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

Zhiguo He† Paymon Khorrami‡ Zhaogang Song§

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Abstract

Two intermediary-based factors—a broad distress measure and a corporate bond inventory measure—explain more than 40% of the puzzling common variation of credit spread changes beyond canonical structural factors. A simple intermediary-based model with partial market segmentation accounts for the magnitude and patterns of this comovement and delivers further implications with empirical support. First, whereas bond sorts on risk-related variables produce monotonic loading patterns on intermediary factors, non-risk-related sorts produce no pattern. Second, dealer inventory comoves with corporate-credit assets only, whereas intermediary distress comoves even with non-corporate-credit assets. Third, dealers' inventory responds to (instrumented) bond sales by institutional investors.

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

JEL classification: G12, G18, G21, E58

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†Booth School of Business, University of Chicago, and NBER; 5807 South Woodlawn Avenue, Chicago, IL 60637; zhiguo.he@chicagobooth.edu

‡Imperial College Business School, Imperial College London; Kensington, London SW7 2AZ London; paymon.khorrami@gmail.com.

§The Johns Hopkins Carey Business School, 100 International Drive, Baltimore, MD 21202; zsong8@jhu.edu.

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 more than 40% 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.

We construct the quarterly dealer inventory factor based on the cumulative customer order flows (in par value) with all dealers, using the enhanced TRACE database of corporate bond transactions with untruncated trade size and anonymous dealer codes. 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 been 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 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. This "noise" measure captures market information more directly, albeit less primitively (relative to HKM leverage); HPW provide substantial evidence that "noise" is tightly connected to disruptions in funding costs for arbitrageurs and other intermediaries (in fact, Treasury securities constitute the major collateral in repo funding). Our intermediary distress measure is the first principal component (PC) 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% of the variation can be explained by the first PC, indicating a large systematic component not captured by structural credit factors.

We connect the two intermediary factors—intermediary distress and dealer inventory—to this common variation of credit spread changes. Our two intermediary factors explain 51% of the variation of the first PC of credit spread residuals (43% of the total variation). About two-thirds of this explanatory power is attributable to intermediary distress and one-third to dealer inventory. Given the low correlation between distress and inventory, our empirical results document a two-factor structure of the common unexplained credit spread variation.

Furthermore, we find that factors loadings are 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 3–40 and 4–70 basis points depending on rating groups, respectively.

Motivated by these two findings, we present an equilibrium model with hedgers and intermediaries trading multiple assets. We assume some market segmentation: a different group of hedgers trades in each asset class (e.g., corporate credit, equities, asset-backed securities, and options), as in "preferred-habitat" models (Vayanos and Vila, 2021). Hedgers can be thought of as institutional investors that specialize in an asset class and face liquidity shocks, e.g., insurance companies and pension funds trading corporate bonds. Risk-averse intermediaries absorb asset supply coming from hedgers, but they demand a risk premium for these services.

Our model features a single dominant factor in bond pricing—the average risk aversion of intermediaries and bond hedgers—that governs all non-fundamental movements in asset prices. With asset market segmentation, fluctuations in this bond factor are not spanned by aggregate market factors, which permits non-trivial CGM residuals.

This latent factor—the average bond trader risk aversion—is unobservable, but our model allows us to relate it to the demand and supply for corporate bonds, which are closely linked to our two empirical factors. We consider two types of shocks: intermediary wealth shocks and hedger liquidity shocks. Intermediary wealth decreases are (negative) "demand shocks" in the sense that intermediaries' risk aversion increases, which shifts their 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, modeled as an increase in hedger risk aversion, are asset "supply shocks" in the sense that more bonds arrive onto intermediaries' balance sheets, lowering bond prices. In theory, our two empirical factors—dealer inventory and intermediary distress—respond to both "supply shocks" and "demand shocks"; however, the signs of our measured factor loadings imply that the inventory factor mainly captures "supply", whereas the distress factor mainly captures "demand." Finally, the model produces factor loadings that are monotone in asset riskiness, consistent with our credit rating sorts.

Overall, model-based regressions with dealer inventory and leverage reproduce the qualitative patterns of all our baseline empirical findings. We also show how our baseline results rely on two key assumptions: asset market segmentation and investor heterogeneity (i.e., intermediaries versus hedgers). In particular, without asset market segmentation, CGM factors would soak up all systematic credit spread variations, while without investor heterogeneity, there can be no role for dealer inventory to affect credit spreads.

Guided by the model, we develop three sets of additional empirical tests, designed to further corroborate the key channels embedded in our framework. First, since limited intermediary risk-bearing capacity represents the only significant trading cost/friction in our model, sorting bonds by any characteristic unrelated to risk should not produce any pattern in associations to our two intermediary factors. Indeed, sorting by two such variables, maturity and trading intensity (measured by total dollar volume), produces no detectible pattern in the economic magnitude or statistical significance of loadings on our intermediary factors. By contrast, sorting by risk-related variables like credit rating and market beta produces a monotonic loading pattern as predicted by theory.

Second, we enlarge our tests to other assets to further explore market segmentation. In our model, (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 corporate bond inventory ("segmentation effects"); and (c) both types of assets should be sensitive to intermediary distress.

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 heterogeneous investor framework, 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 that insurance companies face regulatory constraints in holding low-rated bonds, bond downgrades cause them to sell, which resembles 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 use fallen angel sales by institutional investors as an instrumental variable for supply shocks to bond dealers. 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. Instrumented by fallen angel sell-offs, dealer inventory increases are highly significant in increasing credit spreads. Finally, 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.

Related literature. This paper contributes primarily to empirical literatures on credit

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

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] We will discuss our main differences with FN shortly. 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 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, and investigate spillovers/segmentation across asset classes. To assist our empirical explorations, we develop a static intermediary-based model that formally defines and investigates a notion of CGM residuals relative to the market portfolio, which is a critical analytical object that helps distinguish between alternative benchmark models. Our main modeling innovation is to formalize supply-demand logic via two types of shocks: (1) liquidity shocks in the vein of Ho and Stoll (1981), Vayanos and Vila (2021),

[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 with 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), 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 (2018), Chen, Joslin, and Ni (2018), Siriwardane (2019), Boyarchenko, Eisenbach, Gupta, Shachar, and Van Tassel (2018), Fleckenstein and Longstaff (2020), and He, Nagel, and Song (2021), among others.

and Greenwood, Hanson, and Liao (2018); and (2) intermediary wealth shocks inspired by standard intermediary models à la He and Krishnamurthy (2012, 2013).

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).[5] FN also fits into this class of papers. We view our intermediary asset pricing approach as complementary to these papers studying bond dealers, which are 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 intermediary services operate as the essential economic forces. The key difference is our focus on the balance sheet health of liquidity providers as a measure of liquidity costs, rather than transaction cost–based measures.

Our paper overlaps with FN, in that we both examine the CGM puzzle and try to explain it with intermediary factors. In particular, FN investigate, in addition to measures of bargaining and search frictions, measures of dealer inventory and intermediary funding costs.[6] Relative to FN, our main contributions include (i) documenting a refined structure of CGM residuals and (ii) introducing a model that closely connects to the empirical regularities. In particular, we uncover a novel two-factor structure of residuals, with monotonic factor loadings. By contrast, FN employ twelve factors and do not investigate loading patterns.[7] Furthermore, our model allows us to give parsimonious risk-based supply-demand

[5]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.

[6]For this purpose, they use the TED spread in their main paper, and the HKM capital ratio as a robustness exercise in their online appendix.

[7]Despite having twelve factors, FN nevertheless deliver slightly lower explanatory power at the monthly frequency. Their PC1 explains about 48% of CGM residual variation, of which their twelve factors account for 23%; thus, their factors have approximately 11% explanatory power. Although our main analyses are quarterly, we also do a monthly analysis for comparison (see Internet Appendix A.5): our two factors explain 15% of residual yield spread variation. Section 1.3.1 of the paper contains more detailed comparison with FN's results.

interpretation to the results. By explicitly identifying necessary assumptions for a model to rationalize these results, we are able to develop direct tests of these assumptions, all of which are new.

1 Intermediary Factors and Credit Spread Changes

In this section, we first introduce the data sample of U.S. corporate bond transactions. We then construct our two intermediary factors and connect our intermediary factors to credit spread changes. We shall introduce other datasets (used in Section 3), including the Lipper eMAXX database of institutional investors' corporate bond holdings, as well as returns on agency MBS, CMBS, ABS and S&P 500 index options, as they arise.

1.1 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).[8] These data contain 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 (e.g., Bao and Hou, 2017). 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.

[8]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).

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, have a fixed coupon rate, have an available credit rating, do not have embedded options except possibly make-whole calls, are issued by non-financial and non-utility firms, and with issue sizes greater than $10 million. We keep only secondary market trades by removing 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 one year and 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 the yield of the corresponding Treasury security.[9] 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. We scale $\Delta cs_{i,t}$ to a 90-day change.[10] 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 four years of consecutive quarterly observations of $\Delta cs_{i,t}$ to ensure enough observations for regressions on structural model factors.

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

[10] Though at a monthly frequency, Bao and Hou (2017) perform similar adjustments for trade exclusions, synchronization with Treasuries, and scaling of the resulting $\Delta cs_{i,t}$. Our choice to only include trades separated by 45-120 days is motivated to balance sample size considerations with relevance considerations (i.e., better synchronization with other quarterly variables we use in our analysis).

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.[11] Around 35% of the observations are on high-yield bonds, defined as having 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).

1.2 Intermediary Factors

1.2.1 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 1.1 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, 2020).

[11] Our baseline dataset is quarterly, but we also perform similar adjustments/filters to monthly data in order to directly compare to existing studies. After all data filters, our monthly sample has 3324 bonds and more than 185,000 bond-month observations; see Table A.1. For comparison, Bao and Hou (2017) use a sample of about 10 years from July 2002 to December 2013; 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.

Second, to correct for maturing bonds, we assume dealers' inventory of this bond turns zero at its maturity date and hence remove this amount of inventory on that date.[12]

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 $\Delta Inventory$, is the baseline dealer inventory factor in our analysis.[13]

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, and the other is the Flow of Funds report on holdings of security broker-dealers, released by the Federal Reserve.[14]

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

[12]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. Another potential issue of our inventory measure is that it does not include dealers' in-kind transactions with ETF sponsors (which are not reported to the TRACE). However, we deem this effect to be small; Pan and Zeng (2019) show that during 2010 to 2015 ETF activities accounted for less than 5% of the corporate bond market trading volume, of which dealers' in-kind transactions were only a fraction.

[13]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.

[14]See, respectively, https://www.newyorkfed.org/markets/gsds/search.html and https://www.federalreserve.gov/apps/fof/DisplayTable.aspx?t=l.130.

positions prior to April 3, 2013, are extrapolated backward.[15] The Flow of Funds series is the holding amounts of "corporate and foreign bonds" (FL663063005.Q) that includes 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).[16]

1.2.2 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 price–based "noise" measure proposed in HPW.

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 $\Delta\text{NLev}_t^{\text{HKM}} := (\text{Lev}_t^{\text{HKM}})^2 - (\text{Lev}_{t-1}^{\text{HKM}})^2$, motivated by the nonlinear effect of intermediary constraints on asset prices suggested by theory.[17]

[15] 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.

[16] 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, compared to \$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 (2020) 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.

[17] Intermediary-based theories suggest that conditional time-t risk premia should be proportional to $(\text{Lev}_t^{\text{HKM}})^2$. In fact, acknowledging this, the forecasting regressions of HKM use $(\text{Lev}_t^{\text{HKM}})^2$ as their fore-

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).[18] "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, 2352). Given this reasoning, we view HPW noise and HKM leverage as capturing similar ideas, but with noise circumventing the many measurement-error issues inherent in balance-sheet variables like leverage. 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.

casting variable. In the previous NBER working paper version (He, Khorrami, and Song, 2019), we used the leverage-related variable $(\text{Lev}_t^{\text{HKM}} - \text{Lev}_{t-1}^{\text{HKM}}) \times \text{Lev}_{t-1}^{\text{HKM}}$, which is approximately equal to $\frac{1}{2}\Delta \text{NLev}_t^{\text{HKM}}$ for small shocks and delivers slightly stronger explanatory power. In unreported calculations, we have also repeated our analysis using $\Delta \text{Lev}_t^{\text{HKM}} := \text{Lev}_t^{\text{HKM}} - \text{Lev}_{t-1}^{\text{HKM}}$, rather than our nonlinear factor $\Delta \text{NLev}_t^{\text{HKM}}$, and found a small reduction in explanatory power. Overall, as our analysis is quarterly, a frequency at which nonlinearities matter more, we deem it important to correctly capture the appropriate functional form of the state variables, i.e., to keep the nonlinearities.

[18]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.

1.2.3 Summary Statistics

To gauge the variation of the two intermediary factors, Figure 1 plots the quarterly time series of $\Delta Inventory$ and $\Delta Distress$ (both scaled to have zero mean and unit variance) in the top panels. Dealer inventory has comparable frequent variation across different subperiods 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 -0.028 (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 0.41 (Table 2). Our measure $\Delta Distress$, equal to the first principal component of $\Delta Noise$ and $\Delta \text{NLev}^{\text{HKM}}$, 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 0.466 correlation with ΔVIX (which is one of the CGM structural factors), the correlation of $\Delta Inventory$ with ΔVIX is low and statistically insignificant. In addition, the correlations of our intermediary factors with ΔILiq, the illiquidity factor of corporate bond trading of Dick-Nielsen, Feldhütter, and Lando (2012), are quite low in the range of 0.2 to 0.3; it is marginally significant for $\Delta Inventory$, but insignificant for $\Delta Distress$. We control for ΔILiq when studying the effects of intermediary factors on credit spreads.

1.3 Credit Spread Changes and Intermediary Factors

We show that intermediary factors have strong explanatory power for credit spread changes. Additionally, sensitivities to these intermediary-based factors are monotone in credit risk, a pattern that is robust to many other alternative specifications.

1.3.1 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:

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

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 above, 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 terms 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. Our much higher adjusted R^2 in 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.10, 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 (80%), similar to CGM and FN.[19]

[19] Our PC1 explains 80% of grouped residual variation, similar to the 76% found in CGM. This is a bit

1.3.2 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 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*" (CGM, 2202). 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 the following time series regressions:

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

where $\varepsilon_{g,t}$ is the average residual of cohort g $(= 1, \ldots, 15)$.[20] Panels A and B of Table 4 report univariate regressions on dealer inventory and intermediary distress, respectively, and Panel C reports bivariate regressions. We find that dealer inventory and intermediary distress both comove positively with residuals of credit spread changes.[21] Further, factor loadings across

higher than the 48% documented in FN. To directly compare to these studies, we 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.10 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.

[20]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.

[21]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.5 of the Internet Appendix, have more balanced number of observations, and the statistical significance of both intermediary factors is strong in univariate regressions.

our bond cohorts show a salient pattern: lower-rated bonds have greater 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 3–40 basis points (4–70 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.

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 $\Delta Inventory$ and $\Delta Distress$. 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

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

where $G \in \{\text{short, medium, long, all}\}$.

As reported in the last column of Table 4, the two intermediary factors explain 28%, 53%, and 45% of the total variation of residuals of credit spread changes for short, medium, and long term bonds, respectively, and 43% for all bonds. Similar calculations for dealer inventory and intermediary distress separately show that two-thirds of this explanatory power can be attributed to intermediary distress and one-third 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^{HKM} (14%). Likely, this is because $\Delta Noise$, a 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 (i) dealer inventory and intermediary distress have significant effects on common changes in credit spread *residuals*, (ii) the effects are positive and monotonically decreasing with bond ratings, and (iii) the two factors, having low correlation, together account for almost half of the unexplained variation of credit spread changes: one-third and two-thirds are attributable to dealer inventory and intermediary distress, respectively. Several robustness checks are in Internet Appendix A.

1.3.3 Comparison to Microstructure Measures of Liquidity

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.

As reported in Table 2 and discussed earlier, ΔILiq is only modestly correlated with our two intermediary factors. Importantly, we find 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 relatively small (Table A.7).[22] Given our somewhat different focus, we acknowledge several reasons that could drive the relatively small explanatory power of these commonly

[22] Similar patterns are found using the corporate bond illiquidity measure of Bao, Pan, and Wang (2011), available at the monthly frequency up to 2009.

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 $\text{corr}[\Delta\text{ILiq}, \Delta VIX] = 0.38$, 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."

2 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' risk aversion, which initiate portfolio liquidations that increase bond supply in the market. In addition, it will be important that hedgers are partially segmented across asset classes, similar to "preferred-habitat" models like Vayanos and Vila (2021) and Greenwood, Hanson, and Liao (2018). Demand shifts come from shocks to intermediary wealth: because intermediaries are risk-averse, balance sheet shocks affect required returns on intermediation, as in He and Krishnamurthy (2012, 2013). We show how model-based regressions with dealer inventory (a proxy for bond supply) and dealer leverage (a proxy for intermediary wealth) reproduce the patterns of our bond-level regressions. Finally, we derive further tests guided by the model. Analyses, proofs, and extensions of the model are in Internet Appendix B.

2.1 The Model

Assets. There are multiple 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.

Given that CGM residuals are computed for corporate bonds relative to "market" that includes other assets, we consider mutually exclusive asset classes $\mathcal{A}_1, \ldots, \mathcal{A}_N$, where each $\mathcal{A}_i$ is a subset of the set of assets $\{1, \ldots, A\}$. Examples of asset classes might be equities, corporate bonds and related credit derivatives, asset-backed securities, options, foreign exchange, commodities, etc. Below, we will formalize exactly how asset classes are segmented. Examples without segmentation can be studied by setting $N = 1$.

Hedgers. As in Kondor and Vayanos (2019), hedgers inherit random endowment $h'\delta$, with $h \geq 0$, and have mean-variance preferences. However, hedgers are segmented across asset classes. One can interpret segmentation as a reduced-form for some specialization not modeled here.

The representative hedger in asset class $\mathcal{A}_n$ receives endowment $\sum_{a \in \mathcal{A}_n} h_a \delta_a$ and solves

$$\max_{\theta_H} \mathbb{E}[W_{H,n}] - \frac{\rho_n}{2} \mathrm{Var}[W_{H,n}] \quad \text{where} \quad W_{H,n} := \sum_{a \in \mathcal{A}_n} h_a \delta_a + \sum_{a \in \mathcal{A}_n} \theta_{H,a} (\delta_a - p_a). \tag{4}$$

Hedgers of different asset classes may have different risk aversions ρ_n, the vehicle we use to model asset supply shocks. Specifically, the *supply shocks* would be changes to $(\rho_n)_{n=1}^N$, which will induce trades between hedgers and intermediaries. While this setup features "completely segmented" hedgers in the sense that there is no overlap in portfolios of hedger n and hedger $n' \neq n$, this is not actually required. In Internet Appendix B.3, we consider a more general model allowing hedgers to have partially-overlapping portfolios, and we prove that this more general model is actually approximately isomorphic to the model in our main text, with some correlation in the shocks to $(\rho_n)_{n=1}^N$ as a reduced-form stand-in for the underlying portfolio overlap. This approximate isomorphism may be of some independent interest.

Intermediaries. Intermediaries are mean-variance optimizers, who are integrated across asset classes unlike hedgers. The intermediary optimization problem is

$$\max_{\theta_I} \mathbb{E}[W_I] - \frac{\gamma(w)}{2}\text{Var}[W_I] \quad \text{where} \quad W_I := w + \theta_I \cdot (\delta - p). \tag{5}$$

The intermediary risk aversion $\gamma(w)$ is assumed to be a decreasing function of their wealth w, as in He and Krishnamurthy (2012, 2013).[23] The *demand shocks* we consider are shocks to w, which affects intermediary risk aversion, thus willingness to intermediate.

Market clearing. For simplicity, all risky assets are in zero net supply, meaning[24]

$$\theta_H + \theta_I = 0. \tag{6}$$

The aggregate "market" portfolio will be important for us to compare the model to our empirical findings. Because all assets are in zero net supply, we define market using the endowments as portfolio weights. Thus, the market cash flow is $x'\delta$, and its price is $x'p$, where $x_i := h_i / \sum_{j=1}^{A} h_j$ is the "weight" on asset i.

CGM residuals. To compare our model closely to the data, we will construct a proxy for CGM residuals. Let $\mathrm{d}p$ denote equilibrium price changes in response to supply and demand shocks $(\mathrm{d}\rho_n)_{n=1}^{N}$ and $\mathrm{d}w$. Because the CGM procedure conditions on volatility and jump factors, interest rate factors, and firm leverage, we presume from the outset that $\bar{\delta}$ and Σ are constant over time for our analysis (i.e., they are not part of our "shocks"). For each asset i, define the market beta $\beta_{a,\text{mkt}} := \frac{\text{Cov}[\delta_a + \mathrm{d}p_a, x'\delta + \mathrm{d}(x'p)]}{\text{Var}[x'\delta + \mathrm{d}(x'p)]}$. Here and always, we compute this beta using both fundamental variation and price changes, as would occur in data. Then, we

[23] In Internet Appendix B, we also allow γ to be a function of a regulatory tightness variable z. Using this more general setup, Internet Appendix B.4 develops additional predictions about how bond prices and dealer balance sheets comove with regulatory shocks, which are pervasive in our sample period (2005–2015). These predictions are then tested and verified in Internet Appendix A.8.

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

define a proxy for CGM residuals by

$$\epsilon_a := \mathrm{d}p_a - \beta_{a,\mathrm{mkt}} \mathrm{d}(x'p). \tag{7}$$

To affect residuals $(\epsilon_a)_{a=1}^{A}$, non-fundamental shocks must differentially drive asset prices and in a way that is not spanned by market betas.

2.2 Benchmarks

No segmentation benchmark. Suppose first that $N = 1$, so all markets are integrated. Let ρ denote the representative (integrated) hedger risk aversion. In this case, it is straightforward to show that equilibrium asset prices are given by

$$p = \bar{\delta} - \Gamma \Sigma h, \tag{8}$$

where $\Gamma := (\rho^{-1} + \gamma^{-1})^{-1}$ denotes the aggregate risk aversion index. A critical drawback of (8) is that Γ is a market-wide scalar. Furthermore, asset a's loading on Γ is $(\Sigma h)_a = \mathrm{Cov}[\delta_a, h'\delta]$, the fundamental covariance to the market. Thus, running a regression of any asset on the market portfolio will soak up price variation due to variation in Γ, which is the only variable affected by our shocks (ρ, w). Consequently, this full-integration model cannot produce CGM residuals that comove with proxies of intermediary balance sheets or liquidity shocks. Hence, relevant CGM residuals require some market segmentation.

Lemma 1. *If $N = 1$ (full integration), ϵ_a is independent of $\mathrm{d}w$ and $\mathrm{d}\rho$.*

No heterogeneity benchmark. We reintroduce segmentation ($N > 1$) with one of the asset classes being corporate credit, which we call $\mathcal{A}_{\mathrm{bonds}}$. Before delving into our full model, consider a benchmark without intermediaries; this benchmark model has a representative investor in each segment $\mathcal{A}_n$, with risk aversion ρ_n. Equilibrium asset prices in such a model are given by

$$p_a = \bar{\delta}_a - \rho_{n(a)}(\Sigma h)_a, \tag{9}$$

where $n(a) := \sum_{n=1}^{N} n \mathbf{1}_{a \in \mathcal{A}_n}$ indicates to which segment asset a belongs. Thus, the representative bond investor's risk aversion (ρ_{bonds}) acts like a common factor driving bond prices. Such a model could plausibly produce CGM residuals ϵ_a that comove with our empirical dealer distress variable; for example, if dealers are biased towards bond intermediation, shocks to their balance sheets will affect ρ_{bonds} (more so than ρ_{equities}, ρ_{MBS}, etc.) and transmit to bond prices. However, such a model cannot reproduce the two-factor structure of our empirical results simply because we cannot even define a measure of dealers' bond inventory. Hence, with a representative bond investor, there can be no price impact from a trade of bonds between different individual investors, contrary to the core idea underlying a role for dealer inventory.

2.3 Market Segmentation and Investor Heterogeneity

Now we proceed with an environment consisting both of intermediaries and hedgers, as well as asset market segmentation (i.e., hedger "habitats"). As this model is analytically cumbersome, we make the following assumption to facilitate clear formulas and intuition.

Assumption 1. Corporate bond fundamentals are positively correlated: any two assets $a, a' \in \mathcal{A}_{\text{bonds}}$ have $\text{Cov}[\delta_a, \delta_{a'}] > 0$. By contrast, assets in different classes have weak fundamental correlation: for $a \in \mathcal{A}_n$ and $a' \in \mathcal{A}_{n'}$, with $n \neq n'$, assume $\text{Cov}[\delta_a, \delta_{a'}] \approx 0$.

It is sensible that fundamentals are less correlated "between" asset classes than "within," especially if segmentation is endogenous; the approximation of the "between" correlation by zero is for analytical clarity.[25] Going forward, when a relation holds approximately (indicated by $\approx$), this is due to the weak-correlation approximation in Assumption 1.

[25] In addition, note that Assumption 1 could be replaced by an alternative whereby intermediary trading is segmented along the same dimensions as hedger trading. Indeed, segmented traders trade as if the "between" correlations are zero. See Internet Appendix B.5.

Equilibrium prices. Under Assumption 1, equilibrium asset prices take the following form

$$p_a \approx \bar{\delta}_a - \Gamma_{n(a)}(\Sigma h)_a, \quad \text{where} \quad \Gamma_n := (\rho_n^{-1} + \gamma^{-1})^{-1}, \tag{10}$$

where recall $n(a)$ indicates the segment to which asset a belongs. Equation (10) mirrors (8) closely (the simplicity of the formula is due to Assumption 1), but with a critical modification: Γ_n is no longer market-wide, but rather asset-class-specific. As a result, a broad market index will not fully capture bond price variation due to Γ_n, which introduces a role for non-fundamental shocks to affect bond residuals.

Before we delve into the details of our bond regressions, note that this model is consistent with a single dominant principal component for the residuals, as documented in CGM and our Table 3. Indeed, all non-fundamental shocks alter bond prices by affecting Γ_{bonds} in (10); this single pricing factor is common to all bonds. Bonds load on this single factor through the bond-specific quantity $(\Sigma h)_a$, analogous to bonds' eigenvector loadings on their first principal component (see right-hand column of Table 3). Of course, the "single factor" Γ_{bonds} is hard to measure, so below we identify proxies for shocks that drive it.

Non-fundamental shocks. The non-fundamental shocks are to $(\rho_n)_{n=1}^N$ and w.[26] Rather than allowing arbitrary shock structures, we will take a more parsimonious and illustrative approach. Supply shocks will be modeled as "segment-wide" but not "market-wide," in the sense that the aggregate market portfolio capital gains $\mathrm{d}(x'p)$ is independent of $(\mathrm{d}\rho_n)_{n=1}^N$. One can thus think of supply shocks as a change that induces hedger rebalancing in their portfolio holdings, e.g., from bonds to other asset classes. Because of our focus on bonds,

[26] As suggested earlier, Internet Appendix B.3 shows that pricing formula (10) also holds in a more general model with partially-overlapping hedger portfolios. The only nuance is that ρ_n^{-1} should be interpreted as the sum of risk tolerances of individual hedgers participating in asset class n. For instance, suppose each hedger i has risk tolerance $\hat{\rho}_i^{-1}$ and suppose hedgers $i_1, \ldots, i_k$ invest in asset class n. Then, we show that $\rho_n^{-1} = \hat{\rho}_{i_1}^{-1} + \cdots + \hat{\rho}_{i_k}^{-1}$ is a sufficient statistic that justifies formula (10). As a consequence, investor overlap induces greater correlation in shocks to $(\rho_n)_{n=1}^N$ than is present in the shocks to individual-hedger risk aversions. However, nothing in Proposition 1 below hinges on this cross-correlation, so all of our main results continue to hold in the more general model.

let the bond supply shock be

$$s := \log(\rho_{\text{bonds}}).$$

As shocks to w are the only demand shocks, the analysis is reduced to the two-dimensional shock $(\mathrm{d}w, \mathrm{d}s)$. Finally, assume $\mathrm{d}w$ is independent of $\mathrm{d}s$.

Bond regressions. Recall in Section 1.2 our empirical pricing factors are "bond inventory" and "intermediary distress." In the model, these are defined as

$$(\textit{Inventory}) \quad \xi := \log\Big(\sum_a \theta_{I,a} \mathbf{1}_{a \in \mathcal{A}_{\text{bonds}}}\Big)$$
$$(\textit{Distress}) \quad \lambda := \log\Big(\sum_a \theta_{I,a}/w\Big).$$

Our model's inventory factor corresponds exactly to our empirical construction. Our model's distress factor is intermediary leverage, mirroring HKM leverage in our empirical construction. As intermediaries are marginal in all markets, shocks to w will also affect Treasury prices, meaning the HPW "Noise" variable can be justified as another proxy for w-shocks.

Next, we regress residuals ϵ_a on these model-based inventory and distress factors:

Proposition 1. *Suppose $N > 1$, and let Assumption 1 hold. If $\mathrm{d}s$ and $\mathrm{d}w$ are the only non-fundamental shocks, then ϵ_a are generically non-zero, and the following hold:*

*(i) [**Explanatory power**] Bond residuals are spanned by ξ and λ:*

$$\epsilon_a \approx \beta_{a,\xi}\mathrm{d}\xi + \beta_{a,\lambda}\mathrm{d}\lambda, \quad a \in \mathcal{A}_{bonds}.$$

*(ii) [**Sign of sensitivities**] $\beta_{a,\xi} < 0$ and $\beta_{a,\lambda} < 0$ for all $a \in \mathcal{A}_{bonds}$ if*

(a) $\frac{\partial \Gamma_{bonds}}{\partial \gamma}$ is high relative to $\sum_n \alpha_n \frac{\partial \Gamma_n}{\partial \gamma}$ (where $\alpha_n \propto \sum_{j \in \mathcal{A}_n} x_j (\Sigma x)_j$ are weights summing to one in this weighted average);

(b) $\partial \xi / \partial s > 0$ and $\partial \lambda / \partial w < 0$; also, $-\frac{\partial \xi / \partial w}{\partial \xi / \partial s}$ and $\frac{\partial \lambda / \partial s}{|\partial \lambda / \partial w|}$ are sufficiently small.

*(iii) [**Monotonic sensitivities**] Factor loadings scale as*

$$\beta_{i,\xi}/\beta_{j,\xi} \approx \beta_{i,\lambda}/\beta_{j,\lambda} \approx (\Sigma h)_i/(\Sigma h)_j, \quad \textit{if} \quad i, j \in \mathcal{A}_{bonds}. \tag{11}$$

Proposition 1 shows that, with market segmentation, we can reproduce all of our main empirical results. First, part (i) says that not only are the CGM residuals non-zero, they are completely explained by our two factors. This stark result, thanks to our reduction of supply and demand shocks to the two-dimensional shock $(\mathrm{d}w, \mathrm{d}s)$, illustrates how the model has the potential to match our large explanatory power in Section 1.3.[27]

Part (ii) outlines what is required to generate bond spreads' positive loading on our factors in Table 4 (if bond prices load negatively, then spreads load positively). There are two steps to understand the intuition for this result. First, bonds should be more sensitive to the shocks $(\mathrm{d}s, \mathrm{d}w)$ than a weighted average of non-bond assets, such that the market portfolio does not adequately control for this non-fundamental variation. For bond supply s, this excess sensitivity is obvious, but for aggregate intermediary wealth w, the excess sensitivity requires a condition like (a), which conveys the economically substantive assumption that intermediaries are important in bond markets, more so than in a typical non-bond asset market. This can happen if ρ_{bonds} is relatively high so that hedgers are relatively reluctant to participate in bond markets. Haddad and Muir (2021) provide some independent evidence showing that corporate credit is the most intermediary-reliant asset class.

The second step requires that each of our factors $\mathrm{d}\xi$ and $\mathrm{d}\lambda$ be reasonable proxies for shocks $(\mathrm{d}s, \mathrm{d}w)$, which is ensured by condition (b). The first half of condition (b) conveys the natural supply-demand intuition of the model: $\mathrm{d}s > 0$ induces selling by hedgers which increases dealer inventory; $\mathrm{d}w < 0$ raises dealer leverage by a mechanical balance-sheet effect. The second part bounds the biases in β_ξ and β_λ that can arise because our proxies

[27] The theoretical explanatory power of our factors would be reduced if some of the non-fundamental variation is idiosyncratic (i.e., if there is bond-specific variation independent of the segment-wide variation).

are imperfect.[28]

Finally, part (iii) says that riskier bonds should have higher loadings on our factors. Intuitively, intermediaries have limited risk-bearing capacity, and riskier bonds require more of this capacity. Our model thus emphasizes a risk-based story for non-fundamental variation, which can help distinguish our results from FN and others. In particular, part (iii) is consistent with our empirical slope coefficients that are monotonically decreasing in credit rating, if credit rating is a good proxy for bond riskiness. Rating as a proxy for risk is sensible given defaults tend to happen in bad times, so that bonds with higher default risk also contain higher risk premia (see, e.g., Chen, 2010). Quantitatively, Table 4 reports $\hat{\beta}_\xi^{\mathrm{B}}/\hat{\beta}_\xi^{\mathrm{AA}} \approx 10$ to 19 and $\hat{\beta}_\lambda^{\mathrm{B}}/\hat{\beta}_\lambda^{\mathrm{AA}} \approx 8$ to 18, which are roughly consistent with each other.[29]

2.4 Additional Testable Implications

To corroborate the key assumptions of the model, we develop additional testable Predictions 1–3 below, which we shall take to data in Section 3.

First, although bonds have many other features besides their riskiness, the model posits that *only these features* interact with intermediary balance sheets; see equation (11). This is because, besides limited intermediary risk-bearing capacity, there are no other significant trading costs or intermediation frictions. Thus, if two bonds differ on some characteristic $k_i \neq k_j$, but they have the same risk, then they will have the same sensitivities to the intermediary factors (ξ, λ), i.e., $\beta_{i,\xi} = \beta_{j,\xi}$ and $\beta_{i,\lambda} = \beta_{j,\lambda}$. Moreover, the model says that

[28] An example story for such biases is the following. Suppose $\mathrm{d}w > 0$ causes inventory ξ to rise; this can occur in our model as wealthier intermediaries are more willing to hold risky bonds. At the same time, bond price residuals ϵ_a rise. The positive induced comovement between ϵ_a and ξ would increase β_ξ, unless such variation is mostly captured by β_λ. In fact, β_λ will capture the variation of this story if $\frac{\partial\lambda/\partial s}{|\partial\lambda/\partial w|}$ is small enough.

[29] Our NBER working paper version (He, Khorrami, and Song, 2019) takes a margin-based interpretation. The analogous result to equation (11) says that relative factor loadings are given by relative margin and/or capital requirements, i.e., $\beta_{i,\xi}/\beta_{j,\xi} \approx \beta_{i,\lambda}/\beta_{j,\lambda} \approx m_i/m_j$. There we discuss how regulatory capital charges (e.g., Basel II) mandate capital charges that are quantitatively consistent with our regression coefficients. In this version, we take a risk-based interpretation, which we view as broader, since margin and capital requirements are often set according to asset riskiness.

an appropriate measure of "aggregate risk" on which to sort is a bond's covariance with the aggregate endowment, i.e., $(\Sigma h)_i = \text{Cov}[\delta_i, h'\delta]$. This produces the following empirical prediction.

Prediction 1. *Sorting bonds by their covariance to aggregate risk proxies should produce a monotonic pattern in sensitivities on both dealer inventory and intermediary distress. Sorting bonds by a characteristic unrelated to risk should not produce any pattern in sensitivities.*

Second, the model features "spillover effects" that are curtailed by the degree of segmentation between asset classes. For example, when dealers take a risky asset into inventory, they will demand a higher premium on all other risky assets they trade *within that same asset class*. Assets in other segments will be only modestly affected if segmentation is severe. In Internet Appendix B.3, we explore a more general partial-segmentation model (modeled through overlapping hedger portfolios) to formalize how the degree of segmentation matters: asset classes more segmented from corporate bonds experience smaller spillover effects of bond inventory on their prices. On the other hand, when dealers are hit with an aggregate wealth shock like our $\mathrm{d}w$, assets in all segments will be affected. Together, these lead to the following test of our market segmentation hypothesis:

Prediction 2. *Assets in the same class with corporate bonds will be sensitive to bond inventory; other assets less so. All risky assets will be sensitive to intermediary distress.*

Third, Proposition 1, part (ii), shows how the sign of our measured factor loadings supports an interpretation that bond inventory ξ is a good proxy for bond supply shocks s. Using such sign restrictions is a standard way of separating supply and demand shocks in the literature (e.g., Goldberg and Nazawa, 2020), though this line of reasoning depends on the model structure. A more direct test would be to extract plausibly exogenous supply shocks $\mathrm{d}s$ and observe how inventory ξ changes. Furthermore, any associated bond price response highlights the sense in which trades between market participants (e.g., investors and dealers) are non-neutral, supporting our deviation from a representative bond investor benchmark.

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.*

3 Empirical Support to the Economic Framework

In this section, we provide supporting evidence, corresponding to Predictions 1–3 above, that corroborates the key economic mechanisms of our framework.

3.1 Risk-Based Monotonic Loadings

First, we conduct two sets of further analyses on the risk-based explanation for the monotonic loading of credit spread changes on intermediary factors.

Sorting based on trading volume. The first set conducts placebo tests: sorting bonds based on variables unrelated to risk 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 $\Delta Inventory$ and $\Delta Distress$ are roughly similar across maturity groups, a sorting variable not strongly tied to risk.

To present further evidence along this direction, we examine bond sorts on trading volume, which is plausibly unrelated to a bond's riskiness. 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 loadings on both intermediary factors decrease in ratings (consistent with our main results), but remain roughly the same across the terciles by trading volume. This result suggests that, more so than measures based on trading activeness, our two intermediary factors capture a notion of "liquidity" that interacts with intermediary risk-bearing capacity.

Sorting on alternative measures of risk. In the second set of tests, we sort bonds into groups by their regression betas on the S&P 500 and the VIX, which are taken from the CGM regression (1). Note that our beta estimates come from a regression of credit spread changes on the CGM factors, so we multiply them by -1 before sorting to obtain something closer to a return beta (since spreads increase as bond prices fall). The rationale for choosing these two aggregate factors stems from their wide use as measures of aggregate risk and the consensus in the literature on the sign of their risk prices; in particular, riskier bonds are those with higher S&P beta and lower VIX beta.

Sorts based on these measures of risk are potentially better motivated theoretically than our credit rating sorts, as our model says that loadings on our intermediary factors should be proportional to a bond's covariance with some aggregate risk factor (the aggregate endowment in our model); see equation (11). Two caveats are worth pointing out. First, beta estimates can be quite noisy, especially given that we only have a 10-year quarterly sample with potentially missing observations for individual bonds. Second, sorts on a single beta may lead to mis-measurement of bond riskiness in a multi-factor economy and hence mis-classification of bonds into risk-based groups.

Notwithstanding these caveats, Panel A in Table 6 reports results for 15 groups sorted on maturity and quintiles of S&P beta (from "low" to "high"); similarly we report the results in Panel B for VIX beta, but with the opposite order (from "high" to "low"). For both panels, the bonds in second through fifth quintiles display a monotonic loading pattern on both $\Delta Inventory$ and $\Delta Distress$, for each maturity.

We note that the first beta quintile in each maturity sometimes exhibits higher-than-expected loadings on our intermediary factors. Though a full explanation of this non-monotonic pattern is beyond the scope of this paper, it is likely related to the aforementioned caveat of risk mis-measurement using S&P or VIX betas alone. Indeed, as reported in the first column in each panel, the average beta of these bonds differs sharply from other groups. For example, the S&P beta is substantially negative for these first-quintile groups, but positive for the other groups. These supposedly "low-risk" bonds actually have high volatility in general, whereby they will tend to load heavily on other omitted risk factors. By contrast, the rating-based sorts are not subject to this issue: high-rated bonds almost always have low credit spreads and low spread volatility.[30]

3.2 Spillover and Segmentation

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

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

Assets closely related to corporate bonds are likely to be traded by the same hedgers, and these markets 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.

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 $\Delta Inventory^{IG}$.

[30] In unreported results, we find that sorts based on S&P 500 beta estimated in univariate regressions deliver similar results to those based on S&P 500 beta from CGM regressions. Instead, sorting bonds by their credit spread levels and their credit spread volatilities produces uniformly monotonic intermediary loading patterns similar to our baseline credit rating sorts.

Table 7 reports the results when regressing the residuals of credit spread changes on $\Delta Inventory^{IG}$ and $\Delta Inventory^{HY}$ separately, as well as $\Delta Distress$.

Consistent with the spillover effect, $\Delta Inventory^{IG}$ ($\Delta Inventory^{HY}$) has explanatory power for credit spread changes of high-yield (investment-grade) bonds. As the logic of our model suggests, $\Delta Inventory^{HY}$ has overall stronger effects than $\Delta Inventory^{IG}$ because an increase in the former reduces dealers' risk-bearing capacity 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 $\Delta Inventory$ in Table 4. Recall that these results hold for yield spread *residuals*, which are orthogonalized with respect to the structural CGM factors in equation (1), ruling out typical explanations purely based on default risk.[31]

One concern with the interpretation of these results as evidence of spillover effect is that HY and IG inventories may be simply correlated or driven by an unobserved common factor. Yet, the correlation of $\Delta Inventory^{HY}$ and $\Delta Inventory^{IG}$ is -0.277, inconsistent with this alternative interpretation.[32]

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 behave very much like bond yield spread residuals: CDS residuals have a strong common component (PC1) whose variation is significantly

[31] From our perspective, and that of our model, any results which find loading patterns based on CGM residuals should be interpreted as some amount of unspanned default risk that interacts with intermediary balance sheets. Therefore, our statement "purely based on default risk" refers to a benchmark world in which intermediary balance sheets do not matter. A similar discussion can be found in the literature on the interaction between default and liquidity in the corporate bond market (e.g., He and Xiong (2012), He and Milbradt (2014), and Cui, Chen, He, and Milbradt (2017)).

[32] Strictly speaking, our model with "risk-aversion shock only" should predict $\rho_{\text{HY bonds}}$ and $\rho_{\text{IG bonds}}$ to be positively correlated. However, there are alternative ways to model "supply shocks" beyond these risk aversion shocks; for instance, if specific hedgers are hit by idiosyncratic shocks (say, there is a HY firm that issues bonds, just like in our NBER working paper version (He, Khorrami, and Song, 2019)), then this should lead to uncorrelated components of inventory measured from different bond subsets. Furthermore, a sudden inflow of HY bonds onto dealer balance sheets might generate some sales of IG bonds back to institutional investors, given some intermediaries are actively rebalancing; this is an unmodelled force that tends to make the inventory correlations negative.

linked to our to intermediary factors. We emphasize that, similar to the bond results, our CDS results hold for CDS *residuals*, which control for market- and firm-level CGM factors, ruling out typical explanations based purely on default risk.[33]

3.2.2 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 plausibly are partially segmented from corporate credit.[34] 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 these data are in Internet Appendix A.4.

We then run time series regressions of these residuals on $\Delta Inventory$ 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 relatively insensitive to bond inventory changes, but should still respond to aggregate intermediary distress. Table 8 shows results consistent with this prediction.[35] Furthermore, the R-squares suggest that equity options are the most segmented from corporate bonds, followed by Agency MBS, and finally followed by CMBS and ABS.[36] Finally, the magnitude of the distress loadings are in the ballpark of our baseline bond results in Table 4 (the option returns are monthly,

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

[34]For evidence in this direction, see Table 1 in Becker and Ivashina (2015), which shows how various institutional investors (the counterpart of our model's hedgers) hold substantially different portfolios across asset classes.

[35]The only exception is index call options for which even the intermediary distress factor is not significant. This is consistent with the option pricing literature, in which out-of-the-money put options, not call options, are found to carry the large downside tail risk or crash risk (Bollerslev and Todorov, 2011; Gao, Lu, and Song, 2019; Chen, Joslin, and Ni, 2018).

[36]Among these asset classes, Becker and Ivashina (2015) only show the Agency MBS holdings by institutional investors. They report quite low institutional holdings of Agency MBS compared to corporate bonds, suggesting a large segmentation.

so their loading magnitudes should be compared to Table A.10), with higher-risk assets such as low-rated CMBS and ABS featuring larger loadings.

3.3 Institutional Holdings and Supply Shocks

We further delve into bond-level dealer inventories and institutional holdings to provide evidence that the supply of bonds from some regulatory-driven sell-offs by institutional investors leads to changes of dealer inventory. Based on such micro-level evidence, we then construct instruments for the dealer inventory factor at the aggregate level and conduct IV analysis of the effect of dealer inventory on credit spread changes.

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

3.3.1 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).[37] We use the eMAXX

[37] 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

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 these 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, consistent with Li and Yu (2020). 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.

3.3.2 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. To this end, we compute the total inventory change of all dealers for each bond i in each quarter t, denoted as $\Delta Inventory_{i,t}$ from TRACE. We further compute, from eMAXX, 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.

Using the historical rating information provided by Mergent FISD, 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" observa-

pension funds who voluntarily submit data to Thomson Reuters (see Cai, Han, Li, and Li (2019), Becker and Victoria (2015), and Manconi, Massa, and Yasuda (2012) for further details).

tions 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.[38]

Table 9 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. For each investor group, 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 (i.e., average holdings as of quarter $t-1$) are reported. 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 million at quarter t and sold \$0.24–0.47 million the quarter after.

In other 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 9 shows that dealers buy a similar amount of "downgrade (IG)" bonds in quarter

[38] 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.

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.7, 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 similar to the summary statistics in Table 9.

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. Thus, downgrade-induced sell-offs work similarly to our model, in which hedgers sell bonds to intermediaries due to a sudden increase in their risk aversion (increase in ρ_{bonds}), independently from intermediary risk aversion (i.e., γ).[39] In the following, we construct an IV for the dealer inventory factor based on institutional investors' liquidations of "fallen angels."

[39] Given the lack of reversal in our empirical sell-off patterns (i.e., at time $t + 1$, insurance companies, mutual funds, and dealers all reduce their holdings of fallen angels), some unobserved investors (e.g., hedge funds) must be increasing their holdings after the shock. This could be interpreted as activity by some risk-tolerant investors who are better-equipped to hold low-rated bonds. In our model, these risk-tolerant investors could reasonably be lumped together with dealers to comprise our model's "intermediaries."

3.3.3 IV Regressions

To construct a time series IV for the dealer inventory factor $\Delta Inventory_t$, 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.[40] 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. 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 $\Delta Inventory_t$ as a percentage change.

The left panel of Table 10 reports first-stage regressions of $\Delta Inventory$ on $\Delta Holding_t^{FA}$. 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 0.28 standard deviation increase in dealer inventory, indicating the relevance of $\Delta Holding_t^{FA}$ for $\Delta Inventory$.

The right panel of Table 10 reports second-stage regressions of quarterly residuals of credit spread changes on $\Delta Distress$ and $\Delta Inventory$, using $\Delta Holding_t^{FA}$ as an inventory IV. The last two rows report the test statistic for weak instruments by Montiel-Olea and Pflueger (2013) (MP) and associated critical values. We observe that the MP-statistic is larger than the critical value, rejecting the null hypothesis that $\Delta Holding_t^{FA}$ is a weak investment.

[40] Of course, there are other possible liquidity-type shocks one could use to instrument dealer inventory, mutual fund flows being chief among them in the literature (see Goldstein, Jiang, and Ng (2017) for bond-level evidence; see Ben-Rephael, Choi, and Goldstein (2021) and Falato, Goldstein, and Hortaçsu (2020) for aggregate versions that would be appropriate as time series factors). We leave such explorations for future research.

Importantly, we find that $\Delta Inventory$—instrumented by $\Delta Holding^{FA}$—is highly significant in increasing credit spreads.[41] The coefficients in these IV regressions, especially on $\Delta Inventory_t$, are significantly larger than those in the baseline regressions of Table 4.[42] One leading explanation is that dealer inventory changes could be driven by unobserved bond demand shocks (e.g., regulatory changes that impact dealers). A demand shock increases dealer inventory but lowers credit spreads (or vice versa), and this negative inventory-spread comovement biases against the positive supply-driven comovement. Using the IV, which we claim are purely about supply, can purge such demand effects. In Internet Appendix A.8, we directly test the hypothesis that regulatory tightenings on dealers in our sample period acted like negative demand shocks that can help explain the difference between our OLS and IV results.[43]

4 Conclusion

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

[41] In our NBER working paper version (He, Khorrami, and Song, 2019), we also use Property & Casualty insurers' excess disaster-related payouts (e.g., damages from hurricanes) as an IV for bond inventory. While this insurance loss IV is plausibly more exogenous to bond market activity, it is also weaker statistically. Still, the sensitivity of spreads to $\Delta Inventory$ is similar for the insurance IV as the fallen angel sell-off IV.

[42] 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 $\Delta Inventory_t$.

[43] Of course, the much larger coefficients could also result from our IV being relatively weak—see Jiang (2017) for evidence that this is the case in some recent finance research. However, our IV passes a weak-instrument test (following Montiel-Olea and Pflueger, 2013), suggesting this is less likely.

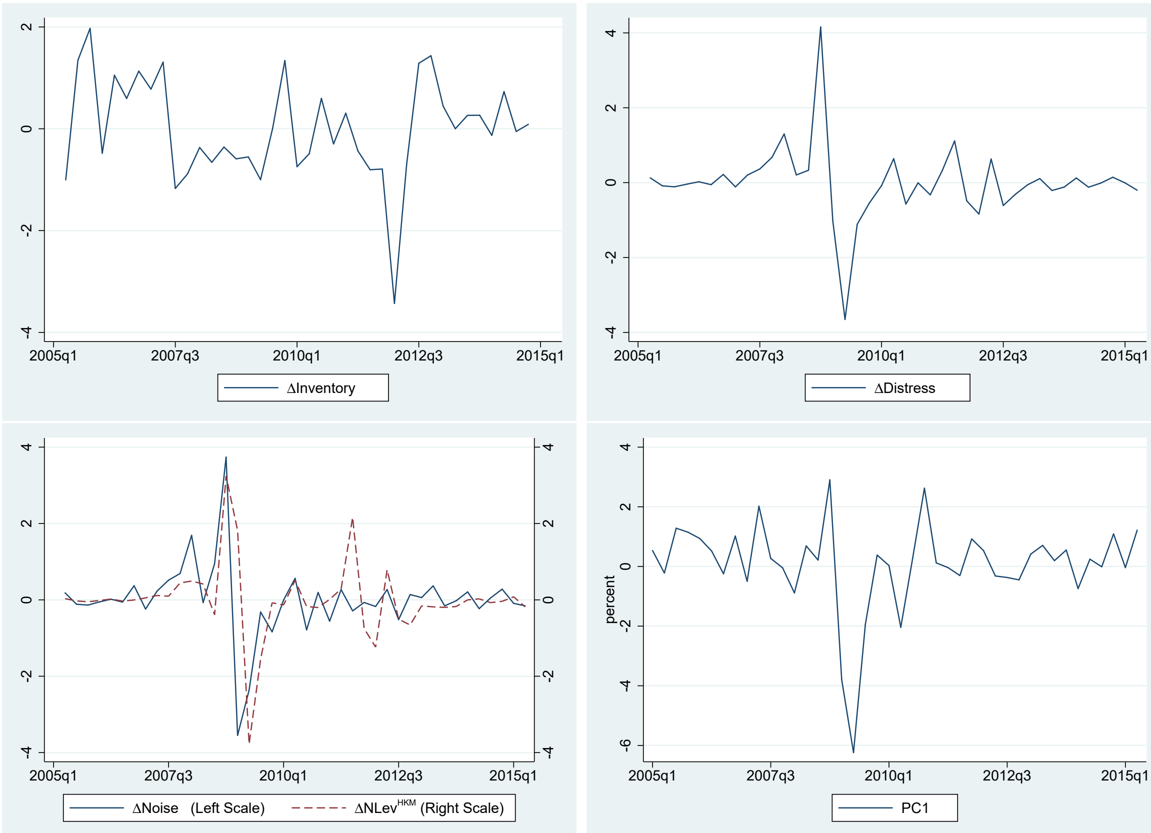
explain more than 40% of the puzzling common variation documented in CGM.

Our simple economic framework combines three key elements: (A1) asset market segmentation, (A2) the supply and demand sides of the bond market, and (A3) limited intermediary risk-bearing capacity. The existence of common variation in the residuals of credit spread changes identifies a role for asset market segmentation (A1). The relevance of our dealer inventory factor identifies a role for investor heterogeneity, corresponding to supply and demand (A2). The monotonicity of factor loadings in bond ratings supports a central role for intermediaries' risk-bearing capacity (A3).

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.14 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 of equation (1), intermediary distress comoves with all return-based factors significantly, unlike dealer inventory. This result suggests intermediary distress provides a potential fundamental-based explanation for return-based factors, while we have yet to find some return-based factors to proxy for dealer inventory.

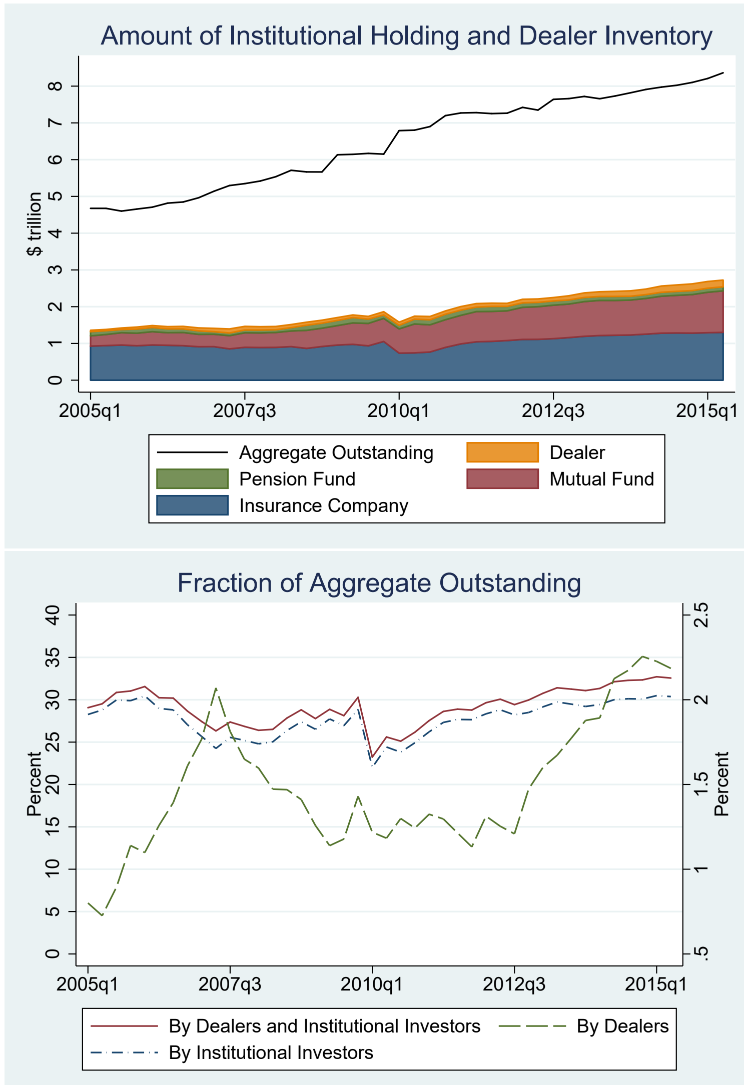
Endeavoring to obtain a more primitive economic understanding of factor-based models can be a fertile future research direction. Such factor modeling typically outperforms economic modeling. For example, the recent paper Kelly, Palhares, and Pruitt (2020) provides a systematic statistical procedure for extracting latent factors driving bond returns, jointly with bond characteristic–based factor loadings using a rich set of 30+ possible characteristics (characteristics like yield spread, duration, and rating emerge as the important determinants of factor loadings, partly justifying the bond sorts we examine). Their procedure performs very well along many metrics (e.g., R-squared), even better than previous studies. But what underlying economic shocks govern the factors, and why do these characteristics govern risk sensitivity? Answering this question can insulate our understanding of the bond market against structural changes and alternative policy regimes. Here, we have proposed factors and factor loadings are driven by asset riskiness interacting with liquidity shocks and intermediary balance-sheet shocks.

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



Note: This figure plots quarterly time series of $\Delta Inventory$, $\Delta Distress$, $\Delta Noise$, $\Delta \text{NLev}^{\text{HKM}}$, 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 U.S., 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 (left scale), by dealers (right scale), and by both (left scale), 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

	$\Delta Inventory$	$\Delta Distress$	$\Delta Noise$	$\Delta\text{NLev}^{\text{HKM}}$	ΔVIX	ΔILiq
$\Delta Inventory$	1.000					
$\Delta Distress$	-0.028	1.000				
$\Delta Noise$	-0.058	0.840***	1.000			
$\Delta\text{NLev}^{\text{HKM}}$	0.011	0.840***	0.411***	1.000		
ΔVIX	0.044	0.466***	0.235	0.548***	1.000	
ΔILiq	0.306*	0.224	0.192	0.185	0.381**	1.000

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

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

Groups		A: Individual Bond Regressions											B: PC	
Maturity	Rating	ΔLev_i	ΔVIX	$\Delta Jump$	Δr^{10y}	$(\Delta r^{10y})^2$	$\Delta Slope$	Ret^{SP}	R^2_{adj}	Bond#	Obs	$\varepsilon_g^{var} / \sum_{g=1}^{15} \varepsilon_g^{var}$	PC1	PC2
Short	AA	1.321	0.018	1.150	−0.164	−0.137	0.234	0.121	0.273	60	628	0.53%	0.057	−0.020
		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%	0.081	−0.024
		−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%	0.124	−0.022
		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%	0.208	−0.075
		7.911	6.257	−2.343	−13.821	3.705	7.564	−29.493						
Short	B	10.609	0.090	2.986	−1.474	0.090	0.449	−5.495	0.560	369	2953	18.25%	0.430	−0.466
		10.791	5.105	1.152	−10.613	0.373	2.433	−29.758						
Medium	AA	0.912	0.010	−0.457	−0.148	−0.204	0.049	−0.797	0.296	56	493	0.58%	0.057	−0.042
		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%	0.096	−0.017
		1.455	6.079	−2.534	−4.556	−4.097	−0.350	−48.926						
Medium	BBB	2.211	0.012	−2.690	−0.278	−0.013	0.024	−2.361	0.444	720	5736	2.09%	0.148	−0.034
		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%	0.235	0.191
		9.057	4.401	−4.018	−10.449	2.412	4.317	−27.551						
Medium	B	8.758	0.070	−2.517	−1.362	0.039	0.250	−3.489	0.617	417	3307	15.93%	0.419	−0.005
		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%	0.049	0.003
		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	−0.000
		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%	0.084	0.832
		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%	0.232	0.173
		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%	0.642	0.121
		8.823	3.704	−1.360	−6.925	−3.470	−0.908	−31.39						
Pct Explained													0.801	0.068
Corr($\Delta Inventory$, PC)													0.270	−0.282
Corr($\Delta Distress$, PC)													0.595	0.309

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 $\Delta Inventory$ 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: $\Delta Inventory$		B: $\Delta Distress$		C: $\Delta Inventory + \Delta Distress$			
Maturity	Rating	$\Delta Inventory$	R^2_{adj}	$\Delta Distress$	R^2_{adj}	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}	% Explained
Short	AA	0.032	0.074	0.035	0.093	0.035	0.041**	0.159	0.283
		(1.587)		(1.506)		(1.431)	(1.996)		
Short	A	0.022	0.024	0.054*	0.143	0.047*	0.062***	0.219	
		(1.121)		(1.946)		(1.859)	(2.584)		
Short	BBB	0.030	0.022	0.099**	0.228	0.064*	0.110***	0.297	
		(1.055)		(2.420)		(1.859)	(3.063)		
Short	BB	0.073	0.033	0.152**	0.136	0.145	0.177***	0.225	
		(0.948)		(2.542)		(1.535)	(3.112)		
Short	B	0.207**	0.084	0.272	0.141	0.340***	0.330**	0.299	
		(2.388)		(1.568)		(3.020)	(2.324)		
Medium	AA	0.021	0.027	0.045***	0.121	0.033	0.050***	0.169	0.531
		(1.293)		(2.577)		(1.612)	(3.691)		
Medium	A	0.040	0.057	0.080**	0.226	0.072**	0.093***	0.355	
		(1.627)		(1.966)		(2.491)	(2.703)		
Medium	BBB	0.074**	0.091	0.128**	0.275	0.105***	0.145***	0.408	
		(2.385)		(2.131)		(2.860)	(2.965)		
Medium	BB	0.147**	0.123	0.227***	0.300	0.199***	0.261***	0.465	
		(2.046)		(3.597)		(2.866)	(5.105)		
Medium	B	0.169**	0.063	0.440***	0.418	0.338***	0.498***	0.594	
		(2.159)		(2.783)		(5.149)	(4.203)		
Long	AA	0.022*	0.046	0.035	0.119	0.024*	0.039*	0.158	0.449
		(1.797)		(1.381)		(1.803)	(1.700)		
Long	A	0.025	0.035	0.059	0.193	0.041*	0.066**	0.261	
		(1.336)		(1.640)		(1.790)	(2.003)		
Long	BBB	-0.058	0.019	0.158***	0.139	-0.069	0.147***	0.158	
		(-0.782)		(4.836)		(-0.927)	(4.400)		
Long	BB	0.102	0.063	0.220***	0.288	0.174***	0.250***	0.416	
		(1.570)		(3.795)		(2.904)	(5.218)		
Long	B	0.206	0.043	0.629**	0.388	0.421***	0.700***	0.513	
		(1.453)		(2.188)		(2.844)	(2.737)		
Total									0.426

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 $\Delta Inventory$ (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 $\Delta Inventory$ 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		
Rating	Trd Volume	TrdVolume ($ million)	Bond#	Obs	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}
AA	Low	2.462	92	527	-0.008	0.032	0.062
					(-0.311)	(1.299)	
AA	Medium	17.779	113	796	0.022	0.051***	0.219
					(1.195)	(3.603)	
AA	High	136.25	129	1084	0.040***	0.041**	0.206
					(2.735)	(1.942)	
A	Low	1.995	684	6173	0.040	0.062***	0.231
					(1.589)	(2.377)	
A	Medium	16.882	741	4700	0.061**	0.080***	0.354
					(2.459)	(3.147)	
A	High	110.411	699	4246	0.043*	0.069*	0.263
					(1.842)	(1.936)	
BBB	Low	2.011	1199	9436	-0.061	0.103***	0.068
					(-0.698)	(3.060)	
BBB	Medium	17.056	1209	7401	0.046	0.158***	0.435
					(1.108)	(6.113)	
BBB	High	106.026	1137	6405	0.083**	0.141***	0.351
					(2.455)	(2.536)	
BB	Low	2.584	431	1972	0.182***	0.225***	0.364
					(2.754)	(3.937)	
BB	Medium	17.777	471	2435	0.199***	0.234***	0.415
					(2.657)	(3.741)	
BB	High	100.298	451	2303	0.169**	0.220***	0.336
					(2.157)	(5.456)	
B	Low	2.360	412	2276	0.339***	0.381***	0.354
					(3.118)	(3.621)	
B	Medium	17.342	468	2973	0.328***	0.455***	0.493
					(4.111)	(2.804)	
B	High	89.654	437	2604	0.401***	0.537***	0.528
					(3.833)	(3.084)	

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 $\Delta Inventory$ 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: Groups by Market and VIX Beta

	A: Market Beta					B: VIX Beta				
		Average	Regression of Residuals				Average	Regression of Residuals		
	Group	β^{SP}	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}	Group	β^{VIX}	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}
Short	1 (Low)	-6.559	0.096	0.115**	0.150	1 (High)	0.185	0.144	0.147**	0.143
			(1.233)	(2.263)				(1.541)	(1.977)	
Short	2	0.330	0.087**	0.104***	0.319	2	0.036	0.080	0.102***	0.203
			(2.313)	(2.844)				(1.631)	(2.687)	
Short	3	1.866	0.080*	0.104***	0.284	3	0.013	0.068	0.093**	0.223
			(1.908)	(3.036)				(1.571)	(2.076)	
Short	4	4.086	0.120***	0.170***	0.419	4	-0.005	0.129***	0.192***	0.503
			(2.651)	(4.551)				(3.427)	(4.562)	
Short	5 (High)	13.917	0.201***	0.245**	0.274	5 (Low)	-0.082	0.128***	0.195**	0.320
			(2.999)	(2.356)				(2.580)	(2.554)	
Medium	1 (Low)	-7.040	0.206***	0.291***	0.561	1 (High)	0.180	0.205***	0.344***	0.453
			(2.636)	(4.404)				(2.717)	(3.193)	
Medium	2	0.330	0.096***	0.129***	0.442	2	0.035	0.088***	0.123***	0.368
			(2.877)	(3.665)				(2.630)	(3.058)	
Medium	3	1.871	0.074*	0.113***	0.330	3	0.013	0.101***	0.159***	0.477
			(1.866)	(2.580)				(2.867)	(4.003)	
Medium	4	3.974	0.119***	0.178***	0.477	4	-0.005	0.162***	0.203***	0.551
			(3.378)	(4.534)				(4.123)	(4.381)	
Medium	5 (High)	13.967	0.316***	0.484***	0.554	5 (Low)	-0.077	0.299***	0.446***	0.648
			(4.234)	(3.886)				(3.805)	(5.242)	
Long	1 (Low)	-7.963	-0.257	0.297***	0.142	1 (High)	0.202	-0.395	0.349***	0.114
			(-1.407)	(3.943)				(-1.439)	(2.706)	
Long	2	0.357	0.042*	0.074**	0.238	2	0.034	0.044*	0.092**	0.310
			(1.772)	(2.304)				(1.860)	(2.389)	
Long	3	1.926	0.062**	0.101***	0.395	3	0.013	0.066***	0.090***	0.349
			(2.236)	(2.766)				(2.583)	(2.591)	
Long	4	3.835	0.094***	0.139***	0.505	4	-0.006	0.079***	0.117***	0.453
			(3.633)	(2.980)				(3.416)	(3.298)	
Long	5 (High)	11.298	0.198***	0.326***	0.483	5 (Low)	-0.065	0.240***	0.327***	0.577
			(4.130)	(3.605)				(3.627)	(5.509)	

Note: This table reports results using 15 cohorts based on maturity and betas (of S&P 500 index return and VIX change as estimate from CGM regressions reported in Table 3. Note that since the betas come from a regression of credit spread changes on the CGM factors, we multiply the betas by -1 for this table (to convert into return betas). For each panel, we report the average beta for each cohort and quarterly time series regressions of each of the 15 residuals of quarterly credit spread changes (in percentage) on $\Delta Inventory$ and $\Delta Distress$. 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 7: Inventories of HY vs IG Bonds

Groups		A: $\Delta Inventory^{HY}$			B: $\Delta Inventory^{IG}$		
Maturity	Rating	$\Delta Inventory^{HY}$	$\Delta Distress$	R^2_{adj}	$\Delta Inventory^{IG}$	$\Delta Distress$	R^2_{adj}
Short	AA	0.017	0.036	0.087	0.022	0.037	0.098
		(0.925)	(1.159)		(1.215)	(1.164)	
Short	A	0.044*	0.067*	0.197	0.006	0.062	0.136
		(1.755)	(1.909)		(0.294)	(1.631)	
Short	BBB	0.065*	0.122**	0.301	0.011	0.115**	0.233
		(1.943)	(2.570)		(0.351)	(2.253)	
Short	BB	0.125	0.204***	0.196	0.069	0.198***	0.158
		(1.267)	(2.604)		(1.084)	(2.905)	
Short	B	0.198	0.353*	0.212	0.202*	0.353*	0.215
		(1.304)	(1.753)		(1.814)	(1.896)	
Medium	AA	0.032	0.051***	0.177	0.008	0.048**	0.128
		(1.577)	(3.144)		(0.631)	(2.368)	
Medium	A	0.055**	0.087*	0.288	0.016	0.082	0.209
		(2.395)	(1.815)		(0.687)	(1.539)	
Medium	BBB	0.087**	0.145**	0.349	0.023	0.137*	0.259
		(2.485)	(2.129)		(0.714)	(1.834)	
Medium	BB	0.150**	0.261***	0.371	0.068*	0.251***	0.295
		(2.001)	(3.708)		(1.759)	(3.845)	
Medium	B	0.251**	0.520***	0.494	0.175***	0.511***	0.446
		(2.310)	(3.038)		(2.726)	(2.976)	
Long	AA	0.029**	0.031	0.104	-0.010	0.026	0.057
		(2.125)	(0.872)		(-0.619)	(0.657)	
Long	A	0.034*	0.063	0.197	0.012	0.061	0.156
		(1.710)	(1.395)		(0.613)	(1.251)	
Long	BBB	0.017	0.177***	0.155	-0.058	0.168***	0.169
		(0.375)	(3.897)		(-1.185)	(3.686)	
Long	BB	0.136*	0.256***	0.410	0.058	0.246***	0.334
		(1.926)	(4.210)		(1.295)	(4.711)	
Long	B	0.261*	0.730**	0.470	0.246**	0.729**	0.465
		(1.650)	(2.388)		(2.021)	(2.383)	
FVE				0.364			0.340

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 8: Non-Corporate-Credit Assets

		A: Agency MBS			
	FN30y	FN15y	FG30y	FG15y	
$\Delta Inventory^A$	0.027	0.008	0.029*	-0.006	
	(1.554)	(0.466)	(1.925)	(-0.399)	
$\Delta Distress$	0.049***	0.054***	0.058***	0.046***	
	(2.840)	(3.282)	(3.666)	(2.756)	
R^2_{adj}	0.138	0.197	0.153	0.127	
		B: CMBS			
	Duper	AM	AJ		
$\Delta Inventory^A$	0.040	-0.185	-0.278		
	(0.411)	(-1.177)	(-1.436)		
$\Delta Distress$	0.270***	0.877***	0.915***		
	(3.225)	(3.128)	(3.464)		
R^2_{adj}	0.178	0.346	0.321		
		C: ABS			
	Credit Card	Auto AAA	Auto A	Auto BBB	
$\Delta Inventory^A$	-0.020	-0.002	-0.004	-0.067	
	(-0.797)	(-0.085)	(-0.050)	(-0.709)	
$\Delta Distress$	0.185***	0.046	1.210***	1.216**	
	(3.194)	(0.857)	(2.657)	(2.349)	
R^2_{adj}	0.248	0.009	0.436	0.378	
		D: S&P 500 index options			
	Call: 0.90	Call: 0.95	Call: ATM	Call: 1.05	Call: 1.10
$\Delta Inventory^A$	0.047	0.033	0.022	0.028	-0.133
	(0.411)	(0.279)	(0.184)	(0.199)	(-0.924)
$\Delta Distress$	-0.062	-0.085	-0.058	-0.121	-0.242
	(-0.113)	(-0.143)	(-0.088)	(-0.171)	(-0.304)
R^2_{adj}	0.002	0.003	0.001	0.004	0.014
	Put: 0.90	Put: 0.95	Put: ATM	Put: 1.05	Put: 1.10
$\Delta Inventory^A$	-0.226	-0.155	-0.114	-0.082	-0.074
	(-0.800)	(-0.705)	(-0.683)	(-0.637)	(-0.648)
$\Delta Distress$	0.302	0.291*	0.300***	0.286***	0.267**
	(0.941)	(1.800)	(2.941)	(3.042)	(2.290)
R^2_{adj}	0.020	0.024	0.034	0.040	0.037

Note: This table reports quarterly time series regressions of residuals of quarterly yield spread changes of agency MBS (in panel A), CMBS (in panel B), and ABS (in panel C) on $\Delta Inventory$ and $\Delta Distress$. Monthly time series regressions of residuals of one-month (unannualized) returns are reported for S&P 500 index option portfolios (in panel D). All the series of yield spreads and returns are in percent. Each 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 through January 2012 for options.

Table 9: 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 10: IV Regressions

First Stage		Second-Stage			
		Maturity	Rating	$\Delta Inventory_t$	$\Delta Distress_t$
$\Delta Holding_t^{FA}$	-0.279***	Short	AA	0.264***	0.001
	(-4.532)			(3.197)	(0.009)
$\Delta Distress$	0.443**	Short	A	0.267**	0.084
	(2.245)			(2.487)	(1.019)
$\Delta Holding_t^{D}$	0.055	Short	BBB	0.234	0.210**
	(0.333)			(1.551)	(2.455)
ΔVIX	-0.003	Short	BB	0.640*	0.338
	(-0.175)			(1.750)	(1.575)
$\Delta Jump$	-11.428*	Short	B	0.918***	0.668**
	(-1.653)			(2.728)	(2.502)
Δr^{10y}	0.571**	Medium	AA	0.269*	-0.008
	(2.117)			(1.759)	(-0.082)
$\left(\Delta r^{10y}\right)^2$	-0.443**	Medium	A	0.244	0.097
	(-2.000)			(1.328)	(0.937)
$\Delta slope$	-0.293	Medium	BBB	0.246**	0.233***
	(-1.573)			(2.130)	(2.804)
ret_t^{SP}	6.109***	Medium	BB	0.691**	0.320*
	(4.519)			(2.445)	(1.799)
Intercept	0.027	Medium	B	0.859***	0.709***
	(0.167)			(3.687)	(4.266)
R^2_{adj}	0.372	Long	AA	0.203***	0.000
				(3.009)	(0.001)
		Long	A	0.284*	0.043
				(1.746)	(0.441)
		Long	BBB	0.257*	0.224
				(1.719)	(1.633)
		Long	BB	0.479***	0.390***
				(3.340)	(4.397)
		Long	B	0.808***	1.278***
				(3.661)	(8.386)
		MP Test		12.574	
		Critical Value		[12.374]	

Note: The left panel reports the first-stage regressions of residuals of quarterly credit spread changes (in percentage) using $\Delta Holding_t^{FA}$ as instrument for $\Delta Inventory$. 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 bond-level regression (1). All measures except the six time series variable from (1) are scaled to have zero mean and unit variance. The right panel reports coefficients of second-stage regressions on $\Delta Inventory$ and $\Delta Distress$, with those on control variables ($\Delta Holding_t^{D}$ and the six time series variables used in (1)) omitted for simplicity of reporting. 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 weak instrument test statistic of Montiel-Olea and Pflueger (2013) (MP) is reported,; the critical value at a significance level of 10% for the worst-case bias greater than 20% of the OLS bias is in the bracket. The sample period is 2005:Q1–2015: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}, $(r_t^{10y})^2$, 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 15,000 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).[1] 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 percentage, 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 Robustness

Here, we present a number of robustness checks.

First, Table A.5 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 75% of the total unexplained variation of credit spread changes. In regressions, credit spread residuals comove 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 39% of the unexplained total variation of credit spread changes.

[1]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.

Second, one may be concerned that the strong explanatory power documented is mainly due to the inclusion of the 2008 financial crisis. Table A.6 reports results following the baseline procedure but excluding the 2008 financial crisis period (defined as 2007:Q3 - 2009:Q1 similar to Bao, O'Hara, and Zhou (2018), Schultz (2017), and others). From Panel A of the PC analysis, we observe a strong common variation with the PC1 accounting for 80% of the total unexplained variation of credit spread changes. From Panel B of the quarterly bivariate series regressions 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 43% of the unexplained total variation of credit spread changes, similar to that in the baseline Table 4 including the crisis observations.

Third, 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 low correlations with our two intermediary factors. Table A.7 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). Panel B shows that adding ΔILiq to our two intermediary factors only increases the explained fraction by 0.6% (from 42.6% to 43.2%).[2]

Fourth, recall we have constructed the intermediary distress factor $\Delta Distress$ as the first PC of $\Delta Noise$ and $\Delta\text{NLev}^{\text{HKM}}$; 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: $\Delta\text{NLev}^{\text{HKM}}$ has a more direct economic interpretation, but market price–based $\Delta Noise$ is measured better. In Table A.8, we regress credit spread residuals on these two factors separately. 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 14% of $\Delta\text{NLev}^{\text{HKM}}$; the higher explanatory power of $\Delta Noise$ is likely due to its superior measurement as a price-based variable. In addition, $\Delta Noise$ and $Delta\text{NLev}^{\text{HKM}}$ jointly explain 36% of the unexplained total variation in bivariate regressions, so they have overlapping but nontrivial individual explanatory power.

Fifth, Table A.9 reports quarterly time series regressions of baseline residuals on baseline intermediary factors, controlling for two other potential measures of intermediary distress, the leverage measure of broker-dealers in Adrian, Etula, and Muir (2014), here constructed in the same nonlinear way as in our baseline HKM measure, i.e., $\Delta\text{NLev}_t^{\text{AEM}} := (\text{Lev}_t^{\text{AEM}})^2 - (\text{Lev}_{t-1}^{\text{AEM}})^2$ (in panel A) and TED spread computed as the difference between three-month Libor and T-bill rates (in panel B).

[2]The corporate bond illiquidity measure proposed by Bao, Pan, and Wang (2011) is available at the monthly frequency and only up to 2009. In unreported results, 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). Moreover, in an alternative approach, we add ΔILiq as an explanatory variable to the individual-bond regression (1). Consistent with the pattern in Table A.7, it mainly adds to the explanatory power (adjusted R^2) of high-rated cohorts but not low-rated cohorts.

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.

Finally, Table A.10 reports results following the baseline procedure except using monthly credit spread changes. The first PC still accounts for 75% 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 15% 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.

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, Yan, and Zhou, 2021).[3] 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.11 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 43% for bonds, but still reaches 31%.[4]

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.12 report results

[3] 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.

[4] One may be concerned that the sensitivity of CDS spreads to bond inventory reflects some latent unobservable common credit risk factor. Two findings 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.

based on the following regression:

$$\Delta Holding_{i,t+\tau} = Intercept + \beta_1 \times \text{Fallen}_{i,t} + \beta_2 \times \text{Downgrade}_{i,t} + \beta_3 \times log(\text{Amt}_{i,t+\tau}) \\ + \beta_4 \times log(\text{Size}_i) + \beta_5 \times \text{Age}_{i,t+\tau} + \beta_6 \times \text{Time-to-Mature}_{i,t+\tau} + \sum_t \text{FE}_t + \varepsilon_{i,t+\tau}, \tag{12}$$

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

The sample includes "downgrade (IG)," "fallen angels," and "no rating change" observations. Thus, the coefficient on $\text{Downgrade}_{i,t}$ captures the $(t+\tau)$ change of institutional investors' holdings of "downgraded (IG)" bonds in quarter t, relative to that of bonds without rating change contemporaneously. Similarly, the coefficient on $\text{Fallen}_{i,t}$ 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 (12) are reported in the last column.

Consistent with summary statistics in Table 9, Table A.12 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 Regulatory Shocks

As discussed in Section 3.3, 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 Appendix B.4, which develops this prediction in an extended version of our model with regulatory shocks); this 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:

$$\varepsilon_{g,t} = \rho_g + \beta_{1,g} \times \Delta Inventory_t + \beta_{2,g} \times \Delta Distress_t + \beta_{3,g} \times D_{RegShock,t} \\ + \beta_{4,g} \times \Delta Inventory_t \times D_{RegShock,t} + \beta_{5,g} \times \Delta Distress_t \times D_{RegShock,t} + u_{g,t}, \tag{13}$$

where $\varepsilon_{g,t}$ is the average residual of cohort g $(= 1, \ldots, 15)$. Table A.13 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.

A.9 Bond Return Factors

Finally, as discussed in the conclusion of our main text, Table A.14 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 Analysis and Extensions

B.1 Benchmark Model without Segmentation

Hedger's mean-variance optimal portfolio is

$$\theta_H = (\rho\Sigma)^{-1}(\bar{\delta} - p) - h. \tag{14}$$

Intermediaries' optimal portfolio is given by

$$\theta_I = (\gamma(w)\Sigma)^{-1}(\bar{\delta} - p). \tag{15}$$

Market clearing (6) then implies

$$p = \bar{\delta} - (\rho^{-1} + \gamma(w)^{-1})^{-1}\Sigma h. \tag{16}$$

Using the definition $\Gamma(w) := (\rho^{-1} + \gamma(w)^{-1})^{-1}$ in equation (16), we obtain equation (8).

Proof of Lemma 1. Recall the definition of market beta $\beta_{a,\text{mkt}} := \frac{\text{Cov}[\delta_a + \text{d}p_a, x'\delta + \text{d}(x'p)]}{\text{Var}[x'\delta + \text{d}(x'p)]}$. Note that $\text{d}p_a = -(\Sigma h)_a \text{d}\Gamma$, so $\text{d}(x'p) = -(x'\Sigma h)\text{d}\Gamma$. Then, the result for beta is

$$\beta_{a,\text{mkt}} = \frac{(\Sigma x)_a + (x'\Sigma h)(\Sigma h)_a \text{Var}[\text{d}\Gamma]}{x'\Sigma x + (x'\Sigma h)^2 \text{Var}[\text{d}\Gamma]} = \frac{(\Sigma x)_a}{x'\Sigma x} \frac{(x'\Sigma x) + (h'\Sigma h)(x'\Sigma x)\text{Var}[\text{d}\Gamma]}{x'\Sigma x + (x'\Sigma h)^2 \text{Var}[\text{d}\Gamma]} = \frac{(\Sigma x)_a}{x'\Sigma x}.$$

Then,

$$\epsilon_a := \text{d}p_a - \beta_{a,\text{mkt}} \text{d}(x'p) = -\Big[(\Sigma h)_a - \frac{(\Sigma x)_a}{x'\Sigma x}(x'\Sigma h)\Big]\text{d}\Gamma = 0. \tag{17}$$

Since $\epsilon_a = 0$, the residuals must trivially be independent of all shocks. □

B.2 Model with Asset Class Segmentation

To write the formulas compactly, we need some notation. Let $\tilde{\Sigma}_n$ be the $A \times A$ quasi-covariance matrix pertaining only to assets in $\mathcal{A}_n$, i.e.,

$$(\tilde{\Sigma}_n)_{ij} = \begin{cases} \Sigma_{ij}, & \text{if } i, j \in \mathcal{A}_n; \\ 0, & \text{otherwise.} \end{cases}$$

Define $\Sigma_\rho := \sum_{n=1}^N \rho_n \tilde{\Sigma}_n$. Without loss of generality, we can relabel the assets such that classes include consecutive assets, i.e., $\mathcal{A}_n = \{a_{n-1} + 1, a_{n-1} + 2, \ldots, a_n\}$ (with $a_0 = 0$ and $a_N = A$). This means that Σ_ρ is a block-diagonal matrix, which will be convenient. Then, the optimal hedger portfolios are determined from

$$\theta_H = \Sigma_\rho^{-1}(\bar{\delta} - p) - h. \tag{18}$$

The intermediary portfolio is still given by (15).

Combining (18) with (15) and market clearing (6), we obtain

$$p = \bar{\delta} - \tilde{\Gamma}\Sigma h, \tag{19}$$

where $\tilde{\Gamma} := (\gamma^{-1} I + \Sigma\Sigma_\rho^{-1})^{-1}$. Under the weak cross-class correlation part of Assumption 1, we have $\Sigma \approx \sum_{n=1}^N \tilde{\Sigma}_n$, so that $\Sigma\Sigma_\rho^{-1} \approx \sum_{n=1}^N \rho_n^{-1} \mathbf{1}_{\mathcal{A}_n}$, which finally implies

$$\text{Assumption 1} \;\Rightarrow\; \tilde{\Gamma} \approx \sum_{n=1}^N \Gamma_n \mathbf{1}_{\mathcal{A}_n},$$

where recall $\Gamma_n := (\gamma^{-1} + \rho_n^{-1})^{-1}$ is a composite risk aversion measure. Using this result, the pricing formula (19) becomes

$$\text{Assumption 1} \;\Rightarrow\; p_i \approx \bar{\delta}_i - \Gamma_{n(i)}(\Sigma h)_i. \tag{20}$$

This is result (10) in the text.

Differentiating this result, we obtain

$$\mathrm{d}p_i \approx -\Gamma_{n(i)}(\Sigma h)_i \Big[\frac{\Gamma_{n(i)}}{\rho_{n(i)}} \mathrm{d}\log\rho_{n(i)} + \frac{\Gamma_{n(i)}}{\gamma}\mathrm{d}\log\gamma\Big].$$

For simplicity, recall that we assumed "redistributive supply shocks" in the sense that the market capital gain $\mathrm{d}(x'p)$ has no sensitivity to any of the $\mathrm{d}\rho_n$ shocks. In that case,

$$\mathrm{d}(x'p) \approx -\Big(\sum_{a=1}^A x_a (\Sigma h)_a \frac{\Gamma_{n(a)}^2}{\gamma}\Big)\mathrm{d}\log\gamma.$$

Thus, the market beta is

$$\beta_{i,\mathrm{mkt}} \approx \frac{(\Sigma x)_i + \big(\sum_{j=1}^A x_j (\Sigma h)_j \Gamma_{n(j)}^2\big)(\Sigma h)_i \Gamma_{n(i)}^2 \gamma^{-2}\nu_\gamma}{x'\Sigma x + \big(\sum_{j=1}^A x_j (\Sigma h)_j \Gamma_{n(j)}^2\big)^2 \gamma^{-2}\nu_\gamma},$$

where $\nu_\gamma := \mathrm{Var}[\mathrm{d}\log\gamma]$ is the variance of intermediary risk aversion shocks. Then,

$$\epsilon_i := \mathrm{d}p_i - \beta_{i,\mathrm{mkt}}\mathrm{d}(x'p) \approx C_{\rho,i}\mathrm{d}\log\rho_{n(i)} + C_{\gamma,i}\mathrm{d}\log\gamma,$$

where

$$\begin{aligned} C_{\rho,i} &:= -\frac{(\Sigma h)_i}{\rho_{n(i)}}\Gamma_{n(i)}^2 \\ C_{\gamma,i} &:= \frac{(\Sigma h)_i}{\gamma} \frac{\sum_{j=1}^A x_j (\Sigma x)_j [\Gamma_{n(j)}^2 - \Gamma_{n(i)}^2]}{x'\Sigma x + \big(\sum_{j=1}^A x_j (\Sigma h)_j \Gamma_{n(j)}^2\big)^2\gamma^{-2}\nu_\gamma}. \end{aligned}$$

Before proving Proposition 1, we make the following useful observations. First, the residuals ϵ_i are completely explained (up to the approximation) by two factors: shocks to (local) hedger and intermediary risk aversions. Second, clearly both $C_{\rho,i}$ and $C_{\gamma,i}$ scale with $(\Sigma h)_i$ within asset class $n(i)$. Third, using Assumption 1 that assets in the same class are positively correlated, we obtain $C_{\rho,i} < 0$; we also obtain $C_{\gamma,i} < 0$ if $\Gamma_{n(i)}$ is high relative to enough of the other $\Gamma_{n(j)}$. This condition is equivalent to saying $\frac{\partial \Gamma_{n(i)}}{\partial\gamma}$ is high relative to other $\frac{\partial \Gamma_{n(j)}}{\partial\gamma}$ (this is the mathematical assumption stated in part (ii) of the proposition; and it is clear that the weights given in the proposition appear in this formula).

Proof of Proposition 1. Recall inventory ξ and distress λ are defined in the model by

$$\begin{aligned} (\textit{Inventory}) \quad & \xi := \log(\theta_I \cdot \mathbf{1}_{\mathcal{A}_{\text{bond}}}) \\ (\textit{Distress}) \quad & \lambda := \log(\theta_I \cdot \mathbf{1}/w). \end{aligned}$$

Using (15) and the approximate pricing formula (19), we may calculate

$$\theta_I \approx \gamma^{-1}\Sigma^{-1}\text{diag}[(\Gamma_{n(a)})_{a=1}^A]\Sigma h.$$

Thus,

$$\xi \approx \log\Big[h'\Sigma\text{diag}[(\frac{\Gamma_{n(a)}}{\gamma})_{a=1}^A]\Sigma^{-1}\mathbf{1}_{\mathcal{A}_{\text{bond}}}\Big] \tag{21}$$

$$\lambda \approx \log\Big[h'\Sigma\text{diag}[(\frac{\Gamma_{n(a)}}{\gamma})_{a=1}^A]\Sigma^{-1}\mathbf{1}\Big] - \log(w) \tag{22}$$

The shocks in Proposition 1 are (s, w), where $s := \log(\rho_{\text{bonds}})$ represents the bond supply shock and w is aggregate intermediary wealth. For some extensions, we will want to study a variable z which measures the degree of regulatory tightness (see Appendix B.4 for implications of regulatory shocks), so we allow this more general possibility in the following computation of regression slopes on our factors. In particular, we allow intermediary risk aversion $\gamma = \gamma(w, z)$ to be a function of wealth w and the regulatory tightness z; γ is decreasing in w and increasing in z.

First, by differentiating ξ and λ and then inverting the expressions, we obtain expressions for the shocks in terms of our empirical proxies:

$$\begin{aligned} \text{d}s &= \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\frac{\text{d}\xi}{\partial\xi/\partial s} - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\text{d}\lambda}{\partial\lambda/\partial w} - \Big(\frac{\partial\xi/\partial z}{\partial\xi/\partial s} - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w}\Big)\text{d}z\Big] \\ \text{d}w &= \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\frac{\text{d}\lambda}{\partial\lambda/\partial w} - \frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\frac{\text{d}\xi}{\partial\xi/\partial s} - \Big(\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w} - \frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\frac{\partial\xi/\partial z}{\partial\xi/\partial s}\Big)\text{d}z\Big] \end{aligned}$$

Using the results above, and the fact that $\epsilon := \text{d}p - \text{d}(x'p) = C_s\text{d}s + C_w\text{d}w + C_z\text{d}z$ for some $A \times 1$ vectors C_s, C_w, C_z, we obtain a regression-like equation

$$\begin{aligned} \epsilon &= \beta_\xi\text{d}\xi + \beta_\lambda\text{d}\lambda + \beta_z\text{d}z \\ \beta_\xi &:= \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\frac{C_s}{\partial\xi/\partial s} - \frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\frac{C_w}{\partial\xi/\partial s}\Big] \\ \beta_\lambda &:= \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\frac{C_w}{\partial\lambda/\partial w} - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{C_s}{\partial\lambda/\partial w}\Big] \\ \beta_z &:= C_z - \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\Big(\frac{\partial\xi/\partial z}{\partial\xi/\partial s} - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w}\Big)C_s + \Big(\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w} - \frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\frac{\partial\xi/\partial z}{\partial\xi/\partial s}\Big)C_w\Big] \end{aligned}$$

For the purposes of Proposition 1, we simply set $\text{d}z = 0$ in the formula above. This proves part (i) of Proposition 1, as long as ϵ is generically non-zero, which will follow from the subsequent analysis.

Next, let us investigate the properties of β_ξ and β_λ. For bonds, we have that $C_{s,i} = C_{\rho,i} < 0$, because $s = \log(\rho_{\text{bonds}})$. Also, since $\gamma = \gamma(w, z)$ is a function of (w, z), we have $C_{w,i}\text{d}w + C_{z,i}\text{d}z = C_{\gamma,i}\text{d}\log\gamma = C_{\gamma,i}[\frac{\partial\log\gamma}{\partial w}\text{d}w + \frac{\partial\log\gamma}{\partial z}\text{d}z]$. This identifies $C_{w,i} = C_{\gamma,i}\frac{\partial\log\gamma}{\partial w}$ and $C_{z,i} = C_{\gamma,i}\frac{\partial\log\gamma}{\partial z}$. Using the assumption that $\frac{\partial\log\gamma}{\partial w} < 0$ and the previously derived fact that $C_{\gamma,i} < 0$ for bonds, we have $C_{w,i} > 0$ for bonds. Thus, bonds have $C_{s,i} < 0$ and $C_{w,i} > 0$; furthermore, both of these coefficients scale with $(\Sigma h)_i$ within an asset class.

Under the stated assumptions $\partial\xi/\partial s > 0$ and $\partial\lambda/\partial w < 0$, we then immediately see that $\beta_\xi < 0$ and $\beta_\lambda < 0$, as long as $\frac{\partial\lambda/\partial s}{|\partial\lambda/\partial w|}$ and $-\frac{\partial\xi/\partial w}{\partial\xi/\partial s}$ are small enough. This proves part (ii). Part (iii) is a direct consequence of the scaling properties of $C_{s,i}$ and $C_{w,i}$. □

B.3 Generalized Model with Partial Segmentation

Here, we consider a model with only *partial asset class segmentation*, which is more general than the baseline. The primary goal is to show that all of our results go through in this more realistic setting. The secondary objective is to formalize the natural idea that "more segmentation" implies "smaller spillover effects" (i.e., a more nuanced version of Prediction 2).

In particular, suppose there are N hedgers, indexed by $i = 1, \dots, N$. Each hedger has risk aversion $\hat{\rho}_i$, with these risk aversions subject to shocks (to be described later). Hedger i can trade assets in set $\hat{\mathcal{A}}_i$, which is a strict subset of all assets $\{1, \dots, A\}$. The novelty here is that these trading sets can overlap with one another (they were disjoint in the baseline model). By contrast, we continue. denote asset classes by $\mathcal{A}_1, \dots, \mathcal{A}_N$, where classes these form a partition of all assets.[5] The only assumption we make is that each hedger's trading set is a collection of asset classes (e.g., their trading sets do not cut asset classes in half). To formalize this, put

$$\hat{\mathcal{A}}_i := \bigcup_{n \in \mathcal{N}_i} \mathcal{A}_n, \quad \forall i, \tag{23}$$

where $\mathcal{N}_i$ is a subset of $\{1, \dots, N\}$ such that $\mathcal{N}_i \neq \mathcal{N}_j$ for all $i \neq j$ (different hedgers trade different assets classes) and such that $\cup_{i=1}^N \mathcal{N}_i = \{1, \dots, N\}$ (all asset classes are traded by someone).

As in the baseline model, we assume hedgers receive an endowment whose risks coincide with their trading set. This assumption is only for ease of notation in what follows, but it is also sensible given a hedger would want to pick their trading set to hedge their endowment risks. Mathematically, hedger i receives endowment $\hat{h}_i'\delta$, where $\hat{h}_i'(\mathbf{1} - \mathbf{1}_{\hat{\mathcal{A}}_i}) = 0$ (endowment can be replicated by the hedger's trading set) and $\sum_{i=1}^N \hat{h}_i = h$ (definition of aggregate endowment vector).

Hedger i chooses a portfolio vector $\hat{\theta}_i^H$ to solve a similar optimization problem as in the baseline model: i.e., in problem (4), replace $\mathcal{A}_i$, ρ_i, h_a, and θ_a^H by $\hat{\mathcal{A}}_i$, $\hat{\rho}_i$, $\hat{h}_{i,a}$, and $\hat{\theta}_{i,a}^H$, respectively. Hedgers are subject to the constraint that $\hat{\theta}_{i,a}^H = 0$ for all $a \notin \hat{\mathcal{A}}_i$. Intermediaries continue to choose portfolio vector θ^I to solve (5). Asset markets are still in zero net supply, so market clearing conditions now read

$$\theta_a^I + \sum_i \hat{\theta}_{i,a}^H, \quad \forall a.$$

The hedger FOCs say

$$\bar{\delta}_a - p_a = \hat{\rho}_i \Sigma_a (\hat{h}_i + \hat{\theta}_i^H), \quad \text{for assets } a \in \hat{\mathcal{A}}_i, \tag{24}$$

where Σ_a is the ath row of Σ. The intermediary FOCs are still given by (15).

To rewrite (24) in a more convenient way, we need some additional notation. Define the $A \times |\hat{\mathcal{A}}_i|$ "selection matrix" $\hat{U}_i$ whose columns are the non-zero columns of the diagonal matrix $\text{diag}(\mathbf{1}_{\hat{\mathcal{A}}_i})$. In other words, if we look at the submatrix of $\hat{U}_i$ consisting only of rows corresponding to indexes in $\hat{\mathcal{A}}_i$, we see the identity matrix $\mathbb{I}_{|\hat{\mathcal{A}}_i|}$. Premultiplying by $\hat{U}_i'$ selects from a vector the rows corresponding to $\hat{\mathcal{A}}_i$ and then shortens the result by truncating entries with zeros (whereas premultiplying by $\hat{U}_i'$ elongates vectors by surrounding existing entries with zeros corresponding to the complement of $\hat{\mathcal{A}}_i$).

[5] For all results below, it is inconsequential that the number of asset classes equals the number of investors.

Then, FOC (24) is equivalent to

$$\hat{U}_i'(\bar{\delta} - p) = \hat{\rho}_i \hat{U}_i' \Sigma \hat{U}_i (\hat{U}_i' \hat{h}_i + \hat{U}_i' \hat{\theta}_i^H).$$

The usefulness of this expression is that $\hat{U}_i' \Sigma \hat{U}_i$ is an invertible matrix (it is the submatrix of covariances corresponding to assets only in $\hat{\mathcal{A}}_i$). Thus, we have

$$\hat{\rho}_i^{-1} (\hat{U}_i' \Sigma \hat{U}_i)^{-1} \hat{U}_i' (\bar{\delta} - p) = \hat{U}_i' (\hat{h}_i + \hat{\theta}_i^H). \tag{25}$$

We now apply market clearing. To do so, recall that $\hat{h}_i$ and $\hat{\theta}_i^H$ have zeros in the entries outside of trading set $\hat{\mathcal{A}}_i$. Since $\hat{U}_i \hat{U}_i' = \text{diag}(\mathbf{1}_{\hat{\mathcal{A}}_i})$, this implies $\hat{U}_i \hat{U}_i' \hat{h}_i = \hat{h}_i$ and $\hat{U}_i \hat{U}_i' \hat{\theta}_i^H = \hat{\theta}_i^H$. Premultiplying expression (25) by $\hat{U}_i$, using the aforementioned results, using market clearing and expression (15) for the intermediary portfolio, and doing some algebra, we obtain the equilibrium expression

$$p = \bar{\delta} - \hat{\Gamma} \Sigma h, \tag{26}$$

$$\text{where} \quad \hat{\Gamma} := \Big[\gamma^{-1} \mathbb{I}_A + \sum_{i=1}^N \hat{\rho}_i^{-1} \Sigma \hat{U}_i (\hat{U}_i' \Sigma \hat{U}_i)^{-1} \hat{U}_i' \Big]^{-1}.$$

Expression (26) is very similar to the complete-segmentation expression (19), but with a modified risk aversion factor.

To make the analogy extremely precise, we proceed with the weak-correlation Assumption 1 and perform several steps of matrix algebra. We will need the selection matrix U_n, which by analogy to $\hat{U}_i$, is the $A \times |\mathcal{A}_n|$ matrix whose columns are the non-zero columns of the diagonal matrix $\text{diag}(\mathbf{1}_{\mathcal{A}_n})$. Under Assumption 1, Σ is approximately block-diagonal, so we can write it as $\Sigma \approx \sum_{n=1}^N U_n U_n' \Sigma U_n U_n'$. Therefore,

$$\hat{U}_i' \Sigma \hat{U}_i \approx \hat{U}_i \Big(\sum_{n=1}^N U_n U_n' \Sigma U_n U_n' \Big) \hat{U}_i = \hat{U}_i \Big(\sum_{n \in \mathcal{N}_i} U_n U_n' \Sigma U_n U_n' \Big) \hat{U}_i.$$

The second equality is due to the fact that $\hat{U}_i' U_n U_n' \Sigma U_n U_n' \hat{U}_i = 0$ for $n \notin \mathcal{N}_i$. Furthermore, due to the block-diagonal nature of $U_n U_n' \Sigma U_n U_n'$, we can take the inverse of each block separately, so we have

$$(\hat{U}_i' \Sigma \hat{U}_i)^{-1} \approx \hat{U}_i' \Big(\sum_{n \in \mathcal{N}_i} U_n (U_n' \Sigma U_n)^{-1} U_n' \Big) \hat{U}_i.$$

Again using the approximate block-diagonal nature of Σ, we have

$$\Sigma \hat{U}_i \hat{U}_i' \approx \sum_{n \in \mathcal{N}_i} U_n U_n' \Sigma U_n U_n'.$$

Consequently, we have

$$\begin{aligned}\Sigma\hat{U}_i(\hat{U}_i'\Sigma\hat{U}_i)^{-1}\hat{U}_i' &= \Big(\sum_{n\in\mathcal{N}_i} U_nU_n'\Sigma U_nU_n'\Big)\Big(\sum_{n\in\mathcal{N}_i} U_n(U_n'\Sigma U_n)^{-1}U_n'\Big)\hat{U}_i\hat{U}_i' \\ &= \sum_{n\in\mathcal{N}_i}\Big(U_nU_n'\Sigma U_nU_n'\Big)\Big(U_n(U_n'\Sigma U_n)^{-1}U_n'\Big)\hat{U}_i\hat{U}_i' \\ &= \sum_{n\in\mathcal{N}_i}\mathrm{diag}(\mathcal{A}_n)\hat{U}_i\hat{U}_i' \\ &= \mathrm{diag}(\hat{\mathcal{A}}_i)\hat{U}_i\hat{U}_i' = \mathrm{diag}(\hat{\mathcal{A}}_i).\end{aligned}$$

The second line above comes from the fact that $(U_nU_n'\Sigma U_nU_n')(U_m(U_m'\Sigma U_m)^{-1}U_m') = 0$ for $n \neq m$, since each of these matrices are full of zeros outside of the positions corresponding to asset classes n and m. The third line recognizes the product of the two matrices in parentheses as block-diagonal whose non-zero blocks are inverses of each other. The fourth line simplifies.

Using these results, we can rewrite $\hat{\Gamma}$ in (26) as

$$\begin{aligned}\hat{\Gamma} &\approx \Big[\gamma^{-1}\mathbb{I}_A + \sum_{i=1}^N \hat{\rho}_i^{-1}\mathrm{diag}(\mathbf{1}_{\hat{\mathcal{A}}_i})\Big]^{-1} = \Big[\gamma^{-1}\mathbb{I}_A + \sum_{i=1}^N \hat{\rho}_i^{-1}\sum_{n\in\mathcal{N}_i}\mathrm{diag}(\mathbf{1}_{\mathcal{A}_n})\Big]^{-1} \\ &= \Big[\gamma^{-1}\mathbb{I}_A + \sum_{n=1}^N\Big(\sum_{\{i:n\in\mathcal{N}_i\}}\hat{\rho}_i^{-1}\Big)\mathrm{diag}(\mathbf{1}_{\mathcal{A}_n})\Big]^{-1}.\end{aligned}$$

The last line switches the order of summation. Define the following statistics

$$\begin{aligned}\rho_n &:= \Big(\sum_{\{i:n\in\mathcal{N}_i\}}\hat{\rho}_i^{-1}\Big)^{-1} \\ \Gamma_n &:= (\gamma^{-1} + \rho_n^{-1})^{-1}.\end{aligned} \tag{27}$$

Note that ρ_n^{-1} is the sum of risk tolerances for investors that participate in asset class n, whereas Γ_n^{-1} is a composite risk tolerance measure that includes intermediaries, defined exactly as in the baseline full-segmentation model. With these statistics, we may write

$$\hat{\Gamma} \approx \sum_{n=1}^N \Gamma_n\mathrm{diag}(\mathbf{1}_{\mathcal{A}_n}).$$

Consequently, the approximate pricing formula, obtained by taking the ath row of (26) with the formula for $\hat{\Gamma}$ above, is

$$p_a \approx \bar{\delta}_a - \Gamma_{n(a)}(\Sigma h)_a.$$

This formula is identical to the full-segmentation model. The only distinction is that Γ_n^{-1} is a composite sum of risk tolerances for all agents participating in asset class n. Thus, the interpretation of $\mathrm{d}\rho_n$ is now as a response to shocks to the risk aversions of hedgers participating in class n.

Because hedgers have overlapping portfolios, the sufficient statistics $(\rho_n)_{n=1}^N$ will feature more positive correlation than underlying risk aversions $(\hat{\rho}_i)_{i=1}^N$. However, in deriving Proposition 1, the only assumption used regarding cross-correlation of the $(\rho_n)_{n=1}^N$ is that they are "redistributive" in the sense that the aggregate market return features zero loading on these shocks. To obtain this redistributive feature, and hence generate all the results of Proposition 1 in this more general model, we simply require that the underlying correlations of $(\hat{\rho}_i)_{i=1}^N$ be appropriately negative on average, such that a particular weighted average of their shocks is approximately zero. This is always possible, and so we have shown that Proposition 1 still holds in this more general model.[6]

As mentioned above, the second objective of this extension is to see how "more segmentation" implies "smaller spillover effects." We think of "more segmentation" as less overlap in the portfolios of hedgers, which in the extreme becomes our full-segmentation baseline model. But based on the discussion above, the amount of overlap directly dictates the amount of correlation in $(\mathrm{d}\rho_n)_{n=1}^N$.[7] Thus, we think of "more segmentation" as equivalent to "less correlation" in $(\mathrm{d}\rho_n)_{n=1}^N$. Immediately, we can see how the statement on spillover effects should be true: if ρ_{bonds} increases, then $\rho_{\text{non-bonds}}$ is less likely to increase as well when segmentation is more pronounced, meaning that non-bond asset prices will be less likely perturbed (recall: under Assumption 1, the only non-fundamental factors affecting asset class n prices are shocks to γ and ρ_n).

B.4 Regulatory Tightening

With regulatory shocks, we must consider $\mathrm{d}z$ terms in Appendix B.2 above. The parameter z 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 z (which then increases intermediary risk aversion γ) 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.

We make the intuitive assumptions that regulatory tightening induces intermediaries to sell assets and deleverage. Mathematically, we assume $\frac{\partial \xi}{\partial z} < 0$ and $\frac{\partial \lambda}{\partial z} < 0$; since $\mathrm{d}z > 0$ increases γ, these conditions will be true under most model parameterizations (see the formulas (21)-(22) for ξ and λ above, and note that an increase in γ reduces Γ_n/γ for all n). Recall that Proposition 1, part (ii), also made the assumptions $\frac{\partial \xi}{\partial s} > 0$ and $\frac{\partial \lambda}{\partial w} < 0$, as well as assuming $\frac{\partial \lambda/\partial s}{|\partial \lambda/\partial w|}$ and $-\frac{\partial \xi/\partial w}{\partial \xi/\partial s}$ are small enough. We maintain these assumptions here.

[6] In particular, one can show that the market portfolio return features the following $\mathrm{d}\hat{\rho}_i$ terms:

$$\mathrm{d}(x'p) \approx \mathrm{d}\gamma \text{ term } + \sum_{i=1}^N \Big(\sum_{a \in \hat{\mathcal{A}}_i} x_a (\Sigma h)_a \Gamma_{n(a)}^2 \Big) \mathrm{d}\hat{\rho}_i^{-1}.$$

So as an example design, let $(\mathrm{d}z_i)_{i=1}^N$ be a sequence of independent shocks, and then put

$$\mathrm{d}\hat{\rho}_i^{-1} := \mathrm{d}z_i - \sum_{j=1}^N \frac{\sum_{a \in \hat{\mathcal{A}}_j} x_a (\Sigma h)_a \Gamma_{n(a)}^2}{\sum_{k=1}^N \sum_{a \in \hat{\mathcal{A}}_k} x_a (\Sigma h)_a \Gamma_{n(a)}^2} \mathrm{d}z_j.$$

One can easily verify that $\mathrm{d}(x'p)$ only loads on $\mathrm{d}\gamma$ and not $(\hat{\rho}_i)_{i=1}^N$, or equivalently not $(\rho_n)_{n=1}^N$.

[7] To see this clearly, consider an example where $(\mathrm{d}\hat{\rho}_i^{-1})_{i=1}^N$ are iid shocks with common variance ν_ρ. Then,

$$\mathrm{corr}[\mathrm{d}\rho_n^{-1}, \mathrm{d}\rho_m^{-1}] = \frac{\sum_{i \in \mathcal{I}_n \cap \mathcal{I}_m} \hat{\rho}_i^{-2}}{(\sum_{j \in \mathcal{I}_n} \hat{\rho}_j^{-2})^{1/2} (\sum_{k \in \mathcal{I}_m} \hat{\rho}_k^{-2})^{1/2}},$$

where $\mathcal{I}_n := \{i : n \in \mathcal{N}_i\}$ denotes the investors in asset class n. With more overlap in $\mathcal{I}_n$ and $\mathcal{I}_m$, the correlation increases.

Revisit the formula for the regression coefficient on z:

$$\beta_z := C_z - \Big(1 - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\Big)^{-1}\Big[\Big(\frac{\partial\xi/\partial z}{\partial\xi/\partial s} - \frac{\partial\xi/\partial w}{\partial\xi/\partial s}\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w}\Big)C_s + \Big(\frac{\partial\lambda/\partial z}{\partial\lambda/\partial w} - \frac{\partial\lambda/\partial s}{\partial\lambda/\partial w}\frac{\partial\xi/\partial z}{\partial\xi/\partial s}\Big)C_w\Big]$$

Recall that $C_{z,i} = C_{\gamma,i}\frac{\partial \log\gamma}{\partial z}$. Since $C_{\gamma,i} < 0$ for bonds and since $\frac{\partial \log\gamma}{\partial z} > 0$, we have $C_{z,i} < 0$. Also recall that $C_{w,i} > 0$ and $C_{s,i} < 0$. Using these facts, as well as all of the sign and magnitude assumptions from the previous paragraph, we obtain $\beta_z < 0$, consistent with the results of Table A.13. Furthermore, given $\frac{\partial\xi}{\partial z} < 0$ and $\frac{\partial\lambda}{\partial z} < 0$, standard formulas for omitted variable bias imply our estimates of $(\beta_\xi, \beta_\lambda)$ from Section 1.3 will be biased toward zero, and possibly with the wrong sign if the regulatory tightening is the dominant shock in some period of time (i.e., we could obtain $\beta_\xi > 0$ and $\beta_\lambda > 0$ if $\mathrm{d}z$ is the dominant shock, relative to $\mathrm{d}s$ and $\mathrm{d}w$). This explains why we obtain larger magnitude estimates in Table 10 (IV regressions) than in Table 4 (OLS regressions with z omitted).

B.5 Intermediary-Based Segmentation

As mentioned in footnote 25, the presence of segmentation in both hedger and intermediation sectors would generate similar results without the need for Assumption 1 that fundamentals are weakly correlated across asset classes.

We formalize intermediary segmentation as follows. Let w_n denote the initial intermediary wealth in asset class $\mathcal{A}_n$ (the asset class divisions are the same as those across which hedgers are segmented). The representative intermediary in segment n solves

$$\max_{\theta_I} \mathbb{E}[W_{I,n}] - \frac{\gamma(w_n)}{2}\mathrm{Var}[W_{I,n}] \quad \text{where} \quad W_{I,n} := w_n + \sum_{a\in\mathcal{A}_n}\theta_{I,a}(\delta_a - p_a).$$

All intermediaries have the same risk aversion *function* $\gamma(\cdot)$, but because of heterogeneity in their wealths, there is cross-sectional heterogeneity in intermediary risk aversion. The optimal intermediary portfolio is given by

$$\theta_I = \Sigma_\gamma^{-1}(\bar{\delta} - p), \tag{28}$$

where $\Sigma_\gamma := \sum_{n=1}^N \gamma_n\tilde{\Sigma}_n$, and recalling that $\tilde{\Sigma}_n$ is the $A \times A$ quasi-covariance matrix pertaining only to assets in $\mathcal{A}_n$.

Combining (28) with (18) and market clearing (6), we obtain

$$p = \bar{\delta} - (\Sigma_\gamma^{-1} + \Sigma_\rho^{-1})^{-1}h. \tag{29}$$

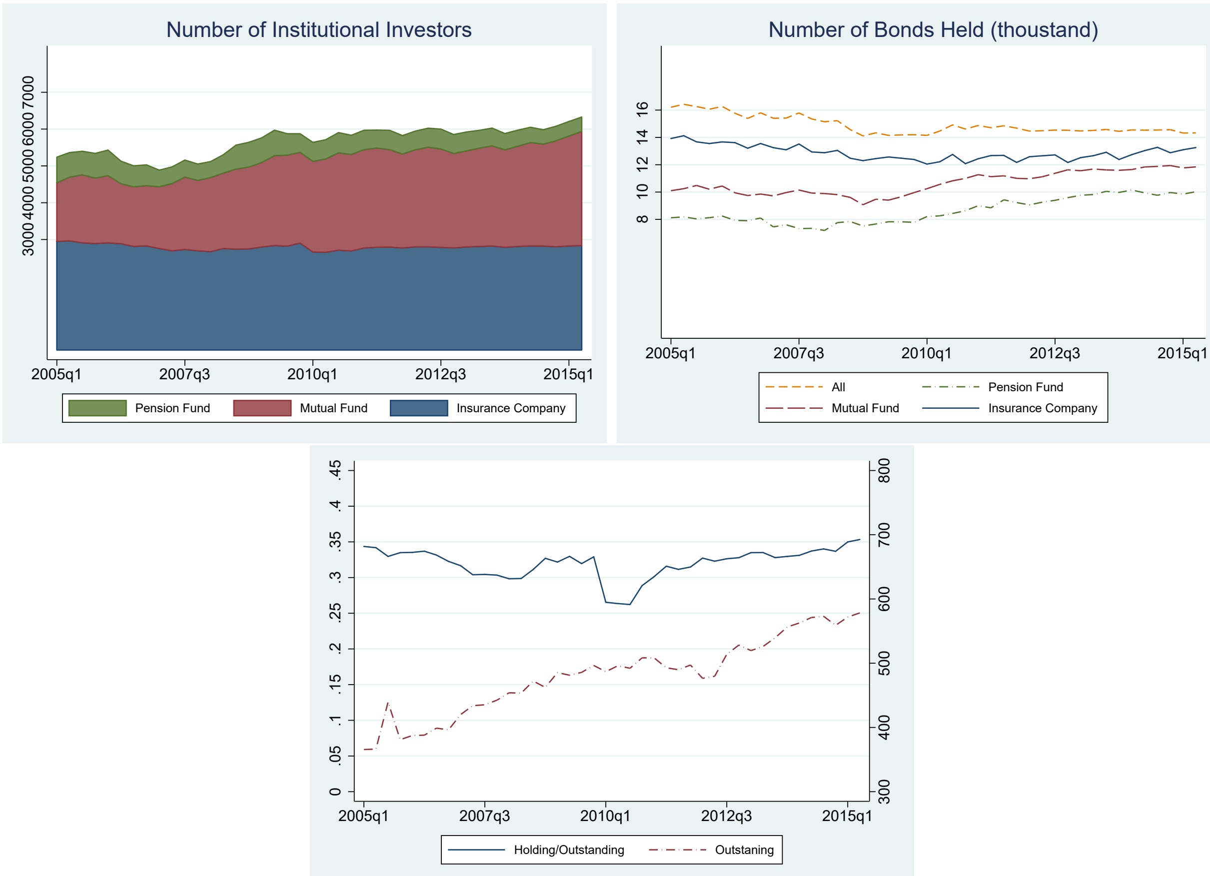
Under the labeling convention that assets in the same class are numbered consecutively, both Σ_γ and Σ_ρ are block-diagonal matrices with a common structure. This allows us to write

$$p_a = \bar{\delta}_a - \Gamma_{n(a)}(\tilde{\Sigma}h)_a, \tag{30}$$

where $\Gamma_n := (\gamma_n^{-1} + \rho_n^{-1})^{-1}$ and $\tilde{\Sigma} := \sum_{n=1}^N \tilde{\Sigma}_n$. Formula (30) is exactly equal to (20), so all the baseline analysis goes through even without Assumption 1.[8]

[8] Note that we would need to continue to consider a shock to aggregate intermediary wealth $w := w_1 + \ldots w_N$. To recover identical results as the baseline model, we would assume that this shock is segment agnostic in the sense that $\mathrm{d}\log w_n = \mathrm{d}\log w$ for all n.

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 A8)	# 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 A8)	# 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. The resulting 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). 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:Q1–2015: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				
FN30y	42	0.158	0.212	-0.045	0.150	0.344
FN15y	42	0.161	0.237	-0.037	0.100	0.317
FG30y	42	0.188	0.227	-0.028	0.176	0.353
FG15y	42	0.223	0.229	0.044	0.175	0.356
		B: Non-agency CMBS				
Duper	39	1.536	1.686	0.730	0.990	1.850
AM	39	2.964	4.026	0.630	1.330	3.410
AJ	39	4.390	6.082	1.210	2.100	4.500
		C: ABS				
Credit Card Loan 5y	40	0.791	0.679	0.470	0.540	0.635
Auto Loan 3y: AAA	37	0.506	0.672	0.190	0.270	0.360
Auto Loan 3y: A	36	1.214	1.366	0.565	0.740	1.225
Auto Loan: 3y BBB	34	1.547	1.367	1.000	1.210	1.750
		D: S&P 500 index options				
Call: 0.90	85	0.088	4.410	-2.043	0.509	2.284
Call: 0.95	85	0.017	4.300	-1.841	0.301	2.048
Call: ATM	85	-0.115	4.136	-1.751	0.036	1.646
Call: 1.05	85	-0.265	3.936	-1.775	-0.139	1.707
Call: 1.10	85	-0.487	3.643	-1.776	-0.353	0.815
Put: 0.90	85	-0.888	7.787	-4.555	-1.948	1.626
Put: 0.95	85	-0.741	6.949	-3.962	-1.576	1.369
Put: ATM	85	-0.537	6.283	-3.340	-1.123	1.779
Put: 1.05	85	-0.382	5.715	-2.999	-0.859	1.678
Put: 1.10	85	-0.318	5.375	-2.825	-0.936	1.703

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 in panels A, B, and C, respectively, as well as summary statistics of monthly series of one-month (unannualized) return of leverage-adjusted S&P 500 index option portfolios. All series are in percent. 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 through January 2012 for options.

Table A.5: Quarterly Series by Leverage Cohort

Groups		A: Sample		B: PC		C: Regressions of Residuals			
Maturity	Leverage	Bond #	Obs	First	Second	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}	FVE
Short	<15%	295	3430	0.094	-0.008	0.052*	0.077***	0.299	0.299
						(1.793)	(2.747)		
Short	15-25%	476	5707	0.131	0.008	0.059	0.096***	0.202	
						(1.305)	(2.797)		
Short	25-35%	414	4686	0.175	-0.043	0.113**	0.125**	0.279	
						(2.321)	(2.540)		
Short	35-45%	212	2110	0.259	-0.047	0.159**	0.215***	0.312	
						(2.302)	(3.013)		
Short	>45%	249	2345	0.424	-0.158	0.279***	0.316**	0.303	
						(2.673)	(2.386)		
Medium	<15%	276	2684	0.113	-0.016	0.080***	0.097***	0.376	0.548
						(2.849)	(2.807)		
Medium	15-25%	453	4053	0.202	0.037	0.131**	0.221***	0.557	
						(2.542)	(4.117)		
Medium	25-35%	436	3917	0.217	0.015	0.140***	0.228***	0.528	
						(3.251)	(4.028)		
Medium	35-45%	255	2331	0.267	0.058	0.208***	0.269***	0.465	
						(3.439)	(4.865)		
Medium	>45%	263	2268	0.433	-0.067	0.330***	0.492***	0.595	
						(4.615)	(3.594)		
Long	<15%	361	5050	0.081	0.006	0.041**	0.073**	0.336	0.324
						(2.100)	(2.089)		
Long	15-25%	506	7049	0.073	0.979	-0.120	0.159***	0.126	
						(-1.221)	(4.302)		
Long	25-35%	418	6029	0.132	0.036	0.080**	0.126***	0.382	
						(2.561)	(2.961)		
Long	35-45%	174	1883	0.198	0.058	0.163***	0.220***	0.536	
						(4.182)	(6.146)		
Long	>45%	166	1789	0.518	-0.045	0.282**	0.475**	0.392	
						(2.108)	(2.167)		
Pct Explained				0.751	0.124				0.388

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 $\Delta Inventory$ (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.6: Excluding the 2008 Crisis

Groups		A: PC		B: Regression of Residuals			
Maturity	Rating	First	Second	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	0.062	-0.019	0.023	0.057***	0.158	0.228
				(0.862)	(2.798)		
Short	A	0.079	-0.026	0.033	0.067***	0.168	
				(1.464)	(2.706)		
Short	BBB	0.125	-0.022	0.054*	0.120***	0.235	
				(1.755)	(2.647)		
Short	BB	0.154	-0.136	0.080	0.079	0.081	
				(1.563)	(0.819)		
Short	B	0.459	-0.394	0.294***	0.364	0.237	
				(2.899)	(1.642)		
Medium	AA	0.050	-0.061	0.012	0.054***	0.122	0.554
				(0.680)	(3.260)		
Medium	A	0.100	-0.020	0.061**	0.132***	0.413	
				(2.087)	(5.117)		
Medium	BBB	0.159	-0.023	0.092**	0.196***	0.424	
				(2.397)	(3.925)		
Medium	BB	0.172	0.099	0.128***	0.228***	0.467	
				(3.310)	(4.081)		
Medium	B	0.443	0.041	0.313***	0.313***	0.606	
				(3.875)	(3.875)		
Long	AA	0.055	0.006	0.018	0.072***	0.307	0.481
				(1.578)	(4.395)		
Long	A	0.077	-0.009	0.035*	0.097***	0.359	
				(1.691)	(3.766)		
Long	BBB	0.069	0.880	-0.106	0.207***	0.165	
				(-1.374)	(4.341)		
Long	BB	0.181	0.102	0.109***	0.219***	0.330	
				(3.360)	(3.438)		
Long	B	0.656	0.156	0.336***	0.938***	0.566	
				(3.010)	(3.912)		
Pct Explained		0.798	0.082				0.430

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 $\Delta Inventory$ and $\Delta Distress$, with robust t-statistics based on Newey and West (1987) standard errors using the optimal bandwidth choice in Andrews (1991) reported in parentheses. Significance levels are represented by * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$ with p as the p-value. The last column of panel B reports the fraction of the total variation of residuals that is accounted for by the two intermediary factors, denoted as FVE and computed as in (3) for short, medium, and long term bonds, as well as all bonds.

Table A.7: Regressions of Credit Spread Changes Residuals on Liquidity Factor

Groups		A: ΔILiq		B: Δ*Inventory*+Δ*Distress*+ΔILiq			
Maturity	Rating	ΔILiq	R^2_{adj}	Δ*Inventory*	Δ*Distress*	ΔILiq	R^2_{adj}
Short	AA	0.042***	0.131	0.038	0.033***	0.037***	0.256
		(2.981)		(1.627)	(2.593)	(6.381)	
Short	A	0.026	0.034	0.048*	0.058***	0.016**	0.231
		(1.061)		(1.944)	(2.908)	(2.228)	
Short	BBB	0.038	0.034	0.065*	0.105***	0.018	0.304
		(0.828)		(1.915)	(3.446)	(1.596)	
Short	BB	0.032	0.006	0.145	0.176***	0.002	0.225
		(0.708)		(1.538)	(3.039)	(0.073)	
Short	B	0.042	0.003	0.339***	0.332**	-0.010	0.299
		(0.243)		(2.981)	(2.531)	(-0.164)	
Medium	AA	0.034***	0.070	0.035**	0.044***	0.026***	0.208
		(2.784)		(1.987)	(4.186)	(3.156)	
Medium	A	0.048	0.080	0.074***	0.085***	0.033***	0.391
		(1.230)		(2.692)	(3.469)	(2.777)	
Medium	BBB	0.045	0.034	0.106***	0.141***	0.020	0.414
		(0.653)		(2.930)	(3.447)	(0.950)	
Medium	BB	0.027	0.004	0.198***	0.266***	-0.020	0.467
		(0.377)		(2.871)	(4.812)	(-0.598)	
Medium	B	0.101	0.022	0.339***	0.495***	0.010	0.594
		(0.444)		(5.092)	(4.698)	(0.160)	
Long	AA	0.042**	0.168	0.026**	0.031**	0.037***	0.279
		(2.321)		(2.199)	(2.248)	(5.024)	
Long	A	0.049	0.130	0.044**	0.057***	0.038***	0.337
		(1.632)		(2.036)	(2.585)	(3.334)	
Long	BBB	0.065	0.023	-0.068	0.141***	0.025	0.161
		(1.321)		(-0.919)	(4.794)	(1.335)	
Long	BB	-0.002	0.000	0.170***	0.262***	-0.051*	0.431
		(-0.030)		(2.688)	(4.960)	(-1.737)	
Long	B	0.214	0.045	0.426***	0.680***	0.086	0.520
		(0.643)		(2.857)	(3.126)	(0.870)	
FVE			0.029				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 ΔILiq in univariate regressions (in panel A) and in multivariate regressions along with Δ*Inventory* and Δ*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.8: Measures of Intermediary Distress

Groups		A: $\Delta Noise$		B: ΔNLev$^{\text{HKM}}$	
Maturity	Rating	$\Delta Noise$	R^2_{adj}	ΔNLev$^{\text{HKM}}$	R^2_{adj}
Short	AA	0.045**	0.149	0.015	0.016
		(2.226)		(0.955)	
Short	A	0.071**	0.245	0.020	0.020
		(2.345)		(1.341)	
Short	BBB	0.112***	0.291	0.054*	0.069
		(3.116)		(1.880)	
Short	BB	0.255***	0.381	0.001	0.000
		(2.804)		(0.020)	
Short	B	0.307**	0.180	0.150	0.043
		(2.161)		(1.075)	
Medium	AA	0.060***	0.215	0.015*	0.014
		(2.759)		(1.831)	
Medium	A	0.077**	0.206	0.058**	0.119
		(2.289)		(2.493)	
Medium	BBB	0.118**	0.235	0.096**	0.156
		(2.566)		(2.427)	
Medium	BB	0.292***	0.493	0.090	0.047
		(3.211)		(1.546)	
Medium	B	0.381***	0.312	0.359***	0.278
		(3.417)		(3.288)	
Long	AA	0.040**	0.154	0.019	0.035
		(2.100)		(0.954)	
Long	A	0.064**	0.226	0.035	0.069
		(2.032)		(1.642)	
Long	BBB	0.159***	0.141	0.106***	0.063
		(3.481)		(6.061)	
Long	BB	0.278***	0.458	0.092	0.051
		(3.523)		(1.452)	
Long	B	0.609***	0.365	0.447**	0.196
		(2.656)		(2.497)	
FVE			0.315		0.139

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

Table A.9: AEM Leverage Measure and TED Spread

Groups		A: AEM Leverage Measure				B: TED spread			
Maturity	Rating	$\Delta Inventory$	$\Delta Distress$	ΔNLev^{AEM}	R^2_{adj}	$\Delta Inventory$	$\Delta Distress$	ΔTED	R^2_{adj}
Short	AA	0.034	0.043**	0.009	0.165	0.036	0.049***	0.040***	0.276
		(1.387)	(2.328)	(0.465)		(1.633)	(4.146)	(5.458)	
Short	A	0.047*	0.062**	-0.003	0.220	0.047**	0.067***	0.029**	0.259
		(1.906)	(2.301)	(-0.142)		(2.096)	(3.735)	(2.305)	
Short	BBB	0.064*	0.107**	-0.013	0.301	0.065**	0.116***	0.037*	0.329
		(1.916)	(2.465)	(-0.499)		(2.078)	(3.981)	(1.833)	
Short	BB	0.144*	0.173***	-0.019	0.227	0.144	0.185***	0.045	0.236
		(1.656)	(2.745)	(-0.561)		(1.627)	(3.289)	(1.224)	
Short	B	0.336***	0.330**	0.003	0.299	0.337***	0.338**	0.044	0.302
		(3.134)	(2.152)	(0.034)		(3.115)	(2.327)	(0.505)	
Medium	AA	0.032*	0.053***	0.014	0.179	0.034**	0.057***	0.037***	0.249
		(1.734)	(4.384)	(1.257)		(2.031)	(5.487)	(4.897)	
Medium	A	0.071**	0.094***	0.005	0.355	0.072***	0.102***	0.050***	0.438
		(2.553)	(2.856)	(0.211)		(2.881)	(4.684)	(3.638)	
Medium	BBB	0.103***	0.147***	0.009	0.409	0.105***	0.153***	0.043*	0.438
		(2.907)	(2.939)	(0.269)		(3.125)	(3.783)	(1.682)	
Medium	BB	0.199***	0.257***	-0.021	0.468	0.199***	0.271***	0.055*	0.482
		(2.915)	(4.123)	(-0.414)		(3.116)	(5.466)	(1.808)	
Medium	B	0.333***	0.500***	0.015	0.595	0.336***	0.508***	0.056	0.601
		(5.417)	(3.979)	(0.156)		(5.410)	(4.480)	(0.863)	
Long	AA	0.022	0.043***	0.019	0.189	0.025*	0.048***	0.047***	0.358
		(1.543)	(2.652)	(1.142)		(1.949)	(4.642)	(5.436)	
Long	A	0.040*	0.067**	0.006	0.263	0.042**	0.076***	0.051***	0.398
		(1.820)	(2.063)	(0.266)		(2.227)	(3.775)	(4.492)	
Long	BBB	-0.068	0.146***	-0.005	0.158	-0.067	0.158***	0.064**	0.180
		(-0.927)	(4.298)	(-0.144)		(-0.953)	(4.646)	(2.010)	
Long	BB	0.176***	0.237***	-0.065	0.439	0.172***	0.252***	0.015	0.417
		(2.787)	(3.341)	(-1.281)		(2.727)	(4.918)	(0.449)	
Long	B	0.411***	0.713***	0.065	0.517	0.421***	0.735***	0.193	0.548
		(3.101)	(2.849)	(0.436)		(3.255)	(3.362)	(1.468)	
FVE					0.429				0.448

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 $\Delta \text{NLev}^{\text{AEM}}$ (panel A) and the TED spread ΔTED (panel B), together with $\Delta Inventory$ 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.10: Monthly Series by Rating Group

Groups		A: Sample		B: PC		C: Regression of Residuals			
Maturity	Rating	Bond #	Obs	First	Second	$\Delta Inventory$	$\Delta Distress$	R^2_{adj}	FVE
Short	AA	87	2611	0.058	0.117	0.016*	0.013	0.040	0.146
						(1.671)	(0.834)		
Short	A	525	15871	0.086	0.141	0.009	0.035**	0.103	
						(0.865)	(2.341)		
Short	BBB	881	25114	0.142	0.163	0.006	0.049**	0.105	
						(0.563)	(2.185)		
Short	BB	401	7835	0.279	0.261	0.044*	0.115***	0.161	
						(1.782)	(3.102)		
Short	B	485	10061	0.466	0.020	0.059*	0.160***	0.150	
						(1.707)	(4.161)		
Medium	AA	73	1680	0.057	0.109	0.013*	0.020**	0.069	0.104
						(1.862)	(2.211)		
Medium	A	448	9885	0.084	0.164	0.015**	0.013	0.034	
						(2.214)	(0.818)		
Medium	BBB	880	18088	0.142	0.224	0.022**	0.042**	0.086	
						(2.110)	(2.029)		
Medium	BB	491	8989	0.271	0.260	0.054**	0.113***	0.203	
						(2.169)	(3.446)		
Medium	B	593	13111	0.405	0.210	0.032	0.094***	0.064	
						(0.856)	(2.713)		
Long	AA	119	4495	0.053	0.107	0.016***	0.009	0.050	0.189
						(2.815)	(0.922)		
Long	A	638	24132	0.076	0.128	0.014**	0.023*	0.084	
						(2.238)	(1.669)		
Long	BBB	1049	33504	0.104	0.225	0.015	0.028*	0.024	
						(1.421)	(1.842)		
Long	BB	352	6768	0.226	0.238	0.028	0.062***	0.080	
						(1.182)	(2.885)		
Long	B	277	5715	0.580	-0.732	0.109*	0.243***	0.237	
						(1.830)	(2.620)		
Pct Explained				0.752	0.086				0.152

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 $\Delta Inventory$ 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.11: Credit Default Swaps

Groups		A: Sample		B: PC		C: Regression of Residuals			
Maturity	Rating	Firm #	Obs	First	Second	$\Delta Inventory^A$	$\Delta Distress$	R^2_{adj}	FVE
1y	AA	20	939	0.039	-0.029	0.019	0.029*	0.127	0.291
						(1.438)	(1.943)		
1y	A	111	5742	0.041	0.042	0.044***	0.042***	0.502	
						(5.205)	(5.957)		
1y	BBB	200	7942	0.067	0.062	0.059***	0.057***	0.394	
						(4.099)	(3.503)		
1y	BB	128	2309	0.149	0.151	0.125***	0.144***	0.364	
						(3.819)	(4.381)		
1y	B	64	1377	0.651	0.686	0.284***	0.455*	0.283	
						(2.827)	(1.732)		
5y	AA	21	1140	0.031	-0.010	0.023***	0.026***	0.215	0.304
						(3.091)	(2.751)		
5y	A	112	5688	0.043	0.035	0.053***	0.045***	0.487	
						(3.646)	(6.916)		
5y	BBB	208	7995	0.067	0.003	0.078***	0.069***	0.468	
						(3.619)	(3.734)		
5y	BB	132	2377	0.127	0.072	0.055	0.114***	0.176	
						(1.376)	(3.939)		
5y	B	71	1601	0.583	-0.643	0.308***	0.422**	0.313	
						(3.085)	(2.128)		
10y	AA	20	1117	0.023	-0.018	0.020**	0.012	0.094	0.369
						(2.573)	(1.553)		
10y	A	111	5611	0.036	0.035	0.047***	0.042***	0.436	
						(2.983)	(7.023)		
10y	BBB	198	8071	0.055	-0.001	0.057**	0.060***	0.410	
						(2.443)	(4.704)		
10y	BB	127	2426	0.094	0.039	0.066*	0.080***	0.166	
						(1.729)	(6.106)		
10y	B	65	1409	0.413	-0.277	0.265***	0.339**	0.397	
						(2.702)	(2.037)		
Pct Explained				0.830	0.070				0.312

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 $\Delta Inventory$ 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.12: Changes in Institutional Holdings and Dealers' Inventories of Downgraded Bonds

	Insurance	Mutual	Pension	Dealer
A: Changes of Holdings in Quarter t				
	(1)	(2)	(3)	(4)
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 Holdings in Quarter $t+1$				
	Insurance	Mutual	Pension	Dealer
	(1)	(2)	(3)	(4)
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 (12) 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.13: Regulatory Shocks and Intermediary Factors

	AA	A	BBB	BB	B
			A: Short		
$\Delta Inventory$	0.028	0.039	0.050	0.133	0.292***
	(1.143)	(1.577)	(1.574)	(1.413)	(2.973)
$\Delta Inventory \times D_{RegShock}$	-0.005	-0.059	0.032	-0.498***	-0.443**
	(-0.134)	(-0.914)	(0.323)	(-3.845)	(-2.350)
$D_{RegShock}$	0.002	0.024	0.041	0.016	0.062
	(0.060)	(0.531)	(0.638)	(0.182)	(0.320)
$\Delta Distress \times D_{RegShock}$	-0.236***	-0.396***	-0.423**	-1.426***	-2.524***
	(-3.915)	(-3.690)	(-2.560)	(-9.783)	(-7.178)
$\Delta Distress$	0.045**	0.067***	0.116***	0.190***	0.361***
	(2.155)	(3.000)	(3.393)	(3.873)	(2.748)
R^2_{adj}	0.233	0.328	0.398	0.327	0.450
			B: Medium		
$\Delta Inventory$	0.025	0.060**	0.089***	0.203***	0.301***
	(1.275)	(2.213)	(2.579)	(2.773)	(5.545)
$\Delta Inventory \times D_{RegShock}$	-0.058	0.066	0.073	-0.497***	-0.259***
	(-1.131)	(1.133)	(0.659)	(-3.918)	(-2.847)
$D_{RegShock}$	0.021	0.013	0.042	-0.058	-0.064
	(0.402)	(0.233)	(0.467)	(-0.741)	(-0.610)
$\Delta Distress \times D_{RegShock}$	-0.427***	-0.275***	-0.403**	-0.851***	-1.693***
	(-6.788)	(-3.419)	(-2.549)	(-5.281)	(-7.945)
$\Delta Distress$	0.056***	0.098***	0.153***	0.266***	0.518***
	(4.650)	(2.772)	(3.143)	(5.490)	(4.340)
R^2_{adj}	0.325	0.440	0.490	0.490	0.670
			C: Long		
$\Delta Inventory$	0.023	0.035	-0.024	0.183***	0.389***
	(1.622)	(1.510)	(-0.463)	(2.986)	(2.690)
$\Delta Inventory \times D_{RegShock}$	-0.067***	-0.041	-0.810*	-0.363**	-0.133
	(-3.009)	(-1.483)	(-1.937)	(-2.570)	(-0.334)
$D_{RegShock}$	0.017	0.007	-0.458	0.048	0.097
	(0.660)	(0.249)	(-1.473)	(0.552)	(0.359)
$\Delta Distress \times D_{RegShock}$	-0.196***	-0.314***	0.217	-0.487**	-1.406**
	(-4.733)	(-6.628)	(0.346)	(-2.086)	(-2.177)
$\Delta Distress$	0.041*	0.070**	0.128***	0.252***	0.719***
	(1.870)	(2.127)	(3.899)	(5.774)	(2.836)
R^2_{adj}	0.202	0.335	0.461	0.440	0.544

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 $\Delta Inventory$, $\Delta Distress$, 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 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.

Table A.14: Regressions of Bond-Return Factors on Intermediary Factors

	MKT^{Bond}	DRF	CRF	LRF
A: Regressions on Dealer Inventory				
$\Delta Inventory_t$	-0.025	-0.030	-0.010	-0.176
	(-0.227)	(-0.132)	(-0.048)	(-0.703)
R^2_{adj}	0.001	0.000	0.000	0.017
B: Regressions on Intermediary Distress				
$\Delta Distress_t$	-0.429***	-1.025***	-0.744***	-1.215***
	(-3.408)	(-5.098)	(-5.378)	(-5.928)
R^2_{adj}	0.261	0.337	0.228	0.589
C: Regressions on Dealer Inventory and Intermediary Distress				
$\Delta Inventory_t$	0.104	0.281	0.218	0.176
	(0.934)	(1.294)	(1.221)	(0.954)
$\Delta Distress_t$	-0.470***	-1.134***	-0.828***	-1.284***
	(-3.699)	(-4.849)	(-5.855)	(-6.386)
R^2_{adj}	0.281	0.369	0.253	0.605

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 $\Delta Inventory$ 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.