
Long	B	0.797***	0.369***	0.587	0.756***	-0.153	0.497
		(3.784)	(3.064)		(2.994)	(-1.616)	
FVE				0.436			0.355

Note: This table reports quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage), for cohorts based on time-to-maturity and credit rating, on $\Delta Inventory^L$ (in panel A), on $\Delta Inventory^S$ (in panel B), together with $\Delta Inventory^A$ and $\Delta Distress$. Robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) are reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last row reports the fraction of the total variation of residuals that is accounted for, denoted as FVE and computed as in (3), for all cohorts. The sample period is from 2005:Q1 through 2015:Q2.

Table A.8: Correlations of Dealer Inventories of HY and IG Bonds

	$\Delta Inventory^A$	$\Delta Inventory^{HY}$	$\Delta Inventory^{IG}$
A: Raw Change			
$\Delta Inventory^A$	1.0000		
$\Delta Inventory^{HY}$	0.6854*	1.0000	
$\Delta Inventory^{IG}$	0.5718*	-0.2054	1.0000
B: Percentage Change			
	$\Delta Inventory^A$	$\Delta Inventory^{HY}$	$\Delta Inventory^{IG}$
$\Delta Inventory^A$	1.0000		
$\Delta Inventory^{HY}$	0.7135*	1.0000	
$\Delta Inventory^{IG}$	0.7148*	0.0200	1.0000

Note: This table reports quarterly time series correlations of three different measures related to dealer inventory, $\Delta Inventory^A$, $\Delta Inventory^{HY}$, and $\Delta Inventory^{IG}$. Both simple changes (in panel A) and percentage changes (in panel B) are included. Significance levels are represented by * p $<$ 0.1, ** p $<$ 0.05, and *** p $<$ 0.01 with p as the p-value. The sample period is from 2005:Q1 through 2015:Q2.

Table A.9: Summary of Institutional Holdings by Rating Categories

	Insurance Companies		Mutual Funds		Pension Funds	
	Amount ($billion)	Fraction (%)	Amount ($billion)	Fraction (%)	Amount ($billion)	Fraction (%)
AAA	17.18	1.69	16.72	2.71	3.75	3.24
AA	76.45	7.37	37.74	6.05	6.24	5.79
A	368.03	35.45	128.05	18.27	23.57	21.23
BBB	435.67	41.91	193.01	26.76	34.99	31.39
BB	79.40	7.73	103.45	14.77	14.95	13.54
B	33.92	3.30	121.19	17.68	15.76	14.24
CCC	24.84	2.54	90.19	13.76	11.49	10.56
Total	1035.48		690.34		110.75	

Note: This table reports the average (over time) amount in $billions and fraction in percent of the eMAXX quarterly corporate bond holdings of insurance companies, mutual funds, and pension funds, respectively, broken down into seven rating groups. The sample period is from 2005:Q1 through 2015:Q2.