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

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Abstract

Two intermediary-based factors – a broad distress measure and a corporate bond inventory measure – explain 50% of the puzzling common variation of credit spread changes beyond canonical structural factors. A simple margin-based model accounts for this co-movement and delivers further implications with empirical support. First, whereas bond sorts on margin-related variables produce monotonic loading patterns on intermediary factors, non-margin-related sorts produce no pattern. Second, dealer inventory co-moves with corporate-credit assets only, whereas intermediary distress co-moves even with non-corporate-credit assets. Third, dealers' inventory responds to (instrumented) bond sales by institutional investors. Fourth, bond-factor sensitivities flip signs during regulatory tightening.

Keywords: Corporate Bonds, Credit, Dealer, Inventory, Bond Market Liquidity

JEL classification: G12, G18, G21, E58

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1 Introduction

What drives variation in U.S. corporate credit spreads? Standard credit risk factors play a role, yet a substantial amount of excess common variation remains, as documented in Collin-Dufresne, Goldstein, and Martin (2001) (hereafter CGM). The corporate bond market relies crucially on broker-dealers for intermediation, who use their balance sheets to take inventory and absorb bond supply from clients. A natural conjecture is that non-fundamental factors related to the supply and demand for intermediary services constitute a substantial piece of the puzzling excess common variation, à la the expanding literature of intermediary-based asset pricing (see He and Krishnamurthy (2018) for a survey).

In this paper, we provide novel evidence for this intermediary view. In particular, two intermediary factors – (1) a distress measure that captures constraints on the entire intermediary sector and (2) an inventory factor that captures the corporate bond holdings of dealers – are shown to account for about half of the puzzling common variation in credit spread changes. Most importantly, we relate these two factors to shocks to supply and demand for intermediary services in the corporate bond market, illuminating the underlying frictions involved in bond intermediation and their effects on asset pricing.

To construct the dealer inventory factor, we use the enhanced TRACE database of corporate bond transactions with untruncated trade size and anonymous dealer codes. We construct a quarterly measure of aggregate dealer inventory using the cumulative customer order flows (in par value) with all dealers. With the usual caution of imperfect measurement, we do address a few practical difficulties in using transaction records to construct inventory measure, such as the unobservable level of dealers' bond inventory at the beginning of our sample period (2005:Q1), changes to inventory unrelated to transactions (such as bond expiration), and missing primary market transactions from issuing firms to underwriting dealers.

Our measure of intermediary distress combines two existing measures 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); the second is the 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. The HPW "noise"

measure captures the market information more directly, albeit less primitive (relative to HKM leverage); the authors provide substantial evidence that "noise" is tightly connected to disruptions in funding costs (in fact, Treasury securities constitute the major collateral in repo funding). Our intermediary distress measure is the first principal component of these two measures, meant to parsimoniously capture the capital and funding constraints on the aggregate intermediary sector.

Following CGM and more recently Friewald and Nagler (2019) (hereafter FN), our analysis starts by extracting residuals of individual-bond time series regressions of credit spread changes on seven structural factors. 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 these 15 cohort-level residuals. Similar to CGM, but with comprehensive data on corporate bond transactions in recent years, we find 80 percent of the variation can be explained by the first PC, indicating a large systematic component not captured by structural credit factors.

As a first step, we connect the two intermediary factors – intermediary distress and dealer inventory – to this common variation of credit spread changes. Our two intermediary factors explain 53% of the variation of the first PC of credit spread residuals (48% of the total variation). About 2/3 of this explanatory power is attributable to intermediary distress and 1/3 to dealer inventory. Given the low correlation between distress and inventory, our empirical results suggest a two-factor structure of the common unexplained credit spread variation.

Second, and more importantly, we find that the effect is monotonically decreasing in bond ratings for both intermediary factors, an empirical pattern that is crucial to our later theoretical modeling. Economically, one-standard-deviation increases of dealer inventory and intermediary distress are associated with quarterly credit spread increases of about 3-30 and 5-60 basis points depending on rating groups, respectively.

Motivated by these two findings, 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 asset prices, consistent with our empirical evidence and that of CGM. Of course, this latent factor – the Lagrange multiplier – is unobservable.

Our model allows us to link this latent factor to the demand and supply for corporate bonds, which are are closely linked to two empirical factors presented above. We consider two types of shocks – intermediary wealth shocks and hedger liquidity shocks. Intermediary wealth decreases are (negative) "demand shocks" in the sense that balance sheet constraints are tightened, which shifts intermediaries' demand schedules inward. Such wealth shocks are effectively captured by intermediary leverage and a noise-like measure, the building blocks for our distress factor. Hedger liquidity shocks are asset "supply shocks" in the sense that more bonds arrive onto intermediaries' balance sheets, lowering bond prices. The model demonstrates that observed dealer inventory can be affected by "supply shocks" as well as "demand shocks," although our empirical results suggest that the inventory factor mainly captures the hedger liquidity "supply" shocks. Overall, through the lens of our model, bond prices are determined by a supply-demand system with the two types of non-fundamental shocks, with factor loadings that are monotone in margin/capital requirements irrespective of "demand" or "supply" shocks. Indeed, model-based regressions with dealer inventory and leverage reproduce the qualitative patterns of the empirical findings documented above.

Guided by the model, we develop four sets of empirical tests that relate our two intermediary factors to supply and demand shocks and demonstrate their economic effects on credit spread changes.

First, sorting bonds by any characteristic unrelated to margin/capital requirements should not produce any pattern in associations to 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 to explore co-movement. An extended model with heterogeneous, imperfectly-integrated intermediary trading desks (e.g., a corporate credit desk, a Treasury desk, a securitized product desk, an equity desk), each with their own margin constraint, delivers the following testable predictions: (a) corporate-credit assets should be sensitive to dealers' corporate bond inventory, or even inventory computed from a subset of corporate bonds ("spillover effects"); (b) non-corporate-credit assets should

be insensitive to such inventory ("segmentation effects"); (c) 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 these predictions. Results of two tests support spillover effects 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. Moreover, consistent with segmentation effects, 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. Finally, all assets are sensitive to intermediary distress. This last finding is also consistent with the evidence of HKM that the bank-holding companies of primary dealers act as the marginal investor across many asset classes.

Third, in strong support for our model, we establish a direct link between dealer inventory and liquidity shocks hitting other investors. We identify liquidity shocks to long-term institutional investors, show that dealer inventory responds, and measure bond price effects.[1] Specifically, the evidence linking dealer inventory to liquidity shocks uses eMAXX data to measure bond holdings by each of the three groups of institutional investors – insurance companies, mutual funds, and pension funds. Given insurance companies face regulatory constraints in holding low-rated bonds, bond downgrades cause them to sell, hence a liquidity shock (Ellul, Jotikasthira, and Lundblad, 2011; Koijen and Yogo, 2015). Indeed, insurance companies decrease their holdings of downgraded bonds, especially those downgraded from investment-grade to high-yield – so-called "fallen angels" (Ambrose, Cai, and Helwege, 2008) – by about $0.67 million, relative to the average of those that experience no rating change or are downgraded from some IG rating to a lower IG rating. Mutual funds and pension funds take some of the IG-to-IG downgraded bonds, but not "fallen angels." Importantly, dealers' inventories of "fallen angels" increase substantially in the quarter when bonds are downgraded, by about $1.61 million.

Pushing this idea further, we construct two instrumental variables for supply shocks to bond dealers. As the first IV, we take the fallen angels sold off by institutional investors.

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[1]A similar idea is systematically explored in Koijen and Gabaix (2020) in quantifying the inelasticity of U.S. equity prices to institutional demands.

To (partially) address the potential confound that fundamental changes trigger sell-offs and simultaneously lower bond prices, we control for sell-offs of all downgraded bonds. As the second IV, we obtain unexpected insured losses due to natural disasters to proxy for forced sell-offs by insurance companies. 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. Most importantly, we find that dealer inventory increases, instrumented by fallen angel sell-offs, are highly significant in increasing credit spreads. When instrumented by insured losses, the effect of dealer inventory on credit spread changes is weaker statistically, but remains positive. We also observe that the effect of dealer inventory using IVs is larger than that in the baseline analysis, likely because our IVs mitigate the downward bias caused by unobserved demand shocks.

This last observation motivates our fourth and final model-guided exploration, which posits regulatory tightening as one candidate for such "unobserved (negative) demand shocks." Regulatory tightening, while reducing dealer bond demand and raising credit spreads, leads dealers to decrease leverage and shed bond inventory. Consistent with this prediction, around the time when the Dodd-Frank Act and Volcker Rule become effective, the credit spread loadings on dealer inventory and intermediary distress flip signs and become negative.

Related literature. This paper contributes primarily to empirical literatures on credit risk and intermediary asset pricing. In the credit risk literature, the unexplained common variation of credit spread changes, first documented in CGM and most recently studied by FN, is a canonical puzzle in the context of structural models like Merton (1974) and Leland (1994).[2] 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. For example, Longstaff, Mithal, and Neis (2005), Bao, Pan, and Wang (2011), and Bao and Pan (2013) show that illiquidity measures affect credit spreads and corporate bond returns.[3] We contribute to

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[2]Schaefer and Strebulaev (2008) show that structural models capture well the sensitivity of corporate bond returns to equity returns or hedge ratios, which may seem to conflict the negative implication of CGM given the intrinsic relation between returns and yield spread changes. Huang and Shi (2014) find that structural models indeed characterize well the hedge ratios for credit spread changes, but half of variations in credit spread changes are still unexplained even after including explanatory variables or specifications that are important in characterizing hedge ratios.

[3]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). Relatedly, Lin, Wang, and Wu (2011),

this literature by explicitly linking the key liquidity providers – broker-dealers as important intermediaries– to corporate bond pricing.

The broad intermediary asset pricing literature (Adrian, Etula, and Muir, 2014; He, Kelly, and Manela, 2017) has shown that financial intermediary balance sheets have pricing power for large cross-sections of assets.[4] Relative to the existing literature, our study is narrower in scope but richer in detail. We provide evidence on both the supply and demand side of the corporate bond market, connect our results to margin/capital requirements, and investigate spillovers/segmentation across asset classes. To assist our empirical explorations, we develop a static intermediary-based model with margin constraints. Our model is deliberately simple, with the innovation being our focus 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 inspired by standard intermediary models à la He and Krishnamurthy (2012, 2013).[5]

By invoking dealers' special role in taking inventory to provide liquidity, our paper is related to studies that focus on bond dealers' inventory and transaction costs, including Bao, O'Hara, and Zhou (2018), Bessembinder, Jacobsen, Maxwell, and Venkataraman (2018), Schultz (2017), Dick-Nielsen and Rossi (2018), Di Maggio, Kermani, and Song (2017) and Choi, Shachar, and Shin (2019). FN fits into this class of papers, but more similar to us, they also examine the CGM puzzle and show that twelve measures of OTC trading frictions – inventory, search, and bargaining frictions – jointly explain 23% of the CGM PC1.[6]

The intermediary asset pricing approach we take is complementary to these analyses, typically categorized under "market microstructure" or "market liquidity" (see Vayanos and Wang (2013) for a survey). In both approaches, shocks to supply and demand for inter-

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Acharya, Amihud, and Bharath (2013), and de Jong and Driessen (2012) study the pricing of liquidity risk in corporate bond returns.

[4]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.

[5]See Brunnermeier and Pedersen (2008) and Garleanu and Pedersen (2011) for asset pricing models with exogenous margin/capital constraints and Biais, Hombert, and Weill (2017) for equilibrium under endogenous versions of such constraints. Because margin constraints – and hence asset pledgeability – are arguably endogenous to asset fundamentals, most literature on asset pricing with margin constraint has been theoretical, with Chen, Chen, He, Liu, and Xie (2019) being the notable exception who causally estimate the pledgeability premium by exploiting dual-listed bonds in Chinese bond markets.

[6]Two recent studies on equity markets, Carole, Hendershott, Charles, Pam, and Mark (2010) and Hendershott and Menkveld (2014) relate variations of bid-ask spreads and prices to the inventory positions of New York Stock Exchange specialists.

mediary services operate as the essential economic forces. The key difference is our focus on the balance sheet health of liquidity providers (e.g., tightness of broker-dealer margin constraints) as a measure of liquidity costs, rather than transaction-cost-based measures.

2 Intermediary Factors and Credit Spread Changes

In this section, we first introduce the data sample of U.S. corporate bond transactions and construct our two intermediary factors. We then connect our intermediary factors to credit spread changes.

2.1 Data on 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).[7] Importantly, this data contains untruncated principal amounts and an indictor of whether the trade is either between a customer and a dealer or between two dealers. Our sample period is 2005:Q1-2015:Q2.

We first apply a number of filters to account for reporting errors, to assign each trade to the actual trading counterparties, and to examine a sample of bonds that is relatively common to the literature. The resulting data sample after the basic adjustments is used to construct our dealer inventory measure, so we denote it the "bond inventory sample." See Table A.1 in Internet Appendix A for the detailed step-by-step procedure of data filtering and the associated change in sample coverage.

To construct the baseline sample for studying variation of credit spreads, we merge the TRACE database with Mergent FISD (bond characteristics), CRSP (equity prices), and Compustat (accounting information). We exclude unmatched bonds and then restrict to senior unsecured bonds that are denominated in U.S. dollars, with a fixed coupon rate, with available credit rating, without embedded options except make-whole calls (Bao and Hou,

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[7]The TRACE database covers all corporate bond transactions executed by broker dealers registered with FINRA. The missing trades from TRACE 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).

2017), issued by non-financial and non-utility firms, and with issue sizes less than \$10 million. We keep only secondary market trades by removing the those with P1 flag (primary market trades) 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 also those with trade size larger than the issue size.

Our main sample frequency is quarterly. For each bond i, we compute the yield-to-maturity of the last trade in quarter t, and then calculate its credit spread $cs_{i,t}$ by subtracting off the yield of the corresponding Treasury security.[8] 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 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 below 45 or above 120 days. We match the Treasury yield to the exact day of the trade used in each quarter in computing credit spread to eliminate nonsynchronization issues and scale $\Delta cs_{i,t}$ to make it a 90-day change (Bao and Hou (2017) make similar adjustments at the monthly frequency). Finally, we remove upper 1% and lower 1% tails of the credit spread levels to avoid the influence of outliers, and require bonds to have 4 years of consecutive quarterly observations of $\Delta cs_{i,t}$ to ensure enough observations for regressions on structural model factors.

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.[9] Around 35% of the observations are on high-yield bonds, defined as the Moody's crediting rating below BBB. The mean credit spread is 1.52% and 5.27% for investment-grade and high-yield bonds, respectively. The average time-to-maturity is 9.78 years, which is higher for investment-grade bonds (10.85) than high-yield bonds (6.78).

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

[9]For comparison, Bao and Hou (2017) use a sample of about 10 years from July 2002 to December 2013. Because they focus on monthly frequency, they have a larger sample size with more than 230,000 bond-month observations and around 7000-9000 distinct bonds. FN also use a monthly dataset from January 2003 to December 2013. Their sample includes only 974 bonds with 45,000 bond-month observations, substantially smaller than that of Bao and Hou (2017) and our monthly sample (which has 3324 bonds and more than 185,000 bond-month observations; see Table A.1).

2.2 Intermediary Factors

2.2.1 Dealer Inventory

Our measure of dealer inventory is computed using cumulative order flows between customers and dealers from TRACE. As our objective is to study the balance sheet pressure imposed by aggregate dealer inventory, we use the "bond inventory sample" defined in Section 2.1 that includes the whole set of corporate bond transactions.

Using records of transactions to construct measures of inventory poses several practical difficulties, which we address carefully. First, we have no data on the actual level of dealers' bond inventory at the beginning of our sample period. 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 (Schultz, 2017; Goldstein and Hotchkiss, 2019).

Second, to correct for maturing bonds, we calculate cumulative positions of all dealers for each bond, and we assume dealers' inventory of this bond turns zero at its maturity date and hence remove this amount of inventory on that date.[10]

Third, to eliminate primary market trades, we make two adjustments. Starting March 1, 2010, due to a FINRA requirement, we are able to use an identifier for primary market trades. Before March 1, 2010, we remove trades of a bond executed before and on its offering date. 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.

After making these adjustments, we construct a quarterly measure of dealer inventory by aggregating cumulative order flows of all dealers with customers. We use par value rather than market value to avoid the potential confounding effect of price changes when studying the effect of dealer inventory on credit spreads. The quarterly log change of this measure, denoted $\Delta Inventory^A$, is the baseline dealer inventory factor in our analysis.[11]

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[10]Our procedure will miss callable bonds that are being called before maturity, though these callable bonds are removed from inventory at their times of maturity.

[11]Log changes can be problematic if the inventory level becomes negative, which is not the case with our measure and sample period. Note that our inventory measure is only based on bond transactions. Including dealers' derivative positions and short sales may make the inventory go negative.

To the best of our knowledge, data on dealers' exact holding amounts of corporate bonds are unavailable. Besides our method using TRACE transaction data, two data sources based on financial reporting also provide some crude information on dealers' security holdings. One is the FRBNY report on holdings of primary dealers,[12] and the other is the Flow of Funds report on holdings of security broker-dealers, released by the Federal Reserve.[13]

Several differences and issues are worth discussing. First, these sources do not purely track corporate bonds. The FRBNY began collecting primary dealers' holdings of corporate bonds as a separate asset class only starting April 3, 2013; its reported corporate bond positions prior to April 3, 2013 are extrapolated backward.[14] The Flow of Funds series are the holding amounts of "corporate and foreign bonds" (FL663063005.Q) that include corporate bonds as well as all other fixed-income securities (e.g., private-label MBS). Second, our method covers exactly the dealers trading in corporate bonds. The FRBNY report only includes about 20 primary dealers (a subset of ours), while the Flow of Funds series covers a broader set than those intermediating corporate bonds, i.e., all broker-dealers who submit information to the Securities and Exchange Commission through either the Financial and Operational Combined Uniform Single Report (FOCUS) or the Report on Finances and Operations of Government Securities (FOGS).[15]

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.

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[12]See https://www.newyorkfed.org/markets/gsds/search.html.

[13]See https://www.federalreserve.gov/apps/fof/DisplayTable.aspx?t=l.130.

[14]Before April 3, 2013, corporate bonds are not separated 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.

[15]Discrepancies in asset and dealer coverage lead to differences between our dealer inventory measure and the two alternative data sources. First, magnitudes can diverge; for example, FRBNY data shows primary dealer holdings of $250 and $28 billion at the end of 2007Q1 and 2014Q4, respectively, while about $91 and $107 billion from our series. Second, unlike the two alternative measures, our dealer inventory series shows an expansion starting from early 2013 (the measure in Goldberg and Nazawa (2019) shows a similar pattern to ours), consistent with the increasing outstanding balance of corporate debt (Figure 2). That said, all measures share a similar increasing trend from 2003-2007 and a large decline from 2007-2012. In addition, reconstructing our dealer inventory measure using only primary dealers delivers similar results.

The HKM leverage ratio, denoted $\text{Lev}_t^{\text{HKM}}$ for quarter t, is computed as the aggregate market equity plus aggregate book debt divided by aggregate market equity, using CRSP/Compustat and Datastream data, of the holding companies of primary dealers recognized by the FRBNY. In measuring the change or innovation of the leverage ratio, we create the variable $\Delta\text{NLev}_t^{\text{HKM}} := \left(\text{Lev}_t^{\text{HKM}} - \text{Lev}_{t-1}^{\text{HKM}}\right) \times \text{Lev}_{t-1}^{\text{HKM}}$, motivated by the nonlinear effect of intermediary constraints on asset prices suggested by theory.

The HPW "noise" measure is computed as the root mean squared distance between the market yields of Treasury securities and the hypothetical yields implied from yield curve models like that of Svensson (1994).[16] "Noise" is widely used in the literature as a measure of "shortage of arbitrage capital" across various markets. The rationale is that relative value trading across various habitats on the yield curve is conducted at most investment banks and fixed-income hedge funds. 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 marginal players in the market, this symptom applies not only to the Treasury market, but also more broadly to the overall financial market*" (HPW). We denote $\Delta Noise$ the quarterly change of the HPW noise measure (in basis points).

Our measure of intermediary distress, denoted as $\Delta Distress$, is defined as the first principal component of $\Delta\text{NLev}_t^{\text{HKM}}$ and $\Delta Noise$. The former is constructed mainly using balance sheet information of financial intermediaries, while the latter is based on prices in the Treasury market; both differ from the credit risk market which is our focus. Combining the two leads to a parsimonious measure of the capital constraints on the aggregate intermediary sector. As shown in Internet Appendix A.5, both $\Delta\text{NLev}_t^{\text{HKM}}$ and $\Delta Noise$ contribute a nontrivial fraction of the explanatory power of $\Delta Distress$ for credit spread changes.

2.2.3 Summary Statistics

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 panels. Dealer inventory has comparable frequent variation across different sub-

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[16]The Svensson (1994) model is an extension of the yield curve model initially proposed in Nelson and Siegel (1987). These models are widely used in the academic literature and in practice to compute benchmark yield curves (Gurkaynak, Sack, and Wright, 2007). 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.

periods of the sample, whereas intermediary distress exhibits extreme variation in the 2008 crisis but mild variation otherwise. Importantly, the two factors exhibit largely orthogonal variation, with a correlation of only -0.16 (Table 2).

The third 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 is 0.83 (Table 2). Our measure $\Delta Distress$, as the first principal component of them, captures 70% of their total variation.

Table 2 also reports correlations of our intermediary factors with other important variables. Whereas $\Delta Distress$ has a moderate 0.36 correlation with ΔVIX, the correlation of $\Delta Inventory^A$ with ΔVIX is low and statistically insignificant. 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 always control for ΔVIX and, in a robustness check, ΔILiq in studying the effects of intermediary factors on credit spreads.

2.3 Credit Spread Changes and Intermediary Factors

In this section, we show that intermediary factors have strong explanatory power for credit spread changes. Most importantly, sensitivities to these intermediary-based factors are monotone in credit risk, a pattern that is robust to many other alternative specifications.

2.3.1 Commonality of Credit Spread Changes

We first replicate the exercise in CGM and show that the strong commonality persists in the U.S. corporate bond market in our sample of 2005 - 2015. Following CGM, we consider seven determinants, motivated from the Merton (1974) model, of credit spread changes: 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}, a jump factor $Jump_t$ based on S&P 500 index options, and VIX_t. See Internet Appendix A.2 for further details.

We run a time series regression for each bond i:

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\begin{aligned}
\Delta cs_{i,t} &= \alpha_i + \beta_{1,i} \times \Delta Lev_{i,t} + \beta_{2,i} \times \Delta VIX_t + \beta_{3,i} \times \Delta Jump_t \\
&+ \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}, \quad (1)
\end{aligned}
$$

by which an estimate of each regression coefficient for each bond is obtained. To avoid asynchronicity issues, in running this regression for bond i, we match the dates of any structural regressors available at daily frequency (e.g., VIX_t) to the dates of measured credit spreads for bond i. 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.

Panel A reports the regression results. Following CGM, we report 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. The dependence of Δcs on the factors is as expected based on structural frameworks. For example, credit spreads significantly increase with firm leverage and volatility, and decrease with the risk-free rate and the stock market return. The mean adjusted R^2 is about 30-40% for bonds rated equal to or above BBB and about 55% for bonds rated equal or below BB.

There is a strong common factor structure of the regression residuals, as pointed out by CGM. 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. Panel B of Table 3 reports the principal component analysis of the 15 regression residuals, and finds that over 80% of the variation can be explained by the first PC, whereas the second PC explains an additional 6%. 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 $\bar{\varepsilon}_g$ the time series mean of ε_{gt}), as a fraction of the total variation of the 15 cohorts $\sum_{g=1}^{15} \varepsilon_g^{var}$. The BB and B cohorts account for the majority (about 86%) of the total variation. That is, compared to higher-rated cohorts, although the structural factors can explain more of the raw credit spread changes in these two lower-rated cohorts as noted in the last sentence in the previous paragraph, what remains to be explained is still large.

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 in individual bond regressions, 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 individual bond regressions is likely because we use a quarterly sample as opposed to monthly samples of the other two studies (indeed, in the monthly regressions reported in Table A.8, the average adjusted R^2 drops to 26%). The important feature of these residuals is commonality: the fraction of the total unexplained variance of regression residuals that can be accounted for by the first PC is very high (82%), similar to CGM and FN.[17]

2.3.2 Effect of Intermediary Factors on Common Credit Spread Changes

The strong common variation of credit spread changes beyond structural factors implies the existence of a "market" factor specific to the corporate bond market (see similar implications for the MBS market in Gabaix, Krishnamurthy, and Vigneron (2007)). In fact, CGM (Section B.3) show that the PC1 is largely associated with the change in market-level credit spread index, so they conclude "*there seems to exist a systematic risk factor in the corporate bond market that is independent of equity markets, swap markets, and the Treasury market and that seems to drive most of the changes in credit spreads.*" In this section, we show that our two intermediary factors have significant explanatory power for this systematic factor in the corporate bond market.

We study the effect of intermediary factors on common credit spread changes based on

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[17]Our PC1 explains 82% of grouped residual variation, similar to the 76% found in CGM. This is a bit higher than the 48% documented in FN. To directly compare to these studies, we can repeat this analysis at the monthly frequency, in which PC1 accounts for 76% of the variation of the 15 credit spread residuals (see Table A.8 in the next section). 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. FN propose their lower commonality might be explained by CGM's use of dealer quotes instead of actual transaction prices which "potentially works against their conclusion regarding the magnitude of the latent factor" (page 8 in FN). Our results seem inconsistent with this conjecture given that actual transaction prices are also used in our analysis.

the following time series regressions:

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

where $\varepsilon_{g,t}$ is the average residual of cohort g $(= 1, \ldots, 15)$.[18] Panels A and B of Table 4 report univariate regressions on dealer inventory and intermediary distress, respectively, and Panel C reports bivariate regressions. Dealer inventory and intermediary distress both co-move positively with residuals of credit spread changes.[19]

Our most important result of this section is the strength and pattern of factor loadings across our bond cohorts: lower-rated bonds have higher loadings on both inventory and distress. For example, the joint regression in Panel C of Table 4 implies that a one-standard-deviation increase of dealer inventory (intermediary distress) is associated with a quarterly increase of about 3-30 basis points (5-60 basis points) in bond yields, with higher sensitivities for lower-rated bonds. This monotonic pattern is reminiscent of the principal component loadings: lower-rated bond residuals have higher loadings on PC1 in Table 3.

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 rating-maturity groups, we compute the fraction of variation explained by the two intermediary factors as

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

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[18]Equivalent to our "two-stage" approach, one can use a kitchen-sink regression by including the seven structure variables and our two intermediary factors jointly. This alternative approach allows us to see more directly how much explanatory power the intermediary factors bring relative to the structural factors based on the R^2 increase. We use the two-stage approach because it gives a relatively clean gauge on the loadings.

[19]Statistically, dealer inventory is weak in univariate regressions but strong in joint regressions, whereas intermediary distress shows strong statistical significance in both univariate and joint regressions. The weak statistical significance of dealer inventory in univariate regressions is likely due to the unbalanced number of bonds assigned into different cohorts. Indeed, firm-leverage cohorts, used in Table A.7 of the next section, have more balanced number of observations, and the statistical significance of both intermediary factors is strong in univariate regressions.

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 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, consistent with the correlations of these two factors and the PC1 reported in the last row of Table 3. In Internet Appendix A.5, we redo this analysis with the two variables comprising $\Delta Distress$ decomposed. A greater amount of unexplained credit spread variation is accounted for by $\Delta Noise$ (32%) than NLev$^{\text{HKM}}$ (17%). Likely, this is because $\Delta Noise$ – a market price-based measure – better proxies "market distress" relative to $\Delta \text{NLev}_t^{\text{HKM}}$, which admits a more primitive economic interpretation.

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 variation of credit spread changes, with 1/3 and 2/3 attributable to dealer inventory and intermediary distress, respectively. Several robustness checks are in Internet Appendix A.

In addition, given our focus on bond market liquidity providers, it is instructive to understand how much of credit spread changes can be explained by measures of liquidity for secondary corporate bond markets in comparison to our intermediary factors. In the literature, these measures usually aim to capture transaction costs and trading activeness that are more microstructure-oriented (Chen, Lesmond, and Wei, 2007; Bao, Pan, and Wang, 2011; Dick-Nielsen, Feldhütter, and Lando, 2012). We use the aggregate illiquidity measure of Dick-Nielsen, Feldhütter, and Lando (2012), ΔILiq, which is calculated as an equally-weighted average of four metrics: the Amihud (2002) measure of price impact, the Feldhütter (2012) measure of round-trip cost, and respective daily standard deviations of these two measures. That is, ΔILiq captures trading illiquidity due to price impact and transaction costs, as well as liquidity risk, and is aggregated into a time-series factor.

We find that ΔILiq is only weakly correlated with our two intermediary factors (Table 2). Importantly, ΔILiq mainly adds to the explanatory power (adjusted R^2) of high-rated cohorts but not low-rated cohorts, and its explanatory power is relatively small (Table A.5). Similar patterns are found using the corporate bond illiquidity measure of Bao, Pan, and Wang (2011), available at the monthly frequency up to 2009 (Table A.11). Given our some-

what different focus, we acknowledge several reasons that could drive the relatively small explanatory power of these commonly used illiquidity measures: (i) we focus on the quarterly frequency, during which transaction-cost-based illiquidity may simply be less important; and (ii) the first-stage CGM regression may already include variables correlated with this type of liquidity (e.g., Table 2 shows corr$[\Delta\text{ILiq}, \Delta VIX] = 0.38$, so loadings on VIX could crowd-out the contribution of ILiq). Individual-bond-specific liquidity could be important to credit spread variation at the individual bond level; our analysis says that for the common component of credit spread changes, at the quarterly frequency, dealer inventory and intermediary distress seem to better capture the relevant notion of "liquidity".

3   An Economic Framework

We present a simple intermediary-based setting that provides a supply-demand interpretation to our results. Supply shifts come from shocks to hedgers' endowments: because hedgers are risk-averse, shocks to their endowments initiate portfolio liquidations that increase bond supply. Demand shifts come from shocks to intermediary wealth: because intermediaries face margin constraints, balance sheet shocks affect required returns on intermediation. We show how model-based regressions with dealer inventory (a proxy for bond supply) and dealer leverage (a proxy for intermediary wealth) reproduce the qualitative patterns of our bond-level regressions. The model can also accommodate the explanatory role of the Treasury "noise" variable. Finally, we derive further tests guided by the model.

Assets. There are many risky asset contracts numbered $a = 1, \ldots, A$. Asset payoffs 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. Thus, we may think of δ as the net-of-interest payoff as well.

For simplicity, the risky assets are in zero net supply, i.e.,[20]

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

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[20]Allowing positive net supply of assets only slightly alters the equilibrium relationships. Indeed, if q is the asset supply vector, then hedgers' endowments h are replaced in all expressions below by $h + q$.

where θ_H and θ_I are the asset demand (supply if negative) 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:

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

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

where W_H is ex-post hedger wealth, and $1 - w$ is initial hedger wealth. The *supply shocks* we consider are shocks to h, to be described below.

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

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

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. The *demand shocks* we consider are shocks to w, which affect the tightness of this constraint, hence intermediaries' required returns.

While the constraint $\theta_I \cdot m \leq w$ is sufficient to generate most of our empirical results, we also discuss other types of constraints in Internet Appendix B.1. For example, one could argue that long and short positions should both incur margin costs, or that market prices should be in the constraint. These nuances should not dramatically alter the mechanisms we highlight.

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

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

where μ is the Lagrange multiplier on the margin constraint. The optimal hedger portfolio

is given by the standard mean-variance optimization:

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

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 call 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 and decreases in intermediary demand

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both reduce asset prices, as one expects in a supply-demand model. Price declines occur because intermediary margin constraints "tighten" if they are faced with more bond supply or if they have lower wealth. These effects are stronger for higher-margin assets; in fact, both effects are *proportional to asset margin*. This is reminiscent of the monotonic pattern in empirical loadings displayed by bonds grouped by ratings or leverage. We formalize this link in the next section, where we construct model-based proxies for these supply-demand shocks and insert them into a regression framework.

Shock proxies. Recall in Section 2.2 our empirical pricing factors are "bond inventory" and "intermediary distress." For now, we take as given that the distress factor is closely related to w^{-1}, since HKM leverage is a key component of distress. In Internet Appendix B.3, we provide a very simple extension in which the HPW "Noise" variable – as an imperfect measure of arbitrage profits – can be meaningfully defined and linked to corporate bond pricing.

But here, we would like to use the model to demonstrate 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. Given that ξ is affected by both s and w shocks, an important question is whether bond inventory increases reflect bond supply or bond demand. This is ultimately an empirical question that can be settled by examining the regression coefficient of bond prices on inventory. If this coefficient is negative, inventory reflects bond supply to a larger extent, as high bond demand raises prices.

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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*

$$\mathrm{d}p = \beta_\xi \mathrm{d}\xi + \beta_\lambda \mathrm{d}\lambda$$

$$\beta_\xi := -\exp(\xi)m'\bar{h}_{bond}\Big[\bar{h}_{bond} \cdot \mathbf{1}_{bond} - \frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m}\bar{h}_{bond} \cdot m\Big]^{-1}\frac{\alpha m}{m'\Sigma^{-1}m}$$

$$\beta_\lambda := -\frac{w}{\lambda}\Big(m'\bar{h}_{bond}\Big[\bar{h}_{bond} \cdot \mathbf{1}_{bond} - \frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m}\bar{h}_{bond} \cdot m\Big]^{-1}\frac{m'\Sigma^{-1}\mathbf{1}_{bond}}{m'\Sigma^{-1}m} + 1\Big)\frac{\alpha m}{m'\Sigma^{-1}m}.$$

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

Proposition 2 allows us to relate our model directly 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 are *proportional to the margin vector m*, as alluded to earlier. 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 / 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 150% for those below BB-.[21] 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

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[21]See page 23, paragraph 66 of https://www.bis.org/publ/bcbs128b.pdf. The alternative internal ratings-based (IRB) approach assigns capital charges according to self-assessed default probabilities and loss-given-defaults for the underlying securities, and should generate qualitatively similar patterns since lower-rated securities have higher default probabilities and default losses.

approach), and lower-rated corporate bonds tend to be riskier. In line with this discussion, 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 $\hat{\beta}_\xi^{\text{AA}}/\hat{\beta}_\xi^{\text{B}} \approx 10$ to 20 and $\hat{\beta}_\lambda^{\text{AA}}/\hat{\beta}_\lambda^{\text{B}} \approx 7$ to 15, which are in the ballpark of the capital-requirement-implied sensitivity ratios, i.e., $m_{\text{B}}/m_{\text{AA}} = 150\%/20\% = 7.5$ in Basel II.[22]

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 drivers 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 (in the right-hand column of Table 3). Of course, the "single factor" μ is not directly measurable, and faced with this challenge we instead measure proxies for the shocks that drive μ (e.g., inventory as a proxy for s and leverage as a proxy for w).

Developing new tests. Besides putting the empirical results of Section 2.3 into a canonical economic framework, the model also allows us to design new tests. Below, we develop Predictions 1-4, which we shall take to data in Section 4.

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.

Prediction 1. *Sorting bonds by a 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 inven-

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[22]Although we have only included corporate bond 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.

tory 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 $p = \bar{\delta} - \text{diag}(m)(\mu_1 \mathbf{1}_{\mathcal{A}_1} + \mu_2 \mathbf{1}_{\mathcal{A}_2})$.

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, implying that μ_1 is sensitive to $\mathcal{A}_1$ inventory whereas μ_2 is not (see Internet Appendix B.2). However, 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.[23] 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.*

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[23]In practice, institutions can modify the limits on separate trading desks only at a lower frequency, but shocks to their net wealth can be transmitted to all trading desks in a relatively faster way, e.g., when investors pull money out, funds have to downsize on all trading desks immediately.

Third, we have argued that bond inventory is a good proxy for bond supply guided by the model. 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. Given $\beta_\xi < 0$, the model indeed implies that $\partial \xi / \partial s > 0$ (see Proposition 2 and compare with equation (14)). This is a standard way of separating supply and demand shocks in the literature (Goldberg and Nazawa (2019) use this method, for example). But this line of reasoning depends on the model structure. A more direct test would be to extract plausibly exogenous supply shocks ds 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.*

Lastly, because our sample period (2005-2015) contains various regulatory responses to the financial crisis, one naturally wonders how regulatory shocks transmit to bond prices, dealer inventory, and intermediary distress. For instance, the implementation of the Volcker Rule should have a first-order impact on the corporate bond market, as documented in Bao, O'Hara, and Zhou (2018). In this case, dealers face both explicit costs and opportunity costs of implementing required trading reforms (e.g., match buyers and sellers prior to taking bond inventory, or be more selective in which bonds they take on).

To develop a formal prediction that matches this conceptualization of regulation, we extend the model by supposing intermediaries pay a cost $\chi \theta_I \cdot \mathbf{1}$ for their asset holdings θ_I. The the cost parameter χ is a very simple reduced-form stand-in for costs and constraints induced by regulations. In this setting, a regulatory tightening (increase in χ) tends to reduce bond prices and the positions that dealers take in equilibrium (see Internet Appendix B.4). Since a reduction in dealers' holdings tends to reduce their inventory and leverage, we should expect the following, opposite to our baseline results.

Prediction 4. *During periods of significant regulatory tightening, bond prices should be positively related to both dealer inventory and intermediary distress.*

4 Empirical Support to the Economic Framework

In this section, we provide supporting evidence, corresponding to Predictions 1-4 above, that corroborates the key economic mechanism of dealer margin constraints.

4.1 Sorts on Variables Unrelated to Margin

First, 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 not strongly tied to margin requirements.

To present further evidence along this direction, we examine bond sorts on trading volume, which is plausibly unrelated to a bond's margin requirements. For each bond in each quarter, we compute the total trading volume (in dollar market value) in the last month of the quarter. Then in each quarter, we sort bonds independently into one of 15 groups based on quintiles of ratings and terciles of total trading volume. Within each rating category, the average total trading volume differs substantially across the tercile groups, about $2, $17, and $100 million respectively (Table 5, Panel A).

As shown in Panel B of Table 5, the magnitude and statistical significance of coefficients on both intermediary factors increase from high-rated groups to low-rated groups, consistent with the results in Section 2.3, but remain roughly the same across the terciles by trading volume. This result also confirms that our two intermediary factors capture the "liquidity" frictions that are relevant for corporate bond pricing better than measures based on trading activeness.

4.2 Spillover and Segmentation

Second, we show that dealer inventory has spillover effects within the corporate credit market but not outside, while intermediary distress affects various asset classes universally.

4.2.1 Spillover Effects: High-Yield and Investment-Grade Bonds and CDS

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.

Similar to the aggregate inventory measure, we construct dealer inventory of high-yield (HY) and investment-grade (IG) bonds separately, denoted by $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$. Table 6 reports the results when regressing the residuals of credit spread changes on $\Delta Inventory^{IG}$ and $\Delta Inventory^{HY}$ separately, as well as $\Delta Distress$.

Both $\Delta Inventory^{IG}$ and $\Delta Inventory^{HY}$ have 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. Loadings on both inventory measures also feature a similar monotone effect from high-rated to low-rated bonds, as with 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.13 of Internet Appendix reports correlations of the inventory measures that are inconsistent with this alternative interpretation: $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$ are negatively correlated in raw changes and near zero (0.02) in percentage changes.

In Internet Appendix A.6, we demonstrate spillover effects extend to CDS, whose payoffs are tightly linked to corporate bonds and anecdotally traded at similar desks and firms. Consistent with Prediction 2, CDS residuals – after orthogonalizing with respect to the structural CGM factors in equation (1) – behave very much like bond yield spread residuals: CDS residuals have a strong common component (PC1) whose variation is significantly linked to our to intermediary factors.[24]

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[24]We caution that the trading of single-name CDS contracts is very sparse post the 2008 crisis.

4.2.2 Segmentation Effects: Non-Corporate-Credit Asset Classes

The spillover effects just documented 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 of agency MBS (various maturities), CMBS (various ratings), ABS (various ratings), and monthly S&P 500 index options (various moneyness) returns, all over Treasuries, on the time series variables to extract the residuals. Details on this data are in Internet Appendix A.4.

We then run time series regressions of these residuals on $\Delta Inventory^A$ and $\Delta Distress$, at the quarterly frequency for agency MBS, CMBS, and ABS and at the monthly frequency for S&P 500 index options. According to Prediction 2, these assets should be insensitive to bond inventory changes, but should still respond to aggregate intermediary distress. Table 7 shows results consistent with this prediction.[25]

4.3 Institutional Holdings and Supply Shocks

In this section, we delve into bond-level dealer inventories and institutional holdings to provide evidence that the change of dealer inventory is driven by the supply of bonds from some regulatory-driven sell-offs by institutional investors. 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.

Notice that from the perspective of dealers, the actual driver of "supply" shock suffered by institutional investors is irrelevant. In our model in Section 3 the cause of "supply" could include an increase in bond endowments, which would cause institutional investors (hedgers) to hold more bonds in equilibrium; but in the context of regulatory-driven sell-offs hedgers should hold less bonds in equilibrium. Nevertheless, under both scenarios dealers' inventories increase, which is the empirical measure that we are focusing on.

A word of caution: bond downgrades typically contain information about firm fundamentals and economic conditions, so we cannot argue that investor sell-offs are unambiguously

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[25]The only exception is index call options for which even the intermediary distress factor is not significant. This is consistent with the literature of option pricing in that it is out-of-the-money put options, instead of call options, that carry the large downside tail risk or crash risk (Bollerslev and Todorov (2011); Gao, Lu, and Song (2019)).

exogenous "supply shocks" (as in Prediction 3). But recall that when constructing the residuals of credit spread changes we have controlled for firm- and market-level structural factors. Moreover, severe downgrades from IG rating to HY rating, also called "fallen angels," are more likely to serve as pure supply shocks, thanks to regulatory constraints imposed on financial institutions (especially for insurance companies). Our later IV analysis uses "fallen angels" (controlling normal downgrades) together with the insured losses due to natural disasters to instrument the supply shock.

4.3.1 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 corporate bond holdings of insurance companies, mutual funds, and pension funds in North America (based on where the holder is located).[26] 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. More details on this data are in Internet Appendix A.3.

Figure 2 provides a summary of the eMAXX institutional holdings, as well as dealer inventories from TRACE. The top panel plots quarterly time series of institutional investors' holdings and dealers' inventory, as well as the aggregate outstanding balance of U.S. corporate debt securities based on the Flow of Funds. The dollar (par) value of institutional holdings has seen a significant increase from $1.3 trillion to $2.7 trillion, with much of the increase coming after plummeting in the 2008 crisis. The rise of holdings is strongest in mutual funds. At the same time, there has been a sizeable expansion of the whole corporate bond market, from less than $5 trillion to more than $8 trillion outstanding. The bottom panel plots quarterly time series of the fraction of U.S. corporate debt securities held by institutional investors, by dealers, and by both, in percent. The fraction steadily accounts for 25-35% of the aggregate outstanding balance.

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[26]Data on insurance companies' holdings are based on National Association of Insurance Commissioners (NAIC) annual holdings files and quarterly transaction reports to state insurance commissioners. Data on mutual fund holdings are from Lipper, 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) for further details).

4.3.2 Supply Shocks from Institutional Investors: Bond-Level Evidence

We first document that a significant amount of institutional investor sell-offs of downgraded bonds are absorbed into dealers' balance sheet as inventories.

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 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 either 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 a lower IG rating.[27]

Table 8 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 average holdings changes (in \$million) and percentage changes as a fraction of initial holdings are reported, where initial holdings are measured using average holdings $Holding_{i,t-1}$ and dealer inventory $Inventory_{i,t-1}$ as of quarter $t-1$. We also include the average of changes in quarter $t+1$, i.e., one quarter following the rating change, as it may take time for investors to adjust their positions.

For "downgrade (IG)" bonds, both at the downgrade quarter (t) and the next 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 \$0.29-0.38 million at quarter t but sold \$0.16-0.25 million at quarter $t+1$. Insurance companies sold "fallen angels" in both quarters, about \$1.27-1.35 million, while mutual funds and pension funds bought \$0.12-0.20

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[27]Our analysis relies on the sell-offs induced by bond downgrading, so we exclude "upgrade" observations. We also exclude observations with bonds downgraded from HY rating to a lower HY rating, as the different initial rating category makes it hard to compare with "fallen angel" observations.

million at quarter t and sold \$0.24-0.47 million the quarter after.

In words, the sell-offs by insurance companies are larger for "fallen angels" than for "downgrade (IG)" bonds, whereas purchases by mutual funds and pension funds are smaller. 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).

Table 8 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 in small amounts. More importantly, compared with the level of inventory as of quarter $t - 1$, dealers' purchase amount of "fallen angles" is strikingly large, an increase of about 77%, which is substantially greater than "downgrade (IG)" bonds (about 18%), and dwarfs those of mutual funds and pension funds that are below 1%. Dealers – who provide liquidity for insurance companies – should adjust their price quotes actively in response to these relatively large shocks to their balance sheets.

In Internet Appendix A (Table A.15), we conduct a similar analysis in regression format, which allows us to control for firm size, bond age, and time-to-maturity. The results on sell-offs by institutional investors, and intermediation by dealers, are very similar to the summary statistics in Table 8.

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-rated 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' liquidations of "fallen angels."

4.3.3   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. We include all three types of institutional investors when computing $\Delta Holding_t^{FA}$ and $\Delta Holding_t^D$, not 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.[28] We scale $\Delta Holding_t^{FA}$ and $\Delta Holding_t^D$ by their respective levels of holdings as of $t-1$, corresponding to our construction of $\Delta Inventory_t^A$ 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, which are more likely to satisfy the exclusion restriction. 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.[29] 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 (e.g., hurricanes), we assign each year's payout shock to the third quarter and zero to other quarters. The resulting quarterly series is denoted by $InsuredLoss_t$.

The rationale for using $InsuredLoss_t$ as an IV is that insurance companies sell assets to make payments. However, 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 cash out of short-term funding markets. Moreover, insured loses 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.

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

[29]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.

Table 9 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). We observe that a one-standard-deviation decrease in institutional holdings of "fallen angels" is 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 10 reports second-stage regressions of quarterly residuals of credit spread changes 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. 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.[30] One leading explanation is that dealer inventory changes could be driven by (unobserved) demand shocks (e.g., regulatory changes). A demand shock increases dealer inventory but lowers credit spreads (or vice versa), which biases against the positive supply-driven co-movement of dealer inventory and credit spreads. Using our two IVs, which we claim are purely about supply, can purge such demand effects.

The last two rows in each panel of Table 10 reports the test statistic for weak instruments by Montiel-Olea and Pflueger (2013) (MP) and associated critical values (Pflueger and Wang, 2015).[31] The MP-statistic in Panel A is larger than the critical value, rejecting the null hypothesis that $\Delta Holding_t^{FA}$ is a weak investment. In contrast, it is below the critical value in Panel B, so we cannot reject the weak instrument hypothesis for InsuredLoss$_t$. Consequently, we use standard t-statistics when using $\Delta Holding_t^{FA}$ as IV but the Anderson and Rubin (1949) Wald-test and Stock and Wright (2000) S-statistic, both weak-instrument robust, when using InsuredLoss$_t$ as IV. Panel A shows that $\Delta Inventory^A$ – instrumented by

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[30]Another difference between the IV regressions and baseline regressions (2) is that the former includes 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 $\Delta Inventory_t^A$.

[31]This test allows for conditionally-heteroskedastic and serially-correlated errors. In contrast, 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.

$\Delta Holding^{FA}$ – is highly significant in affecting credit spread changes positively. From Panel B, 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. Furthermore, when using both $\Delta Holding_t^{FA}$ and InsuredLoss_t to instrument dealer inventory factor, the MP-statistic in Panel C rejects the weak instrument hypothesis, and the regression coefficients and t-statistics further confirm the positive effect of dealer inventory on credit spread changes.

4.4   Regulatory Shocks

As discussed above, the significantly larger coefficients in IV regressions point to the presence of (unobserved) demand shocks. We now provide evidence on the effect of demand shocks associated with post-crisis regulations.

In particular, as discussed in Bao, O'Hara, and Zhou (2018), the Dodd-Frank Act enacted in July 2010 and the Volcker Rule implemented in April 2014 – as a component of the Dodd-Frank Act specifically prohibiting banking entities from engaging in proprietary trading – both impaired dealers' liquidity provision, raising observed credit spreads. At the same time, these regulatory shocks likely led dealers to simultaneously decrease their leverage and shed bond inventory. During periods of such regulatory tightening, as dealers are adjusting, one naturally expects a negative relationship between our factors and credit spreads (see Prediction 4 of our model), which would bias against finding the positive association we have documented over the full sample.

To investigate this conjecture, we consider the following time series regressions:

$$
\begin{aligned}
\varepsilon_{g,t} &= \alpha_g + \beta_{1,g}\Delta Inventory_t^A + \beta_{2,g}\Delta Distress_t + \beta_{3,g}D_{RegShock,t} \\
&+ \beta_{4,g}\Delta Inventory_t^A \times D_{RegShock,t} + \beta_{5,g}\Delta Distress_t \times D_{RegShock,t} + u_{g,t}, \quad (17)
\end{aligned}
$$

where $\varepsilon_{g,t}$ is the average residual of cohort g $(= 1, \ldots, 15)$. Table 11 reports the regression results with the dummy $D_{RegShock,t}$ for 2010Q1 – 2010Q4 and 2013Q4 – 2014Q3, i.e., eight quarters surrounding the Dodd-Frank enaction and Volcker Rule implementation (similar to Bao, O'Hara, and Zhou (2018)). The coefficients on the interaction terms of $D_{RegShock,t}$

with our two factors are almost all negative and large in magnitude, consistent with our conjectured regulatory tightening effect.

We interpret these results as suggestive evidence that, during periods of regulatory tightening, a significant component of bond price variation is due to pressure on dealers to shed assets and reduce leverage. Unlike normal periods in which inventory is a supply proxy and distress is negatively related to demand, large regulatory changes convert inventory into a demand proxy and produce a positive association between distress and demand.

5 Conclusion

It has been two decades since CGM raised one of the canonical puzzles in asset pricing of credit risk, i.e., the large common variation in credit spread changes beyond structural factors. In this paper, we build on recent developments in intermediary asset pricing and demonstrate the importance of intermediary constraints to explain this canonical puzzle.

In particular, we show that two intermediary-based factors, a distress measure that captures financial constraints of the whole intermediary sector and an 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.

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.

In the spirit of CGM, we have focused on using non-bond-return-based factors to explain the time series variation of credit spreads. A natural question is whether our non-bond-return-based intermediary factors are related to bond-return factors proposed in the literature. As an exploratory analysis, Table A.16 of Internet Appendix A presents regressions of four bond-return factors of Bai, Bali, and Wen (2019) on our two intermediary factors. After orthogonalizing all factors to time series variables in the individual bond regressions

([1](#)), intermediary distress co-moves with all return-based factors significantly, but not dealer inventory. This result suggests intermediary distress provides a potential fundamental-based explanation for return-based factors, while we have yet to find some other return-based-factors to proxy for dealer inventory. This can be a fertile future research direction.

Figure 1: Quarterly Time Series of Intermediary Factors and CGM PC1
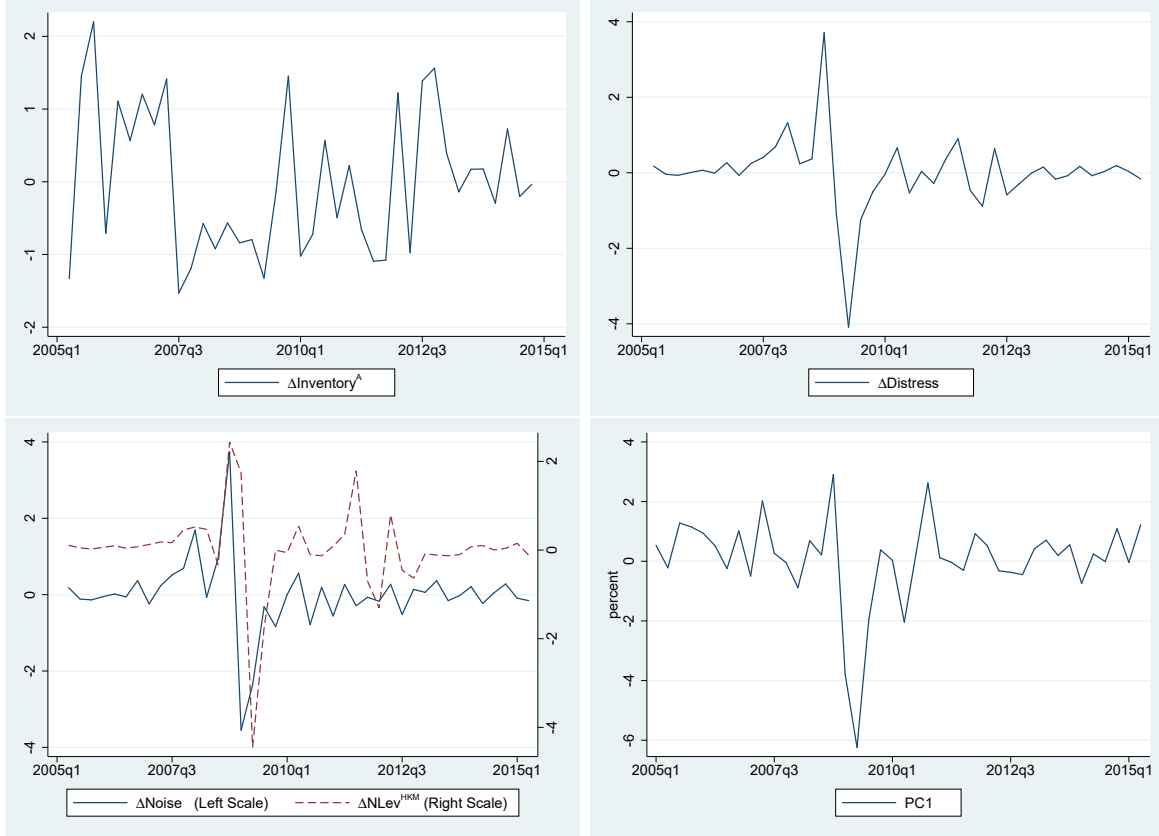
Note: This figure plots quarterly time series of $\Delta Inventory^A$, $\Delta Distress$, $\Delta Noise$, $\Delta\text{NLev}^{\text{HKM}}$, and the first principal component of regression residuals of credit spread changes on structure factors (CGM PC1) as reported in Table 3. The sample period is from 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
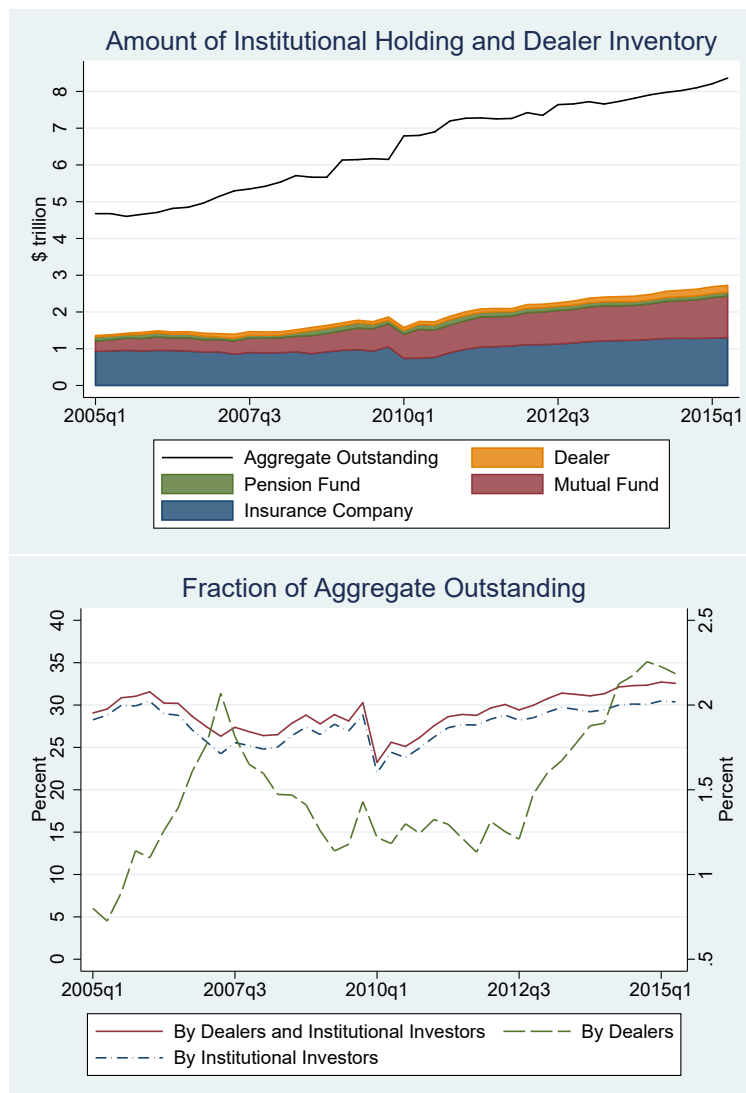
Note: The top panel plots quarterly time series of the holding amount by institutional investors (including mutual funds, pension funds, and insurance companies) based on eMAXX data and by dealers based on TRACE data, as well as the aggregate outstanding balance of U.S. corporate debt securities ("L.208 Debt Securities" series, which is the sum of the outstanding debt securities by nonfinancial corporate business, U.S.-chartered depository institutions, foreign banking offices in the US, finance companies, security brokers and dealers, and holding companies) 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 securities 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

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 R^2_{adj} is the mean adjusted R^2s of individual bond regressions within a cohort. The last three columns report, for each cohort i, the total number of bonds, number of bond×quarter observations, and the ratio of the variation of residuals ε_g^{var} ($=\sum_t(\varepsilon_{gt}-\bar{\varepsilon}_g)^2$) to the total variation of the 15 cohorts $\sum_{g=1}^{15}\varepsilon_g^{var}$, respectively. Panel B 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 rows 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 $\Delta Distress$, 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 5: 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 6: 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 7: Non-Corporate-Credit Assets

	FN30y	FN15y	FG30y	FG15y	
	A: Agency MBS				
$\Delta Inventory^A$	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	

	Duper	AM	AJ		
	B: CMBS				
$\Delta Inventory^A$	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		

	Credit Card	Auto AAA	Auto A	Auto BBB	
	C: ABS				
$\Delta Inventory^A$	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	

	Call: 0.90	Call: 0.95	Call: ATM	Call: 1.05	Call: 1.10
	D: S&P 500 index options				
$\Delta Inventory^A$	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 $\Delta Distress$. Monthly time series regressions of residuals of one-month unannualized returns (in percentage) are reported for S&P 500 index option portfolios (in panel D). Each of residual series is computed by regressing yield spread changes or returns similar to (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 8: Average Quarterly Changes of Institutional Investors' Holdings and Dealers' Inventories of Individual Bonds

	A: Insurance Companies								
	Downgrade (IG)			Fallen Angels			No Rating Change		
	Obs	Amount	% Holding	Obs	Amount	% Holding	Obs	Amount	% Holding
$\Delta Holding_t$	9673	-0.916	-1.249	3261	-1.353	-1.904	416254	-0.390	-0.448
$\Delta Holding_{t+1}$	9604	-1.008	-1.374	3185	-1.274	-1.793	416965	-0.404	-0.464
$Holding_{t-1}$		73.359			71.075			87.087	
	B: Mutual Funds								
	Downgrade (IG)			Fallen Angel			No Rating Change		
	Obs	Amount	% Holding	Obs	Amount	% Holding	Obs	Amount	% Holding
$\Delta Holding_t$	5265	0.376	0.489	1760	0.116	0.153	345154	-0.423	-0.649
$\Delta Holding_{t+1}$	5204	-0.161	-0.209	1701	-0.237	-0.312	345385	-0.390	-0.599
$Holding_{t-1}$		76.882			75.998			65.153	
	C: Pension Funds								
	Downgrade (IG)			Fallen Angel			No Rating Change		
	Obs	Amount	% Holding	Obs	Amount	% Holding	Obs	Amount	% Holding
$\Delta Holding_t$	4566	0.285	1.453	1484	0.204	1.126	304541	-0.321	-2.682
$\Delta Holding_{t+1}$	4508	-0.246	-1.254	1443	-0.474	-2.617	304883	-0.309	-2.581
$Holding_{t-1}$		19.621			18.110			11.971	
	D: Dealers								
	Downgrade (IG)			Fallen Angel			No Rating Change		
	Obs	Amount	% Holding	Obs	Amount	% Holding	Obs	Amount	% Holding
$\Delta Inventory_t$	20254	0.343	17.599	6792	1.311	76.756	687927	0.254	21.381
$\Delta Inventory_{t+1}$	18949	0.022	1.129	6449	-0.275	-16.101	614380	0.028	2.357
$Inventory_{t-1}$		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 three columns) with bonds downgraded from IG rating to IG rating, "fallen angels" observations (in the second three columns) with bonds downgraded from IG rating to HY rating, and "no rating change" observations (in the last three columns) with bond experiencing no rating change. For current quarter and the subsequent quarter, we report the number of observations, the change in holding amount (in $millions), and changes in percentages as a fraction of current quarter average inventory holdings (the inventory holdings in $millions as of the current quarter are reported in the last row of each panel). The sample period is 2005:Q1 - 2015:Q2.

Table 9: 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_{adj}^2	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 10: 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 [0.254] [0.164]	0.014	0.206***	0.005
		(2.375)	(0.057)		(0.177)	(2.945)	(0.090)
Short	A	0.208*	0.081	0.214 [0.074] [0.157]	0.078	0.208**	0.081
		(1.828)	(1.015)		(1.041)	(2.459)	(1.383)
Short	BBB	0.188	0.199***	0.191 [0.089] [0.156]	0.197***	0.188**	0.198***
		(1.642)	(2.662)		(3.596)	(2.205)	(3.660)
Short	BB	0.508*	0.311*	0.762 [0.070] [0.145]	0.185	0.535**	0.298**
		(1.679)	(1.762)		(0.916)	(2.541)	(2.262)
Short	B	0.740**	0.630**	1.463 [0.0004] [0.135]	0.270	0.818***	0.591***
		(2.181)	(2.448)		(0.666)	(3.822)	(3.491)
Medium	AA	0.208**	-0.003	0.140 [0.265] [0.157]	0.031	0.201**	0.001
		(1.973)	(-0.038)		(0.603)	(2.249)	(0.012)
Medium	A	0.194*	0.096	0.165 [0.143] [0.147]	0.110**	0.191**	0.097
		(1.751)	(1.217)		(2.199)	(2.075)	(1.544)
Medium	BBB	0.200*	0.223***	0.260 [0.026] [0.146]	0.193***	0.206**	0.220***
		(1.873)	(2.994)		(2.960)	(2.345)	(3.762)
Medium	BB	0.544*	0.294*	0.561 [0.037] [0.137]	0.285**	0.546**	0.293**
		(1.792)	(1.726)		(1.993)	(2.428)	(2.495)
Medium	B	0.671***	0.668***	0.461 [0.023] [0.174]	0.773***	0.648***	0.679***
		(2.621)	(4.116)		(4.419)	(3.492)	(6.637)
Long	AA	0.123***	0.012	-0.030 [0.757] [0.642]	0.088	0.106**	0.020
		(2.784)	(0.278)		(1.553)	(2.553)	(0.542)
Long	A	0.214**	0.035	0.057 [0.533] [0.383]	0.113**	0.197**	0.043
		(2.225)	(0.472)		(2.432)	(2.426)	(0.697)
Long	BBB	0.144	0.213	0.141 [0.598] [0.295]	0.215*	0.144	0.213*
		(0.848)	(1.214)		(1.886)	(1.345)	(1.807)
Long	BB	0.388***	0.362***	0.151 [0.480] [0.286]	0.481***	0.363***	0.375***
		(2.768)	(4.681)		(5.128)	(2.929)	(6.161)
Long	B	0.654***	1.219***	0.759 [0.002] [0.127]	1.167***	0.666***	1.213***
		(2.795)	(7.768)		(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 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 11: Regulatory Shocks and Intermediary Factors

	AA	A	BBB	BB	B
A: Short					
$\Delta Inventory^A$	0.019	0.028	0.034	0.096	0.227**
	(0.942)	(1.378)	(1.322)	(1.253)	(2.496)
$\Delta Inventory^A \times D_{RegShock}$	0.009	-0.041	0.051	-0.417***	-0.322
	(0.229)	(-0.710)	(0.569)	(-3.160)	(-1.403)
$D_{RegShock}$	0.010	0.039	0.051	0.091	0.170
	(0.266)	(0.907)	(0.751)	(0.890)	(0.740)
$\Delta Distress$	0.047***	0.069***	0.120***	0.192***	0.374***
	(2.711)	(4.191)	(4.713)	(4.234)	(3.428)
$\Delta Distress \times D_{RegShock}$	-0.231***	-0.393***	-0.417**	-1.395***	-2.482***
	(-2.875)	(-3.633)	(-2.375)	(-6.594)	(-4.450)
R^2_{adj}	0.237	0.334	0.414	0.316	0.451
B: Medium					
$\Delta Inventory^A$	0.023	0.049**	0.070***	0.163***	0.243***
	(1.295)	(2.303)	(2.620)	(2.682)	(5.071)
$\Delta Inventory^A \times D_{RegShock}$	-0.050	0.073	0.090	-0.429***	-0.189*
	(-0.905)	(1.298)	(0.911)	(-4.550)	(-1.786)
$D_{RegShock}$	0.039	0.015	0.047	-0.012	-0.011
	(0.829)	(0.301)	(0.576)	(-0.187)	(-0.101)
$\Delta Distress$	0.057***	0.102***	0.159***	0.267***	0.532***
	(6.327)	(3.945)	(4.213)	(5.884)	(5.638)
$\Delta Distress \times D_{RegShock}$	-0.428***	-0.278***	-0.406**	-0.835***	-1.696***
	(-5.873)	(-3.052)	(-2.480)	(-5.767)	(-6.246)
R^2_{adj}	0.337	0.471	0.517	0.483	0.697
C: Long					
$\Delta Inventory^A$	0.018	0.026	-0.026	0.154***	0.321***
	(1.475)	(1.508)	(-0.642)	(2.924)	(3.192)
$\Delta Inventory^A \times D_{RegShock}$	-0.055*	-0.030	-0.711*	-0.310**	-0.058
	(-1.918)	(-1.085)	(-1.916)	(-2.416)	(-0.176)
$D_{RegShock}$	0.027	0.018	-0.426	0.073	0.120
	(1.058)	(0.658)	(-1.622)	(0.832)	(0.482)
$\Delta Distress$	0.045**	0.074***	0.129***	0.251***	0.753***
	(2.478)	(2.923)	(4.853)	(5.584)	(3.855)
$\Delta Distress \times D_{RegShock}$	-0.193***	-0.315***	0.339	-0.464**	-1.420**
	(-3.675)	(-5.828)	(0.509)	(-2.019)	(-2.432)
R^2_{adj}	0.227	0.363	0.470	0.438	0.592

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 $\Delta Inventory^A$, $\Delta Distress$, the dummy variable $D_{RegShock}$ (= 1 in 2010Q1 – 2010Q4 and 2013Q4 – 2014Q3), and their interactions. Robust t-statistics based on Newey and West (1987) standard errors using the optimal band-width 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.

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Internet Appendix

A   Additional Data Summary and Empirical Results

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

A.1   TRACE Data Cleaning and Filtering

First, Table A.1 reports the detailed procedure of sample cleaning and construction.

A.2   Structural Factors and Control Variables

The firm leverage $Lev_{i,t}$ is computed as the book debt over the sum of the book debt and market value of equity. Book debt is defined as the sum of "Long-Term Debt - Total" and "Debt in Current Liabilities - Total" from Compustat, whereas market value of equity is equal to the number of common shares outstanding times the CRSP share price. Debt data from Compustat are available at quarterly frequency, and we follow the literature to assume that such balance sheet information becomes available with a one quarter lag (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; the VIX_t is from CBOE; the jump factor $Jump_t$ is computed S&P 500 index options, from OptionMetrics (see CGM for details).

A.3   eMAXX Data Summary

Figure A.1 and Table A.2 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.2 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.

Table A.3 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).

A.4 Data from 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 the most traded. 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.

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) 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).[32] 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. 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. To avoid illiquidity issues, Constantinides, Jackwerth, and Savov (2013) compute returns of one-month holding horizon regardless of the target maturity (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.

Table A.4 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.

A.5 Additional Analyses and Robustness

Here, we present a several robustness checks.

First, as already mentioned in the main text, we study how much of credit spread changes can be explained by microstructure-oriented illiquidity factors in comparison to our intermediary factors. We use the aggregate illiquidity factor of Dick-Nielsen, Feldhütter, and Lando (2012), ΔILiq, which is an equally-weighted average of four metrics: the Amihud (2002) measure of price impact, the Feldhütter (2012) measure of round-trip cost, and respective daily standard deviations of these two measures. That is, their illiquidity measure captures trading illiquidity due to price impact and transaction costs, as well as liquidity risk, and is aggregated into a time-series factor. Table 2 shows that ΔILiq exhibits

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[32]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.

insignificant correlations with our two intermediary factors. Table A.5 reports quarterly time series regressions of each of the 15 credit spread residuals on ΔILiq, both in univariate regressions (Panel A) and in multivariate regressions along with our two factors (Panel B). The results show that ΔILiq mainly adds to the explanatory power (adjusted R^2) of high-rated cohorts but not low-rated cohorts, and its explanatory power is quite small. In particular, 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-rated cohorts).[33] Panel B shows that adding ΔILiq to our two intermediary factors only increases the explained fraction by 0.6% (from 48.2% to 48.8%).[34]

Second, recall we have constructed the intermediary distress factor $\Delta Distress$ as the first PC of $\Delta Noise$ and ΔNLev$^{\text{HKM}}$; this is partly for parsimony – to emphasize two economic forces on demand and supply – and partly to eliminate the distinct issues carried by each measure separately – ΔNLev$^{\text{HKM}}$ has a more direct economic interpretation, but market-price-based $\Delta Noise$ is measured better. In Table A.6, we instead "let data speak" by regressing credit spread residuals on these two factors separately and jointly. Similar to $\Delta Distress$, both measures have significant positive effects that monotonically decrease with bond ratings. Individually, $\Delta Noise$ accounts for 32% of the unexplained total variation of credit spread changes, higher than the 17% of ΔNLev$^{\text{HKM}}$; the higher explanatory power of $\Delta Noise$ is likely due to its superior measurement as a price-based variable. Jointly, they explain 38%. Therefore, $\Delta Noise$ and ΔNLev$^{\text{HKM}}$ have overlapping but nontrivial individual explanatory power, lending support to our construction of distress as a combination of the two.

Third, Table A.7 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 compared to the rating-based cohorts in the baseline. The 15 residual series share a strong common variation, with the PC1 accounting for 78% of the total unexplained variation of credit spread changes. In regressions, credit spread residuals co-move positively with intermediary factors, with the loadings monotonically increasing with leverage. Compared with the baseline results in Table 4, the statistical significance is stronger (especially for unreported univariate regressions on dealer inventory) probably because of the balanced number of observations, while the economic magnitudes are similar. The two factors together account for about 42% of the unexplained total variation of credit spread changes.

Fourth, Table A.8 reports results following the baseline procedure except using monthly credit spread changes. The first PC still accounts for 76% of the total unexplained variation of credit spread changes, similar to CGM but higher than FN, both of whom use monthly series. Bivariate regressions on the intermediary factors for this monthly sample show similar results to Table 4, with stronger statistical significance, especially for dealer inventory, probably because of the large number 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 quarterly analysis; this is expected because of a larger number of observations and higher level of variation at the monthly frequency.

Fifth, panel A of Table A.9 reports quarterly time series regressions of the baseline residuals on

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[33]The corporate bond illiquidity measure proposed by Bao, Pan, and Wang (2011) is available at the monthly frequency but only up to 2009. As shown in Panel B of Table A.11, monthly regressions using the Bao, Pan, and Wang (2011) measure over 2005-2009 give qualitatively similar results that illiquidity mainly affects credit spreads of high-rated bonds, a pattern also found in Bao, Pan, and Wang (2011).

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

3

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.

Sixth, 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.9 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 $\Delta Inventory^{match}_{it}$ and $\Delta Distress^{match}_{it}$ as the changes of dealer inventory and intermediary distress measures over the same time horizon. We then take the average of $\Delta Inventory^{match}_{it}$ and $\Delta Distress^{match}_{it}$ across all bonds in each quarter t as the aggregate time series measures of intermediary factors, denoted as $\Delta Inventory^{match}_t$ and $\Delta Distress^{match}_t$. That is, these alternative measures take into account the distribution of time horizons of credit spread changes across bonds.

Seventh, Table A.10 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., $\Delta \mathrm{NLev}^{\mathrm{AEM}}_t := (\mathrm{Lev}^{\mathrm{AEM}}_t - \mathrm{Lev}^{\mathrm{AEM}}_{t-1}) \times \mathrm{Lev}^{\mathrm{AEM}}_{t-1}$ (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.

Eighth, Table A.11 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.

Ninth, one may be concerned that the strong explanatory power documented is mainly due to the inclusion of the 2008 financial crisis. Table A.12 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.

Tenth, Table A.13 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.

A.6 Evidence of Spillover Effects from CDS

Recall Prediction 2 of the model: other non-bond assets likely to be traded the corporate bond desks/dealers should be sensitive to dealers' corporate bond inventory. One test of this prediction

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, 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).[35] 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.

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. Similar to the baseline bond result, Table A.14 Panel B reports the principal component analysis of the CDS spread change residuals, and shows that 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% for bonds, but still reaches 37%.[36]

A.7 Institutional Investor Holding Changes: Regression

Here, we conduct regression analysis – which allows us to control for bond characteristics including bond age and time-to-maturity, for instance – to formally test the relation between institutional investors' sell-offs and dealers' inventory changes. The first three columns of Table A.15 report results based on the following regression:

$$
\begin{aligned}
&\Delta Holding_{i,t+\tau} \\
=\ & Intercept + \beta_1 \times \text{Fallen}_{i,t} + \beta_2 \times \text{Downgrade}_{i,t} + \beta_3 \times log(\text{Amt}_{i,t+\tau}) + \beta_4 \times log(\text{Size}_i) \\
&+ \beta_5 \times \text{Age}_{i,t+\tau} + \beta_6 \times \text{Time-to-Mature}_{i,t+\tau} + \sum_t \text{FE}_t + \varepsilon_{i,t+\tau},
\end{aligned}
\tag{18}
$$

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 Downgrade$_{i,t}$ equals 1 if bond i is downgraded in quarter t and 0 otherwise, whereas 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 Downgrade$_{i,t}$ captures the $(t + \tau)$ change of institutional investors' holdings of "downgraded (IG)" bonds in quarter t, relative to that of bonds without rating change contemporaneously. Similarly, the coefficient on Fallen$_{i,t}$ captures the $(t + \tau)$ change of institutional investors' holdings of bonds downgraded from IG rating to HY rating in quarter t, relative to "downgraded (IG)." Panel regressions of changes in dealers' inventories $\Delta Inventory_{i,t+\tau}$, similar to (18) are reported in the last column.

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[35]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.

[36]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.

Consistent with summary statistics in Table 8, Table A.15 shows that insurance companies decrease their holdings of downgraded (IG) bonds in both quarters, about \$0.48-0.80 million, relative to the bonds without rating changes. They sell "fallen angels" even more aggressively, about \$0.67 million more in quarter t and \$0.33 million in quarter $t+1$, relative to bonds that are downgraded but remain in the 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.

A.8   Bond Return Factors

Finally, as discussed in the conclusion of our main text, Table A.16 presents regressions of four bond-return factors of Bai, Bali, and Wen (2019) on our two intermediary factors. After orthogonalizing all factors to time series variables in the individual bond regressions (1), we find that intermediary distress comoves with all return-based factors significantly, but not dealer inventory.

B   Model Extensions

B.1   Alternative Margin Constraints

The form of our margin-like constraint,

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

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

$$\sum_{a=1}^{A} |\theta_{I,a}| m_a \leq w. \tag{20}$$

Constraint (20) 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 (20) equivalent to (19).

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 (19), i.e.,

$$\sum_{a=1}^{A} \theta_{I,a} \bar{m}_a p_a \leq w. \tag{21}$$

Constraints augmented with price, as in (21), will have an additional mitigating force to (19). Indeed, a positive s-shock decreases asset prices and thus loosens constraint (21) through lower margin requirements. Equilibrium prices fall by less than they would under (19). 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 (19).

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:

$$\sum_{a \in \mathcal{A}_1} \theta_{I,a} m_a \leq w_1 \quad \text{and} \quad \sum_{a \in \mathcal{A}_2} \theta_{I,a} m_a \leq w_2. \tag{22}$$

If we interpret (22) 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 (22), there are two Lagrange multipliers, μ_1 and μ_2 associated with each inequality. The pricing condition (8) is modified to be $p = \bar{\delta} - \text{diag}(m)(\mu_1 \mathbf{1}_{\mathcal{A}_1} + \mu_2 \mathbf{1}_{\mathcal{A}_2})$. 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*

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

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

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

$$\phi_1 := \frac{\mathbf{1}'_{\mathcal{A}_1} M\Sigma^{-1} M\mathbf{1}_{\mathcal{A}_2}}{\mathbf{1}'_{\mathcal{A}_1} M\Sigma^{-1} M\mathbf{1}_{\mathcal{A}_1}} \quad and \quad \phi_2 := \frac{\mathbf{1}'_{\mathcal{A}_1} M\Sigma^{-1} M\mathbf{1}_{\mathcal{A}_2}}{\mathbf{1}'_{\mathcal{A}_2} M\Sigma^{-1} M\mathbf{1}_{\mathcal{A}_2}}$$

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

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.[37] 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 Proxy for Treasury "Noise"

In the baseline model, we take for granted that shocks to intermediary wealth w can be captured by our distress factor, given HKM's Leverage comprises one component of distress. But distress also contains HPW's "Noise" which bears a less clear relationship to corporate bonds broadly, and intermediary wealth w in particular.

Noise is essentially an imperfect measure of arbitrage profits: when it is high, banks and hedge funds could in theory form long-short portfolios using Treasuries at different but nearby maturities and collect large premia with a small amount of risk. That said, In our framework, only margin requirements would prevent such trades ad infinitum. Thus, Noise will be proxied well by the Lagrange multiplier on the margin constraint.

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[37]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.

To make this statement precise, we introduce one additional asset which is a near-arbitrage opportunity. This asset, indexed by $a = 0$, has the conditionally-expected payoff $\bar{\delta}_0 = 0$. We suppose only intermediaries can trade this asset, which is in supply z (a random variable) and has margin requirement m_0.

To enrich the predictions of this section, we also assume the following. First, margin must be paid for both long and short positions on this particular asset, i.e., $|\theta_{I,0}|m_0$ is the margin intermediaries pay for position $\theta_{I,0}$ in this asset. This is essentially equivalent to assuming an absolute-value margin constraint like (20) holds, since intermediaries will typically be long assets $a = 1, \ldots, A$ in equilibrium. Second, this arbitrage asset is traded on the Treasury desk, which is partially segmented from the corporate credit desk in the sense of the asset-class-specific constraints of Appendix B.2. Let $\mu_{\text{Treasuries}}$ and μ_{Credit} denote the Lagrange multipliers on the two margin constraints. Under perfect integration across trading desks, we would have $\mu_{\text{Treasuries}} = \mu_{\text{Credit}}$, but here they can differ.

If there were no margin, the equilibrium price of this asset would be zero. Hence, a natural measure of arbitrage profits is the deviation of this price from zero. Bearing that in mind, we define Noise η as

$$\eta := -p_0 = m_0[\mathbf{1}_{z>0} - \mathbf{1}_{z<0} + \zeta\mathbf{1}_{z=0}]\mu_{\text{Treasuries}}, \tag{23}$$

where $\zeta \in [-1, 1]$ is an arbitrary random variable. Equation (23) shows that η is a very good proxy for $\mu_{\text{Treasuries}}$, with some measurement error coming from randomness in supply z.

If z were constant over time, and trading desks were integrated (so that $\mu_{\text{Treasuries}} = \mu_{\text{Credit}}$), then η would be an exact proxy for μ_{Credit}. This provides a rationale for why HPW's Noise measure does a very good job explaining non-fundamental variation in credit spreads. With some random variation in z, but integrated trading desks, η becomes an imperfect proxy for μ_{Credit}. In principle, if our model suggests η is a noisy version of μ_{Credit}, then one might think HPW's Noise should reflect both supply and demand shocks.

But if trading desks are imperfectly integrated (so that $\mu_{\text{Treasuries}} \neq \mu_{\text{Credit}}$), η will better reflect shocks to intermediary wealth w than bond supply s. This argument is developed in more detail in Appendix B.2, but the basic idea is that w-shocks affect all trading desk constraints, whereas s-shocks only affect the corporate credit desk. Consequently, in this environment, Noise η and Leverage $\lambda = w^{-1}$ are both good proxies for w-shocks, matching our empirical finding that HPW Noise and HKM Leverage feature substantial positive correlation (0.388 in changes), whereas Noise and Inventory feature almost no correlation (-0.094 in changes).

B.4   Regulatory Tightening

To address, in the simplest way possible, how the theoretical results are modified when banking regulation tightens, we introduce a holding cost to intermediaries' problem. Now, instead of (7), suppose intermediaries solve

$$\max_{\theta_I} \mathbb{E}[w + \theta_I \cdot (\bar{\delta} - p)] - \underbrace{\chi\theta_I \cdot \mathbf{1}}_{\substack{\text{holding} \\ \text{cost}}} \quad \text{s.t.} \quad \theta_I \cdot m \leq w.$$

The parameter χ should be thought of as a regulatory object that captures a variety of different types of regulation, and we will think of an increase in χ as a regulatory tightening. For example, under the proprietary trading restriction of the Volcker Rule, one can imagine that dealers must adapt their intermediation practices (e.g., match buyers and sellers prior to taking inventory, or be more selective in which inventory they take on). As another example, the various balance-sheet restrictions embedded in the Dodd-Frank Act and Basel III can be conceptualized as a general cost to intermediating assets.

To streamline the results, we have imposed a linear cost on sum of all asset positions $\theta_I \cdot \mathbf{1}$, but the insights below should generalize to more complex balance-sheet-level costs and constraints.

One can repeat the analysis of the model to show that equilibrium prices are given by

$$p = \bar{\delta} - \mu m - \chi \mathbf{1}$$

$$\mu = \frac{\alpha}{m'\Sigma^{-1}m}\Big[h'm - w - \frac{\chi}{\alpha}\mathbf{1}'\Sigma^{-1}m\Big]^+.$$

Differentiating these expressions with respect to χ, using the fact that Σ is positive definite, and applying the Cauchy-Schwarz inequality, we have the following result.

Proposition 3. *Regulatory shocks have the following effect on asset prices and intermediaries' portfolios:*

$$\frac{\partial p}{\partial \chi} = m\Big(\frac{\mathbf{1}'\Sigma^{-1}m}{m'\Sigma^{-1}m}\Big)\mathbf{1}_{\mu>0} - \mathbf{1}$$

$$\frac{\partial \theta_I}{\partial \chi} = (\alpha\Sigma)^{-1}\frac{\partial p}{\partial \chi}.$$

Consequently, in response to a regulatory tightening (χ increase), both asset prices and intermediary positions decrease on average, in the sense that $\mathbf{1}'\Sigma^{-1}\frac{\partial p}{\partial \chi} < 0$ and $\mathbf{1}'\frac{\partial \theta_I}{\partial \chi} < 0$.

The result of Proposition 3 is intuitive: regulatory tightening reduces intermediary asset holdings and equilibrium asset prices together. Holding bond supply and intermediary wealth constant, bond inventory and intermediary leverage are both positively related to intermediary asset holdings. At the same time, credit spreads rise when bond prices fall. Therefore, Proposition 3 suggests that, during periods of significant regulatory tightening, credit spreads should be negatively related to both of our factors (dealer inventory and intermediary distress). This stands in sharp contrast to our expectation for non-tightening periods (see the baseline model, Proposition 2), and it stands in contrast to our baseline results that show spreads positively related to our two factors.

B.5   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

$$\max_{\theta_I} \mathbb{E}[W_I] - \frac{\gamma(w)}{2}\mathrm{Var}[W_I] \tag{24}$$

$$\text{s.t.} \quad W_I := w + \theta_I \cdot (\delta - p) \quad \text{and} \quad \theta_I \cdot m \le w.$$

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

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

Clearing markets with (4), asset prices satisfy

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

where $\Gamma(w) := (\alpha^{-1} + \gamma(w)^{-1})^{-1}$. Notice that asset prices now satisfy a multi-factor model: in addition to non-fundamental variation being driven by μ, the drivers of Σh are a source of fundamental variation, akin to the market portfolio in the CAPM. 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.

Proposition 4. *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 4 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.

Figure A.1: Summary of Institutional Holdings
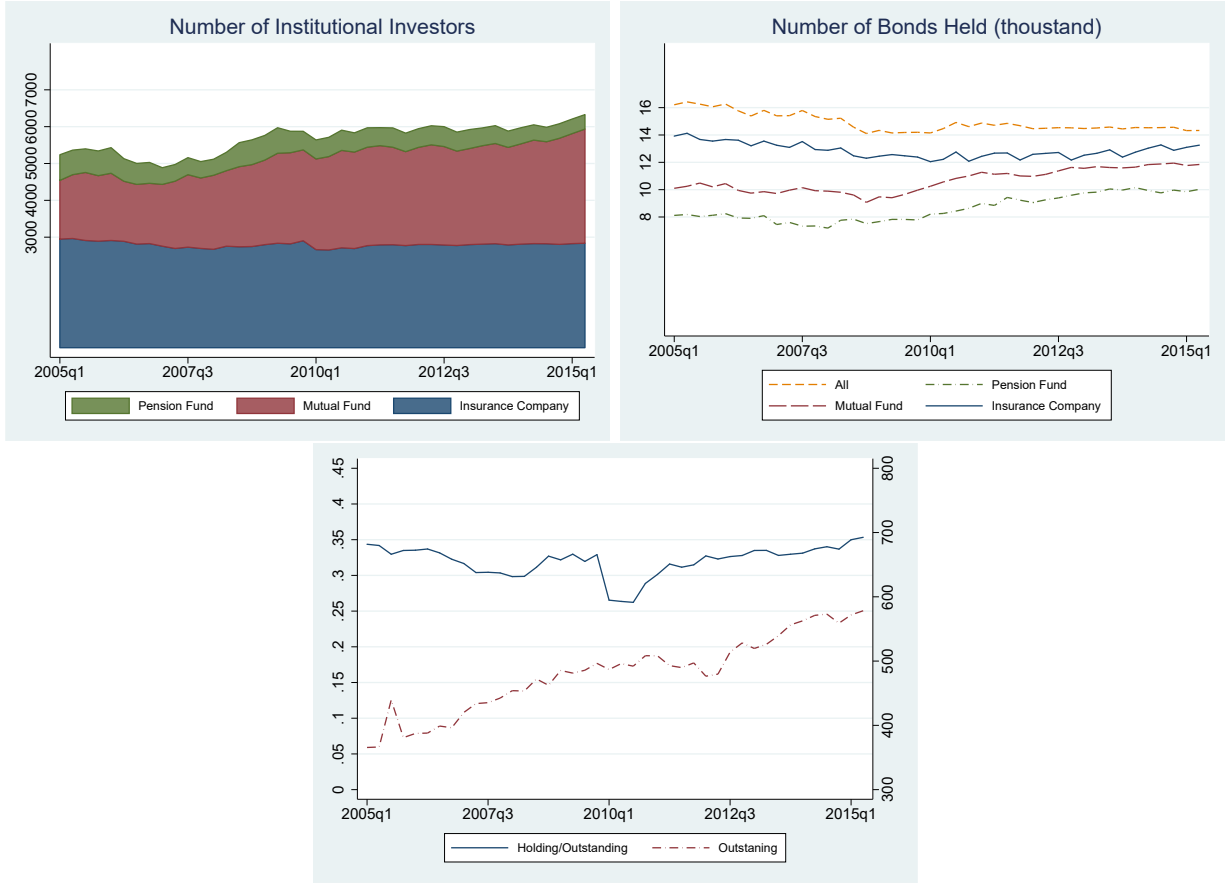
Note: This figure plots quarterly time series, based on eMAXX data of institutional holdings, of the number of institutional investors (top left panel) and the number of bonds in thousands (top right panel), by insurance companies, mutual funds, pension funds, and all institutions separately, as well 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: Bond Sample Cleaning and Construction

A: Trade Sample		# CUSIPs	# Trades
A1:	All CUSIPs with TRACE trade data (canceled/corrected/duplicated trades are excluded)	116,176	111,465,088
A2:	Exclude CUSIPs that do not match to FISD	92,322	106,796,924
A3:	Exclude primary market transactions and transactions with trade size larger than issue size	82,694	103,309,166
A4:	Exclude transactions of bonds with time-to-maturity less than one year	75,242	96,113,326
A5:	Exclude bonds with variable coupon, issue size less than $10 million,		
	bonds issued by financial and utility firms,		
	bonds quoted in a foreign currency,		
	and bonds with embedded options except for make-whole calls.	18,628	45,115,727
A6:	Exclude bonds with no rating information	17,369	43,072,299
A7:	Keep the last trade of a month for each CUSIP	17,369	631,559
A8:	Restrict to September 2004 - June 2015	14,842	524,890

B: Quarterly Sample (based on the sample after A.8)		# CUSIPs	# Quarter×Bond
B1:	Keep the last trade of a quarter for each CUSIP and		
	compute quarterly changes of yield spreads (2005Q1 - 2015Q2)	14,330	180,888
B2:	Match with firm leverage ratio based on CRSP/Compustat	6,520	80,769
B3:	Keep observations with the actual number of days between the trade dates in 45 - 120 days	6,113	72,678
B4:	Exclude a bond if there is less than 4 years of consecutive quarterly observations	2,584	55,398

C: Monthly Sample (based on the sample after A.8)		# CUSIPs	# Month×Bond
C1:	Compute monthly changes of yield spreads (January 2005 - June 2015)	14,348	494,570
C2:	Match with firm leverage ratio based on CRSP/Compustat	6,541	226,958
C3:	Keep observations with the actual number of days between the trade dates in 10 - 60 days	6,377	216,523
C4:	Exclude a bond if there is less than 25 consecutive monthly observations	3,324	185,072

Notes: This table reports step-by-step cleaning of the TRACE corporate bond transactions data. The original data sample is from July 2002 to June 2015 with canceled/corrected/duplicated trades excluded. Panel A reports the cleaning at the trade level. Panel B reports the cleaning at the trade level. The resulting quarterly sample is used to produce the baseline quarterly sample in Panel B, and to produce the monthly sample in Panel C. The procedure in each cleaning step is described in the first column, and the resulting number of unique CUSIPs and total number of observations are reported in the second and third columns, respectively. The bond characteristics are from the Mergent Fixed Income Securities Database (FISD) database. Equity price information and accounting information used to compute firm leverage ratio are from the merged CRSP/Compustat database. Bonds with embedded options excluded in step A.5 are those that are convertible, puttable, asset backed, exchangeable, privately placed, perpetual, preferred securities, and secured lease obligations.

Table A.2: 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.3: 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.

Table A.4: 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.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 A.6: Measures of Intermediary Distress

Groups		A: $\Delta Noise$		B: $\Delta\mathrm{NLev}^{\mathrm{HKM}}$		C: $\Delta Noise + \Delta\mathrm{NLev}^{\mathrm{HKM}}$		
Maturity	Rating	$\Delta Noise$	R^2_{adj}	$\Delta\mathrm{NLev}^{\mathrm{HKM}}$	R^2_{adj}	$\Delta Noise$	$\Delta\mathrm{NLev}^{\mathrm{HKM}}$	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 $\Delta\mathrm{NLev}^{\mathrm{HKM}}$ (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 $\Delta Noise$, $\Delta\mathrm{NLev}^{\mathrm{HKM}}$ 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 A.7: 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 A.8: Monthly Series by Rating Group

Groups		A: Individual Bond Regressions			B: PC		C: Regression of Residuals			
Maturity	Rating	Bond #	Obs	R^2_{adj}	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	87	2611	0.133	0.065	0.124	0.016*	0.014	0.045	0.192
							(1.801)	(1.285)		
Short	A	525	15871	0.164	0.093	0.142	0.012	0.037***	0.129	
							(1.494)	(3.131)		
Short	BBB	881	25114	0.187	0.15	0.16	0.009	0.053**	0.131	
							(0.797)	(2.206)		
Short	BB	401	7835	0.324	0.291	0.251	0.042**	0.127***	0.195	
							(2.095)	(3.818)		
Short	B	485	10061	0.347	0.48	0.065	0.077**	0.172***	0.191	
							(2.097)	(4.422)		
Medium	AA	73	1680	0.171	0.061	0.106	0.013	0.022**	0.077	0.138
							(1.530)	(2.338)		
Medium	A	448	9885	0.166	0.087	0.153	0.016**	0.016	0.043	
							(2.022)	(1.029)		
Medium	BBB	880	18088	0.218	0.146	0.21	0.023*	0.046**	0.104	
							(1.893)	(2.038)		
Medium	BB	491	8989	0.399	0.274	0.218	0.061***	0.122***	0.246	
							(3.482)	(2.875)		
Medium	B	593	13111	0.392	0.402	0.163	0.047	0.106*	0.091	
							(1.353)	(1.828)		
Long	AA	119	4495	0.197	0.058	0.117	0.014**	0.011	0.046	0.235
							(1.966)	(0.965)		
Long	A	638	24132	0.216	0.082	0.131	0.015**	0.024*	0.092	
							(2.082)	(1.731)		
Long	BBB	1049	33504	0.260	0.114	0.262	0.015	0.033*	0.032	
							(1.422)	(1.946)		
Long	BB	352	6768	0.352	0.232	0.204	0.029	0.070***	0.101	
							(1.450)	(2.935)		
Long	B	277	5715	0.361	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, number of observations, and mean adjusted R^2s 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 A.9: 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	0.553	0.029*	0.049***	0.176	0.546
		(1.404)	(4.512)			(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.10: AEM Leverage Measure and TED Spread

Groups		A: AEM Leverage Measure					B: TED spread				
Maturity	Rating	$\Delta Inventory^A$	$\Delta Distress$	$\Delta NLev^{AEM}$	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 $\Delta NLev^{AEM}$ (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.11: 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.

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.13: Correlations of Dealer Inventories of HY and IG Bonds

	A: Raw Change		
	$\Delta Inventory^A$	$\Delta Inventory^{HY}$	$\Delta Inventory^{IG}$
$\Delta Inventory^A$	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.14: 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 A.15: Changes in Institutional Holdings and Dealers' Inventories of Down-graded Bonds

	Insurance	Mutual	Pension	Dealer
A: Changes of Institutional Holdings and Dealer Inventories in quarter t				
	(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 (18) 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 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 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 A.16: 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.