Interdealer Price Dispersion and Intermediation Capacity[∗]

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Abstract

Intermediation capacity varies across dealers, and as a result, misallocation of credit risk reduces the risk-bearing capacity of the dealer sector and increases effective marketlevel risk aversion. When the efficient reallocation of credit risk within the dealer sector is impaired, interdealer price dispersion increases. Empirically, when interdealer price dispersion increases, bond prices decrease. Interdealer price dispersion explains a substantial portion of bond yield spread changes, the cross-section of bond returns, and the changes in the basis between bond spread and fair-value spreads. We conclude interdealer frictions reduce the risk-bearing capacity of intermediaries and are crucial for intermediary bond pricing.

Keywords: OTC markets, intermediaries, dealers, corporate bonds, interdealer price dispersion

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1 Introduction

Interdealer price dispersion explains a substantial amount of the variation in changes in corporate bond yields and is a priced risk factor in the cross section of bond returns. We argue that this is because interdealer price dispersion arises due to frictions within the dealer sector that lead to a misallocation of credit risk among intermediaries. Risk misallocation reduces dealer-sector risk-bearing capacity and increases effective market-level risk aversion due to worse risk sharing. Interdealer illiquidity is priced because greater frictions result in worse allocations and higher effective dealer-sector risk aversion. Or empirical results show that measures of the risk-bearing capacity of the intermediary sector used in intermediary asset pricing can be improved by incorporating our proxy for the negative effects of interdealer frictions and risk misallocation within the dealer sector.

We measure interdealer price dispersion as the cross-sectional dispersion in bond yields of interdealer trades of the same bond at a given moment in time. Without frictions, bond dealers should optimally reallocate risk, and interdealer price dispersion should be zero in a competitive market. However, we observe in the data that interdealer price dispersion is substantial and varies over time. It is high when dealers with additional credit-risk capacity only partially exploit the gains from trading with other dealers who wish to reduce their credit exposure. When it is more costly to reallocate credit risk efficiently, the risk-bearing capacity of the dealer sector is impaired. Bond prices are lower, and credit spreads are higher, consistent with the dealer sector displaying a higher effective risk aversion.

In addition to explaining changes in bond yields and being a priced risk factor in the cross section of bond returns, changes in interdealer price dispersion also explain changes in the basis between credit spreads from OTC market data and credit spreads constructed using exchange-traded equity data and issuers' leverage ratios. This finding supports the idea that the explanatory power of interdealer price dispersion reflects over-the-counter (OTC) frictions within the dealer sector.

When interdealer price dispersion increases, bond yield spreads increase. Interdealer price dispersion explains a substantial portion of the common component in the residuals from a regression of yield spread changes on fundamental credit risk variables [\(Collin-Dufresne](#page-37-0) [et al.,](#page-37-0) [2001\)](#page-37-0). Shocks to interdealer price dispersion are a priced risk factor in corporate bond markets, and bonds with higher exposure to increases in interdealer price dispersion earn a positive risk premium.

The risk-bearing capacity of the dealer sector has been the focus of a large and impactful empirical literature on intermediary asset pricing [\(Adrian, Etula, and Muir,](#page-36-0) [2014;](#page-36-0) [He, Kelly,](#page-38-0) [and Manela,](#page-38-0) [2017;](#page-38-0) [Haddad and Muir,](#page-38-0) [2021\)](#page-38-0). The theoretical motivation for these works typically employs a representative intermediary (see [He and Krishnamurthy,](#page-38-0) [2013;](#page-38-0) [Brunnermeier](#page-36-0) [and Sannikov,](#page-36-0) [2014\)](#page-36-0) and suggests using equity-weighted intermediary-sector leverage as the intermediary asset pricing factor. Our work extends this literature by highlighting the role of dealer heterogeneity in determining dealer-sector risk-bearing capacity. Equity-weighted averages of dealer-level financial soundess fail to capture effects from interdealer frictions on risk misallocation within the dealer sector. Indeed, precisely when interdealer frictions are large and risk-sharing is poor, failing to account for dealer heterogeneity reduces the accuracy of averages as a measure of intermediation capacity. This is because, when dealers are prevented from equating their marginal costs of risk bearing, the average marginal cost is not representative of the aggregate, sector-level marginal cost. We show the effects of risk misallocation on credit spreads using a simple theoretical framework which supports our empirical findings.

The reason why the risk-bearing capacity of the dealer sector in the presence of interdealer frictions depends on dealer heterogeneity can be understood in the context of an efficiency argument. The more efficient the allocation of credit risk among dealers—that is, the greater the ability of the dealer sector to equate participants' marginal costs of risk-bearing—the larger the risk-bearing capacity of the dealer sector is. The intuition is the same as why output is higher among producers with different productivities when capital is allocated to equate marginal products than when there is misallocation [\(Hsieh and Klenow,](#page-38-0) [2009\)](#page-38-0). In asset pricing, the fact that misallocation leads to lower prices and higher risk premia is the core concept behind intermediary asset pricing. However, standard models feature only two types of agents, intermediaries and households, with frictionless interdealer markets and a representative-agent dealer sector.¹

We consider the dealer sector for corporate bonds. Each dealer has exposure to credit risk at any given point in time, which results from prior trade in bonds, loans, or derivatives. In a Walrasian market, these dealers would trade at a single market-clearing price to equalize their marginal costs of credit exposure, and the risk-bearing capacity of the dealer sector would be independent of the initial allocation of risk.² In practice, the most intermediated markets are over-the-counter (OTC) markets (see [Haddad and Muir,](#page-38-0) [2021\)](#page-38-0). There is no one market-clearing price for OTC assets, even for bilateral trades within the dealer sector.

¹For exceptions, see [Kargar](#page-38-0) [\(2021\)](#page-38-0) for a model with two types of intermediaries and households, and [Eisfeldt, Lustig, and Zhang](#page-37-0) [\(2021\)](#page-37-0) for a model in which the joint distribution of wealth and expertise determines aggregate risk-bearing capacity. See also [Bretscher, Schmid, Sen, and Sharma](#page-36-0) [\(2020\)](#page-36-0), which emphasizes the role of heterogeneous institutional bondholders in a demand-system asset pricing model. Finally, [Hugonnier et al.](#page-38-0) [\(2022\)](#page-38-0) develops a methodology for analyzing decentralized markets featuring agents with heterogeneous preferences.

²For an important early paper modeling a Walrasian interdealer market with an emphasis on frictions in customer trading, see [\(Duffie et al.,](#page-37-0) [2005\)](#page-37-0). See also [Lagos and Rocheteau](#page-38-0) [\(2009\)](#page-38-0).

If trading frictions prevent dealers from equalizing their marginal costs of risk-bearing, the result is bilateral price dispersion.

For example, in the OTC network model of [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0), prices are a weighted average of bilateral counterparties' marginal costs of risk-bearing.³ If two dealers with large pre-trade risk exposures transact, bond prices will be lower than in a trade between two less exposed dealers, with lower marginal costs of bearing additional credit risk. Thus, price dispersion within the dealer sector reflects the inability of dealers to efficiently reallocate credit risk and maximize the potential capacity of the dealer sector to absorb credit risk. Related to this mechanism, [Chang and Zhang](#page-36-0) [\(2022\)](#page-36-0) develop a theoretical model to study the relation between price dispersion and heterogeneity in risk-bearing capacity, and consistent with our empirical findings, their model also generates a strong comovement between dispersion in transaction prices and banks' risk-bearing capacity heterogeneity.⁴

We provide substantial evidence that interdealer price dispersion in the corporate bond market reflects impairment to the risk-bearing capacity of the dealer sector. We construct a dataset containing all interdealer corporate bond trades using TRACE data and dealer-level proxies for corporate bond positions from past transactions. We merge this data with data on corporate bond yields and fair-value spreads constructed using equity-market data and a structural model.

We document four main results. First, in a panel regression setting, we show that changes in interdealer price dispersion are positively related to changes in yield spreads. A one percentage point increase in interdealer price dispersion is associated with around 78 basis point increase in yield spreads. Our finding is robust to various controls, including fundamentalbased variables from [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0), the default factor from [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), and risk factors from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0). More importantly, our results are robust to controlling for the measures of inventory and distress of intermediaries from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0) and for the OTC-based frictions variables from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). These results confirm the prominent role of interdealer heterogeneity beyond OTC frictions and other aggregate measures of the financial soundness of the intermediary sector as a whole.

Second, we find that interdealer price dispersion explains a substantial fraction of the basis between bond spreads from the OTC market and fair-value spreads constructed using equity market data. Fair-value spreads are bond spreads computed using exchange-traded equity volatility and issuers' leverage data as inputs to a structural model. We define the

³See [Atkeson et al.](#page-36-0) [\(2015\)](#page-36-0) for a related result in a search model.

⁴Consistent with our mechanism, [Mahanti et al.](#page-39-0) [\(2008\)](#page-39-0), and [Jankowitsch et al.](#page-38-0) [\(2011\)](#page-38-0) show that price dispersion in OTC markets, including corporate bonds, relates to overall market liquidity.

fair-value basis as the raw bond spread from an OTC market trade minus the fair-value spread. A one percentage point increase in interdealer price dispersion is associated with around a 60 basis point increase in the fair-value basis—that is, the difference between yield spreads and fair-value spreads. Hence, interdealer price dispersion widens the gap between yield spreads and fair-value spreads, consistent with the idea that part of the fair-value basis between OTC market bond trades and bond spreads from a structural model using equitymarket data is due to interdealer frictions. Again, our findings are robust to the same set of controls listed above.

Third, interdealer price dispersion explains a substantial fraction of the common component in residuals from a regression of yield spread changes on fundamental credit-risk variables. [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) documented that these residuals feature a strong factor structure, in which the first principal component explains about 20-25% of the total variation. Explaining this first principal component is thus crucial for understanding the co-movement of bond prices. Our measure of interdealer price dispersion helps to explain variation in this first principal component, adding about 10 to 15 percentage points to the coefficients of determination for various specifications from the literature [\(Bessembinder, Kahle, Maxwell, and Xu,](#page-36-0) [2008;](#page-36-0) [He, Kelly, and Manela,](#page-38-0) [2017;](#page-38-0) [He, Khorrami,](#page-38-0) [and Song,](#page-38-0) [2019;](#page-38-0) [Friedwald and Nagler,](#page-37-0) [2019\)](#page-37-0).

Finally, we document that interdealer price dispersion carries a negative price of risk in the cross-section of duration-times-spreads sorted portfolios of bonds and in the cross-section of bonds double-sorted on maturity and size. Bond yields tend to increase when interdealer price dispersion goes up. In terms of returns, when interdealer price dispersion is higher bond returns are lower. Consistent with states of the world with high interdealer price dispersion being "bad" states of the world for bonds, we find that bonds more exposed to interdealer price dispersion have higher average expected returns. Thus, exposure to shocks to interdealer price dispersion earns a positive risk premium and interdealer price dispersion has a negative price of risk. These findings are consistent with the idea that higher interdealer price dispersion indicates a less efficient allocation of risk and lower risk-bearing capacity for the dealer sector overall (i.e. higher effective dealer-sector risk aversion).

Given the infrequent trading of bonds, calculating interdealer price dispersion daily is not feasible. For our baseline results, we measure bond-level interdealer price dispersion using the standard deviation in all interdealer trades occurring each month. Then, in an important set of robustness exercises, we show that within-month volatility does not drive our results.

We conduct three robustness exercises that control for within-month volatility at the bond-level. First, we calculate interdealer price dispersion weekly, thereby increasing data frequency and partially addressing the issue of within-month volatility. In our second exercise, we refine our approach by constructing our interdealer price dispersion measure based on the dispersion in bond-level fair-value bases instead of raw bond spreads. By normalizing each bond-level spread by its daily fair-value basis, we are able to control for any daily fundamental-based variation in bond spreads. Our results remain unchanged. Thus, we conclude that our findings are not driven by within-month volatility.

We conduct two placebo tests as a third exercise to control for within-month volatility of spreads. In the first placebo test, we construct two measures of interdealer price dispersion based on bonds with high and low interdealer price dispersion levels while holding various other bond characteristics fixed via propensity score matching (PSM). We intentionally match bond level volatility, among other characteristics. The dispersion of spreads among bonds with high interdealer price dispersion is the measure we are interested in, while the within-month dispersion among those with low interdealer price dispersion is expected to have a stronger relationship with monthly time-series volatility. Consistent with our intuition and previous results, we estimate a significant relation between changes in credit spreads and interdealer price dispersion based on high-dispersion bonds. Moreover, our results become insignificant when using low-dispersion bonds to construct interdealer price dispersion. This placebo test supports our conclusion that the empirical relation we document is not driven by within-month volatility.

In our second placebo test, we apply propensity score matching again to categorize bonds into groups with high or low fair-value bases while keeping other characteristics constant. A high fair-value basis indicates high trading frictions in the interdealer market. Therefore, interdealer price dispersion among those bonds should better measure interdealer frictions. The results align with our economic mechanism. The relation between changes in credit spreads and changes in interdealer prices is indeed more pronounced when interdealer price dispersion is based on bonds with a high fair-value basis. Also consistent with our mechanism, these findings become insignificant when interdealer price dispersion is based on bonds with a low fair-value basis.

Furthermore, we conduct comprehensive robustness analyses to validate our empirical findings further. We find that our findings are robust to various controls and subsamples: (a) We construct volume-weighted interdealer price dispersion; (b) we build interdealer price dispersion based on interdealer trades of the largest dealers; (c) we repeat our analysis excluding the Global Financial Crisis period to rule out the effects of outliers; (d) we control for bond turnover; (e) we verify the presence of nonlinear effects; (f) we test for the effects of market power by controlling for market concentration; (g) we control for bond-specific inventory and price dispersion; (h) we apply the previous five exercises $(c-g)$ to interdealer price dispersion based on fair-value basis; (i) we sort on credit rating, maturity and leverage sorting; (j) we extend our sample to estimate the effects during the COVID-19 pandemic; and (k) we construct interdealer price dispersion based on more liquid bonds to assess the effects of price impact.

Our study connects to active strands of the literatures on asset pricing, corporate bond pricing, liquidity, and misallocation. Our emphasis on interdealer frictions and dealer heterogeneity builds on several new studies which point to variation in risk-bearing capacity within the dealer market and the importance of individual dealers in determining asset prices [\(Siri](#page-39-0)[wardane,](#page-39-0) [2019;](#page-39-0) [Siriwardane, Sunderam, and Wallen,](#page-39-0) [2021;](#page-39-0) [Lewis, Longstaff, and Petrasek,](#page-38-0) [2017;](#page-38-0) [Munyan and Watugala,](#page-39-0) [2018\)](#page-39-0). [Munyan and Watugala](#page-39-0) [\(2018\)](#page-39-0) document differences in dealers' search costs, risk appetite, and skill, and relate these differences to dealers' roles in market-making. Consistent with these findings, [Eisfeldt, Herskovic, Rajan, and Siriwardane](#page-37-0) [\(2023\)](#page-37-0) document large heterogeneity across dealers in their net credit default swap positions and build a model to illustrate the resulting systemic risk in credit markets. Other recent studies point to an increase in interdealer frictions since the Global Financial Crisis [\(Copeland, Duffie, and Yang,](#page-37-0) [2021;](#page-37-0) [Correa, Du, and Liao,](#page-37-0) [2020\)](#page-37-0), indicating that the impact of dealer heterogeneity may have increased since 2008. These studies support the importance of addressing dealer heterogeneity and trading frictions within the dealer market when constructing measures of intermediary risk-bearing capacity.

In addition to connecting to the literature on intermediary asset pricing, our study contributes to the bond pricing literature by documenting the implications of dealer heterogeneity and interdealer frictions for bond prices. The seminal work by [Collin-Dufresne, Goldstein,](#page-37-0) [and Martin](#page-37-0) [\(2001\)](#page-37-0) documented that several fundamental-based measures are insufficient to explain bond price movements and that changes in bond yields orthogonalized to these fundamental measures feature a strong factor structure. Subsequent research in this area has focused on different metrics and channels to explain changes in bond yields, including default measures and the equity capital ratio of financial intermediaries [\(Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu,](#page-36-0) [2008;](#page-36-0) [He, Kelly, and Manela,](#page-38-0) [2017\)](#page-38-0). More recently, [He, Khorrami, and](#page-38-0) [Song](#page-38-0) [\(2019\)](#page-38-0) highlighted the importance of intermediaries by analyzing the bond-pricing implications of aggregate measures of dealer inventory and distress, and [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0) investigated the pricing implication of OTC-based market frictions. We contribute to this literature by documenting the bond pricing implications of risk misallocation and heterogeneity in financial intermediary risk-bearing capacity. A key difference between our study and that of [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0) is that, while their focus is on a large list of market-wide OTC frictions on bond prices, our study utilizes a single measure to highlight the impact of inter-dealer frictions on dealers' risk sharing and the resulting dealer-sector risk aversion.

We also contribute to the related literature that studies the bond pricing implications of measures of liquidity.⁵ Indeed, [Jankowitsch et al.](#page-38-0) [\(2011\)](#page-38-0) use price dispersion in OTC corporate bond markets as a measure of bond-market liquidity.⁶ They focus on price dispersion across all transactions between both dealers and customers to capture inventory and search costs in corporate bond markets. Our emphasis (and our measure) is different. While we endorse the idea that price dispersion measures trading frictions, and hence bond market liquidity, our focus is on the effects of these trading frictions on risk aversion, as measured by dealer-sector risk-bearing capacity. We show that, as a result of trading frictions and illiquidity, risk is misallocated and thus intermediary risk-bearing capacity is lower. Our measure exclusively uses interdealer transactions to capture dealer heterogeneity and interdealer frictions. This distinction is crucial for interpreting our findings. High interdealer price dispersion is evidence that the dealer sector faces trading frictions and cannot effectively allocate risk among themselves. As a result of this misallocation, the intermediary-sector risk-bearing capacity is lower, while dealer-sector risk aversion and required risk premia are higher. Thus, our study supports a specific explanation for why illiquidity is priced. Illiquidity leads to risk misallocation and therefore results in lower risk-bearing capacity overall.

The robustness of our results to an extensive set of OTC liquidity, search, and inventory cost variables from the literature provides evidence that the economic channel linking liquidity and prices we document is distinct from results in the existing literature on bond market liquidity. Key evidence of this is that when we estimate the price of risk of interdealer price dispersion, we control for bond liquidity. Thus, while our findings are entirely consistent with those from the liquidity literature, and indeed interdealer price dispersion results from trading frictions in our framework, our study offers a novel channel for the impact of liquidity on prices. We emphasize that liquidity inhibits risk-sharing in the cross section, reducing intermediation capacity. This emphasis is distinct from links between liquidity and prices based on the impact of liquidity on the ability to convert illiquid assets into cash.

Finally, we contribute to the misallocation literature, exemplified by the seminal work of [Hsieh and Klenow](#page-38-0) [\(2009\)](#page-38-0). That literature studies the effect of misallocation of the factors used in production across more and less productive establishments on aggregate productivity. We apply this insight to an important financial setting. Just like a misallocation of productive inputs such as capital and labor lowers aggregate productivity, a misallocation of risk across dealers with higher and lower marginal costs of risk-bearing leads to lower dealer-sector risk-

⁵See [Longstaff et al.](#page-39-0) [\(2005\)](#page-39-0) [Chen et al.](#page-37-0) [\(2007\)](#page-37-0); [Bao et al.](#page-36-0) [\(2011\)](#page-36-0); [De Jong and Driessen](#page-37-0) [\(2012\)](#page-37-0); [Schestag](#page-39-0) [et al.](#page-39-0) [\(2016\)](#page-39-0); [Bongaerts et al.](#page-36-0) [\(2017\)](#page-36-0); [Goldberg and Nozawa](#page-38-0) [\(2021\)](#page-38-0). See [Schultz](#page-39-0) [\(2001\)](#page-39-0) for an early contribution to meauring corporate bond trading costs.

⁶See also [Green et al.](#page-38-0) [\(2007\)](#page-38-0) who study price dispersion between small and large counterparties in municipal bond markets.

bearing capacity. Our theoretical framework extends the work of [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0) by applying their network-based framework to risk misallocation.

The remainder of the paper proceeds as follows. Section 2 provides a simple theoretical framework to motivate the relation between interdealer price dispersion and credit spreads. Sections [3](#page-13-0) and [4](#page-14-0) describe our data and the construction of interdealer price dispersion, respectively. Section [5](#page-18-0) describes our main empirical estimations and results. Section [6](#page-28-0) presents robustness practices which construct alternative interdealer price dispersion by controlling for within-month volatility of bond yields. Section [7](#page-32-0) presents several other robustness exercises and Section [8](#page-35-0) concludes.

2 Motivating model

In this section, we develop our theoretical framework of risk misallocation. Specifically, we present a simple, intuitive and tractable model in the main text, and in Internet Appendix [A,](#page-1-0) we discuss its micro-founded version along with formal results.⁷ Our tractable framework highlights the key economic channel leading to risk misallocation and how risk misallocation relates to interdealer price dispersion and average credit spreads. We also show how misallocation renders the measures of financial soundess commonly used in intermediary asset pricing incomplete.

Suppose there is a continuum of heterogeneous dealers indexed by $i \in [0,1]$, who differ in their risk aversion and pre-trade credit risk exposures. For simplicity, there is one asset representing aggregate credit risk (e.g., corporate bonds) with expected payoff and variance given by μ and σ^2 , respectively. Dealer i is initially endowed with ω_i units of credit risk exposure and trades with other dealers in the interdealer market. For instance, we interpret pre-trade exposure as the corporate bonds which dealers hold, including those obtained across all its customer-dealer relationships. Given initial endowments of credit risk, dealers trade to reallocate risk subject to trading frictions. The total amount of each dealer's post-trade net credit risk exposure acquired across all interdealer transactions is given by its initial endowment ω_i , plus the exposure acquired through interdealer trading, z_i . We can write dealer *i*'s post-trade credit risk exposure as follows:

Post-trade
\ncredit exposure = Optimal Exposure w/
\nPerfect Risk Sharing
\n
$$
+ \underbrace{\text{Risk Misallocation}}_{\sigma_{\varepsilon} \varepsilon_i}.
$$
\n(1)

⁷Specifically, Internet Appendix [A.4](#page-66-0) discusses the precise mapping between the micro-founded version of the model and the one discussed in the main text.

Equation [\(1\)](#page-8-0) is a general decomposition of credit risk exposure and can be applied to different models. It states that post-trade credit risk exposure, including initial endowments plus exposures gained through interdealer risk reallocation, is the combination of two terms: the optimal exposure under perfect risk sharing plus a risk misallocation term. The misallocation term has a cross-sectional standard deviation of σ_{ε} , as we normalize $\text{Var}(\varepsilon_i) = 1$.

Without imposing any modeling assumptions, we highlight a useful property of risk misallocation. Note that bond market clearing conditions imply $\int z_i di = 0$ as bonds are in fixed supply. Also, by construction, the optimal exposure under perfect risk sharing clears the market, which means that the optimal exposure across all dealers adds to the aggregate risk exposure, $\int OptExp_i di = \int \omega_i di$. Thus, by aggregating Equations [\(1\)](#page-8-0) across all dealers, we have that risk misallocation has zero mean:⁸

$$
\int \varepsilon_i di = 0. \tag{2}
$$

Although the mean is zero, misallocation reduces risk-bearing capacity because natural buyers' exposure is too low, while natural sellers' exposure is too high.

While this decomposition and intuition are general, the precise source of misallocation (and the optimal risk exposure under perfect risk sharing) depends on specific modeling choices. We further develop our illustrative framework based on the network model of [Eis](#page-37-0)[feldt, Herskovic, Rajan, and Siriwardane](#page-37-0) [\(2023\)](#page-37-0).⁹ The interdealer market of corporate bonds is modeled as an over-the-counter market in which dealers trade with one another but face convex bilateral trading costs. These trading costs have significant implications for risk sharing as dealers end up reducing trade, stopping short of perfect risk sharing. Specifically, buyers with low initial endowments would like to buy more bonds, while sellers with higher initial endowments would like to sell more bonds in equilibrium. Bilateral trading costs increase the marginal cost of buying and selling, curbing trading activity and risk sharing. Hence, in our framework, bilateral trading costs are the source of risk misallocation.

We model dealers as risk-averse investors with mean-variance preferences due to riskmanagement constraints (e.g., [Brunnermeier and Pedersen,](#page-36-0) [2009\)](#page-36-0). Thus, the optimal credit risk exposure under perfect risk sharing is inversely proportional to dealers' risk aversion. In other words, less risk-averse dealers hedge the credit risk of more risk-averse dealers under

⁸Using these two market clearing conditions, $\int OptExp_i di = \int \omega_i di$ and $\int z_i di = 0$, we have from Equa-tion [\(1\)](#page-8-0) that $\int \omega_i di + \int z_i di = \int OptExp_i di + \sigma_{\varepsilon} \int \varepsilon_i di \implies \int \varepsilon_i di = \frac{1}{\sigma_{\varepsilon}} \left[\int \omega_i di + \int z_i di - \int OptExp_i di \right] =$ $\frac{1}{\sigma_{\varepsilon}}\left[\int\limits_{\mathcal{I}}\omega_{i}di+0-\int\omega_{i}di\right]=0.$ See Proposition [A3](#page-66-0) in Internet Appendix [A.4.](#page-66-0)

⁹See, for example, [Di Maggio et al.](#page-37-0) [\(2017\)](#page-37-0) for the importance of trading networks in OTC markets, and [Colliard et al.](#page-37-0) [\(2021\)](#page-37-0) for a model emphasizing the connection between dealer inventories and pricing.

perfect risk sharing. Let α_i be dealer i's risk aversion, we can write Equation [\(1\)](#page-8-0) as follows:

$$
\omega_i + z_i = \frac{C}{\alpha_i} + \sigma_{\varepsilon} \varepsilon_i,\tag{3}
$$

where C is a constant term that depends on the distribution of risk aversion (α) and pre-trade exposures $(\omega's)^{10}$

When agents have mean-variance preferences, their marginal shadow cost of risk-bearing is equal to their risk exposure multiplied by their respective risk aversion and the asset's variance. Thus, for agent i, it is given by σ^2 α_i ($\omega_i + z_i$). Risk aversion effectively drives the agent-specific price of risk by converting the quantity of risk into a marginal cost of risk-bearing. Using Equation (3) the shadow cost of risk-bearing for dealer i is given by:

$$
\sigma^2 \alpha_i \left(\omega_i + z_i \right) = \sigma^2 C + \sigma^2 \sigma_\varepsilon \alpha_i \varepsilon_i, \tag{4}
$$

where the constant term is the marginal cost of risk-bearing when there is perfect risk sharing and the second term measures the additional cost due to misallocation. With perfect risk sharing, the last term would be zero for all agents.

Equation (4) is intuitive because misallocation measures credit risk exposure in excess of perfect risk-sharing. When $\varepsilon_i > 0$, dealer i has more credit risk exposure than it would under perfect risk-sharing and, therefore, faces a higher marginal cost of risk-bearing. In other words, agent i requires a higher credit spread in order to hold additional credit risk exposure. Alternatively, when $\varepsilon_i < 0$, dealer i has lower credit risk exposure compared to perfect risk sharing, and its shadow cost of risk-bearing is lower. In this case, agent i requires a lower credit spread to hold additional credit risk exposure.¹¹

In our framework, the average credit spread at which dealers trade with one another is equal to the average shadow cost of risk-bearing. Formally, we define $\mu - P_{ij}$ as the expected bond payout minus the price at which dealers i and j trade. As an equilibrium outcome of the model, when dealers i and j trade, they do so at the price given by the midpoint between their marginal cost of risk-bearing, $\mu - P_{ij} = \frac{\sigma^2}{2}$ $\frac{\tau^2}{2} [\alpha_i (\omega_i + z_i) + \alpha_j (\omega_j + z_j)].$ The

¹⁰Formally, $C = \frac{\int \omega_i d_i}{\int 1/\alpha_i d_i}$. See Equation [A15](#page-62-0) in the Internet Appendix.

¹¹In related work, [Chang and Zhang](#page-36-0) [\(2022\)](#page-36-0) highlights a similar mechanism. They study interbank risk allocation through the lens of a dynamic model with ex-ante homogeneous risk-averse banks with diminishing cost of risk-bearing. In their model, agents become heterogeneous when the initial asset position is realized, and they start trading sequentially with one another. Their framework features price dispersion precisely because agents become heterogeneous in term of their risk exposure and value the asset differently because of their risk aversion and the diminishing marginal cost of risk-bearing.

term $\mu - P_{ij}$ is our measure of credit spread, and the average credit spread is given by:¹²

$$
\mathbb{E}\left(Credit\;{\} \;log\right) = \mathbb{E}\left(\mu - P_{ij}\right) = \sigma^2 \int \alpha_i \left(\omega_i + z_i\right) di = \sigma^2 C + \sigma^2 \sigma_\varepsilon \text{Cov}\left(\alpha_i, \varepsilon_i\right),\tag{5}
$$

where $Cov(\alpha_i, \varepsilon_i) \equiv \int \alpha_i \varepsilon_i di - \int \alpha_i di \int \varepsilon_i di = \int \alpha_i \varepsilon_i di$ is the cross-sectional covariance between risk misallocation and risk aversion. As an endogenous response to trading frictions, in our framework, we have:

$$
Cov(\alpha_i, \varepsilon_i) > 0.
$$
\n⁽⁶⁾

This result is Proposition [A4](#page-67-0) in Internet Appendix [A.4,](#page-66-0) which contains further details on our illustrative model. As discussed earlier, trading frictions curb trading and risk sharing, but on average, low-risk-averse dealers still buy bonds from high-risk-averse dealers in equilibrium. As net sellers of credit risk, high-risk-averse dealers would like to further reduce their credit risk exposure by selling even more bonds, but they cannot due to trading fractions. This results in risk misallocation, with high-risk-averse dealers holding more credit risk exposure than they would under a perfect risk-sharing scenario. Hence, misallocation covaries positively with risk aversion in the cross-section of the dealers, that is, Cov $(\alpha_i, \varepsilon_i) > 0$. Intuitively, dealers who dislike risk the most (i.e., high-risk-averse dealers) are more exposed to credit risk as a result of risk misallocation. A key implication of the Equations (5) and (6) is that credit spreads are higher compared to perfect risk sharing. Risk misallocation inhibits the dealer sector from effectively sharing risk, leading to higher credit spreads.

To understand how risk misallocation relates to interdealer price dispersion, notice that the cross-sectional dispersion in spreads is proportional to the cross-sectional dispersion in the marginal cost of risk-bearing and can be written as: 13

$$
\text{Std}(Credit\;Spreads) = \frac{\sigma^2 \sigma_{\varepsilon}}{\sqrt{2}} \text{Std}(\alpha_i \varepsilon_i),\tag{7}
$$

where Std $(\alpha_i \varepsilon_i)$ is the cross-sectional standard deviation of the distortions in the marginal cost of risk-bearing, which is the misallocation scaled by risk aversion. We interpret the term Std $(\alpha_i \varepsilon_i)$ as representing dealer heterogeneity and interdealer market frictions leading to risk misallocation.

 $\frac{12}{\pi} \mathbb{E}(\mu - P_{ij}) = \int \int \mu - P_{ij}di\, = \frac{1}{2}\sigma^2 \int \int \left[\alpha_i (\omega_i + z_i) + \alpha_j (\omega_j + z_j)\right] di\, = \sigma^2 \int \alpha_i (\omega_i + z_i) \, di = \sigma^2 C + \sigma^2 \int \alpha_i (\omega_i + z_i)$ $\sigma_{\varepsilon} \int \alpha_i \varepsilon_i di = \sigma^2 C + \sigma_{\varepsilon} \text{Cov}(\alpha_i, \varepsilon_i)$, where the last equality holds because $\int \varepsilon_i di = 0$ and $\text{Cov}(\alpha_i, \varepsilon_i) \equiv$ $\int \alpha_i \varepsilon_i di - \int \alpha_i di \int \varepsilon_i di = \int \alpha_i \varepsilon_i di$. See details in the Internet Appendix.

¹³Std [*Credit Spreads*] = Std $[\mu - P_{ij}]$ = Std $\left[\frac{\sigma^2}{2}\right]$ $\left[\frac{\sigma^2}{2} \left(\alpha_i \left(\omega_i + z_i \right) + \alpha_j \left(\omega_j + z_j \right) \right) \right] = \text{Std}[\frac{\sigma^2}{2}]$ $\frac{\sigma^2}{2}(2C + \sigma_{\varepsilon} \alpha_i \varepsilon_i +$ $\sigma_{\varepsilon} \alpha_j \varepsilon_j] = \frac{\sigma^2 \sigma_{\varepsilon}}{2} \text{Std} [\alpha_i \varepsilon_i + \alpha_j \varepsilon_j] = \frac{\sigma^2 \sigma_{\varepsilon}}{\sqrt{2}} \text{Std} [\alpha_i \varepsilon_i]$

Equations [\(4\)](#page-10-0) through [\(7\)](#page-11-0) illustrate why, in the presence of interdealer frictions, dealersector risk-bearing capacity cannot be fully captured by simply aggregating or averaging across dealers. When dealers are prevented from equating their marginal costs of riskbearing, risk is misallocated and a covariance term arises in effective risk aversion. The higher the degree of misallocation, the less accurate simple aggregate or average measures of dealer-sector health will be. Similarly, the greater interdealer frictions are, for example due to regulation, information asymmetries, or agency problems, the more important it is to account for the effects of misallocation.¹⁴

Asset volatility also influences the spread dispersion, as Equation [\(7\)](#page-11-0) indicates. In our empirical analysis, we control for asset volatility (σ^2 in the model) to ensure that our analysis captures the risk misallocation channel.¹⁵ Throughout our empirical analysis, we also control for aggregate inventory and distress factors, which map to holding the average risk aversion fixed in the model, to again interpret our findings as a result of risk misallocation. We also show that our measure of misallocation and interdealer frictions adds information beyond that captured by existing measures of intermediary risk-bearing capacity.

In our framework, risk misallocation is directly related to the cross-sectional dispersion in credit spreads, and by combining Equations [\(5\)](#page-11-0) and [\(7\)](#page-11-0), we can write average credit spreads as a function of interdealer price dispersion:

$$
\mathbb{E}\left(Credit\ Spreads\right) = a + b \times \text{Std}\left(Credit\ Spreads\right) \tag{8}
$$

where $a = \sigma^2 C$ is the credit spread under perfect risk sharing and $b =$ √ $\overline{2} \frac{\text{Cov}(\alpha_i, \varepsilon_i)}{\text{Std}(\alpha_i \varepsilon_i)} > 0$ is the sensitivity of credit spreads with respect to the interdealer price dispersion that results from risk misallocation. Equation (8) shows a positive relation between credit spreads and interdealer price dispersion. We empirically document the positive relation between credit spreads and interdealer price dispersion in the next few sections. Our empirical results provide support for the idea that interdealer price dispersion indicates risk misallocation and a corresponding reduction in dealer-sector risk-bearing capacity.

In Figure [1,](#page-40-0) we depict the model-implied relation between risk misallocation, interdealer price dispersion and average spreads through a simulation exercise. We assume that the average spread under perfect risk sharing is 100 basis points (i.e., $C = 0.01$), and risk aversion follows a log-normal distribution with a mean of 2 and a standard deviation of 4. We set $\sigma_{\varepsilon} = 1$ for normalization purposes. The model considers excess credit risk exposure (ε) and log risk aversion to be jointly normal. We vary the correlation between risk aversion

¹⁴See, for example, [Dick-Nielsen et al.](#page-37-0) [\(2012\)](#page-37-0), [Adrian et al.](#page-36-0) [\(2017\)](#page-36-0), and [Bao et al.](#page-36-0) [\(2018\)](#page-36-0) for evidence that trading frictions increased after the Great Financial Crisis.

¹⁵The analyses in Section [6](#page-28-0) are specifically designed to control to asset volatility.

(α) and excess risk exposure (ε), namely $\rho_{\varepsilon,\alpha}$, from zero to one. This variation represents different levels of risk misallocation and allows us to assess implications for interdealer price dispersion and average spreads.

For each level of $\rho_{\varepsilon,\alpha}$, we simulate 1 million economies, each with 25 dealers, and compute dealer's post-trade credit risk exposure (Equation [1\)](#page-8-0), the average spread in the interdealer market (Equation [5\)](#page-11-0) and the interdealer price dispersion (Equation [7\)](#page-11-0).

Our simulation findings are presented in two panels of Figure [1.](#page-40-0) Panel (a) plots a heatmap, showing the relation between dealers' risk aversion and total risk exposure. In the x-axis, we vary the correlation between risk exposure and risk aversion. When the correlation between risk exposure and risk aversion is low, we see credit risk being roughly equally distributed among dealers, with high-risk-averse dealers having slightly lower credit risk exposure. When the correlation between risk exposure and risk aversion is higher, we see more credit risk misallocation, with credit risk exposure being more concentrated in the hands of high-risk-averse dealers. Panel (b) plots the average spread in the interdealer market as well as the interdealer price dispersion. We also vary the correlation between risk exposure and risk aversion in the x-axis. When misallocation increases, both interdealer price dispersion and average spreads increase.

[Figure [1](#page-40-0) about here.]

3 Data description

We use the enhanced Trade Reporting and Compliance Engine (TRACE) data set from January 2004 to December 2019 as the main data set for interdealer price dispersion and bond credit spreads. This data set provides counterparty information. In particular, it allows us to identify interdealer trades vs. trades involving customers as counterparties. The financial institutions registered as member firms of the Financial Industry Regulatory Authority (FINRA) are labeled dealers in TRACE.¹⁶ We filter the data following the standard procedure in [Dick-Nielsen](#page-37-0) [\(2014\)](#page-37-0). Then we merge the filtered data set with the Mergent Fixed Income Securities Database (FISD) to obtain bond fundamental characteristics. We exclude variable-coupon, convertible, exchangeable, puttable and newly issued bonds. We also exclude asset-backed securities, privately placed instruments, and bonds denominated in foreign currencies or issued by foreign companies.

¹⁶Member firms of FINRA mainly include broker-dealers, exchanges and crowdfunding portals. Member firms must submit reports to FINRA after completing corporate bond transactions. The reports include detailed information on realized transactions, including bond ID, counterparty ID, price, volume, execution time, etc. Each report must be submitted within 15 minutes after the corresponding transaction happens.

We use the academic version of the TRACE data to compute dealers' cumulative inventory of bonds, and we use the data on bond-level fair value spreads from [Chang, d'Avernas,](#page-36-0) [and Eisfeldt](#page-36-0) [\(2021\)](#page-36-0) to calculate the OTC fair-value basis, which measures the non-default component of the credit spread. Specifically, we define the OTC fair-value basis as the bond spread from OTC bond market trades less the corresponding bond spread from leverage and equity volatility data combined with a structural model. For data describing all other bondand market-level controls, we next merge our data with CRSP, Compustat, OptionMetrics, Chicago Board Options Exchange (CBOE) and the economic data from the Federal Reserve Bank of St. Louis to obtain issuers' and primary dealers' equity prices and accounting information, the Standard & Poor's $(S\&P)$ 500 index, the volatility index (VIX), the 10-year Treasury constant maturity rate, the slope of the yield curve, implied volatilities of options on S&P 500 futures, and the effective yields of U.S. investment-grade (IG) and high-yield (HY) corporate bond portfolios.

The merged data sample consists of monthly observations at the bond level. Following the standard practice in the academic literature, we only consider bonds for which we have at least 25 observations of monthly credit spread/basis changes. Our final data sample includes 10,537 bonds issued by 5,869 firms. The total outstanding amount of all the bonds is 19.6 billion dollars, with 73% rated BBB and above. The average age is 3.2 years, the average time-to-maturity is 7.2 years, and the average trade size is \$880,000 across all transactions.

4 Interdealer price dispersion: Stylized Facts

In this section, we establish four stylized facts, namely, that (1) interdealer price dispersion exists, (2) it varies substantially over time, (3) higher price dispersion is associated with higher dispersion in dealer-level inventories, and (4) higher price dispersion is associated with higher bond yields.

4.1 Measuring interdealer price dispersion

We construct a measure of the interdealer price dispersion as the cross-sectional standard deviation of yields of interdealer transactions. First, for each bond i in month t , we compute interdealer price dispersion as:

$$
\sigma_{i,t}^{D2D} = \sqrt{\frac{\sum_{j=1}^{N_{i,t}} (yd_{j,i,t} - \overline{yd}_{i,t})^2}{N_{i,t} - 1}},\tag{9}
$$

where $N_{i,t}$ is the total number of interdealer transactions of bond i at month t, and $yd_{j,i,t}$ is the yield of interdealer transaction j . Second, we compute the average dispersion across all bonds in a given month as our main measure of interdealer price dispersion (D2D Dispersion):

$$
\sigma_t^{D2D} = \frac{1}{M_t} \sum_i \sigma_{i,t}^{D2D},\tag{10}
$$

where M_t is the number of bonds traded in month t.

4.2 Inventory dispersion

To support our measure of interdealer price dispersion as a measure of dispersion in dealers' marginal costs of risk-bearing, we construct a measure of the heterogeneity in dealers' marginal cost of risk-bearing based on the cross-sectional variation in their bond inventories. We show that the cross-section dispersion in inventories varies substantially over time, and covaries with interdealer price dispersion.

The basic idea is as follows. We utilize dealer inventory as a proxy for post-trade credit exposures $\omega_i + z_i$. In general, we expect heterogeneity in dealer-level inventories due to fixed (or slow moving) differences in dealers' aversion to bearing credit risk (e.g., due to a higher credit rating, looser regulatory constraints, or a stronger "risk-on" view). In our theoretical framework, these differences are represented by dealer-specific risk aversion α_i . When trading frictions are larger, we expect more dispersion in dealer-level inventory because riskreallocation is more costly. Indeed, Equation [4](#page-10-0) states that the dealer-level shadow cost of risk-bearing is given by $\sigma^2 \alpha_i(\omega_i + z_i)$. If inventories are relatively more disperse, the shadow cost of risk-bearing also displays more cross-sectional variation. Higher dispersion in the cost of risk-bearing then results in higher dispersion in trading prices. Bilateral prices are given by $\mu - P_{ij} = \frac{\sigma^2}{2}$ $\frac{\partial z}{\partial z} [\alpha_i (\omega_i + z_i) + \alpha_j (\omega_j + z_j)]$, so when post-trade exposures (inventories) and marginal costs of risk-bearing are more disperse, so are the prices at which a given dealer i trades with any other dealers. Consistent with this reasoning, we show a positive relation between inventory dispersion and interdealer price dispersion. Our interpretation of interdealer price dispersion as a measure of risk misallocation is also supported by our robustness checks. First, the negative correlation between trading volume and price dispersion is inconsistent with an interpretation of price dispersion as disagreement (see [Scheinkman](#page-39-0) [and Xiong](#page-39-0) [\(2003a\)](#page-39-0)). Second, to rule out an explanation based on market power we show in the Internet Appendix that our results are unaffected by (a) using only the largest dealers and (b) controlling for dealer HHI.

Our inventory measure is constructed as follows. First, we compute total exposure to

credit risk from dealers' bond inventory:

$$
RC_{d,t} = \sum_{i \in I_d} Inv_{d,i,t} \times DTS_{i,t}, \qquad (11)
$$

where $RC_{d,t}$ is the risk-bearing capacity of dealer d in month t, I_d is the set of bond traded by dealer d, $Inv_{d,i,t}$ is dealer-d's cumulative inventory of bond-i, $DTS_{i,t}$ is bond-i's durationtime-spread. We follow [Ben Dor et al.](#page-36-0) [\(2007\)](#page-36-0), and use duration-times-spread (DTS) as a proxy for bond-level exposure (β) to bond-market risk. The DTS-weighted cumulative inventory is our measure of dealers' risk-bearing capacity and it includes exposure to aggregate credit risk from all bonds traded by dealer d. The cumulative inventory of bond i held by dealer d in month t is calculated according to the following inventory model:

$$
Inv_{d,i,t} = Inv_{d,i,0} + \sum_{s=1}^{t} q_{d,i,s},
$$
\n(12)

where $q_{d,i,s}$ is the signed net trading volume of bond i traded by dealer d in month s, and $Inv_{d,i,0}$ is the initial inventory. The signed net trading volume $(q_{d,i,s})$ is positive if dealer i is a net buyer of bond i in month s , and negative if the dealer is a net seller. We set the initial level of inventory, $Inv_{d,i,0}$, to zero for all dealers and bonds.

4.3 Stylized facts

[Figure [2](#page-41-0) about here.]

Figure [2](#page-41-0) plots our measure of interdealer price dispersion over time (red solid line). On average interdealer price dispersion is 40.5 basis points, but there is significant time variation. For example, in September 2008, dealers' corporate bond trades displayed price dispersion of over 400 basis points at the height of the Global Financial Crisis. Figure [2](#page-41-0) also plots the cross-sectional dispersion of dealers' marginal cost of risk-bearing, as proxied by variation in dealer DTS-weighted inventory. The black dashed line is the cross-sectional inter-quartile range of dealers' inventories, which comoves strongly with interdealer price dispersion. The two series share a correlation of 55.8%. Consistent with our previous intuition, when dealers are more heterogeneous (i.e., higher dispersion in inventories), there is more price dispersion in the interdealer market in a given month. Thus, this figure shows that interdealer price dispersion exists and varies systematically with dispersion in dealer inventories and with known episodes of interdealer market disruptions.

These facts can be understood in the context of models in which frictions in interdealer markets prevent dealers from exploiting gains from trade and from efficiently reallocating risk within the dealer sector [\(Eisfeldt et al.,](#page-37-0) [2023;](#page-37-0) [Atkeson et al.,](#page-36-0) [2015\)](#page-36-0). Essentially, any trading friction in the interdealer market will prevent dealers from fully taking advantage of price dispersion by buying low and selling high. In the models developed in [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0); [Atkeson et al.](#page-36-0) [\(2015\)](#page-36-0), prices reflect the weighted average of counterparties' riskbearing capacities. When trade is inhibited by transaction costs, information asymmetries, or search frictions, the dealer sector fails to execute trades that would reallocate risk more efficiently. As a result, at any point in time, we observe trades amongst sets of dealers who have not equated their marginal costs of risk-bearing (or, equivalently, their marginal valuations of the asset absent trading costs). Across pairs of counterparties, we observe trades at higher and lower prices. Higher spread trades occur between less well-positioned counterparties while lower spreads reflect trades among intermediaries with more capacity on average. Higher price dispersion then reflects a combination of more heterogeneity in dealers' risk-bearing capacity, more frictions in the interdealer market, or both.

[Figure [3](#page-42-0) about here.]

Figure [3](#page-42-0) displays the marginal cost of risk-bearing of individual dealers as measured by the time series average of each dealer's accumulated inventory for four subperiods based on the Global Financial Crisis (GFC) of 2007-2008: (i) before June 2007 (pre-GFC), (ii) from July 2007 to August 2009 (CFG), (iii) from September 2009 to February 2014 (post-CFG), and (iv) after March 2014 (Volcker). In Panel (a), we plot the marginal cost of risk-bearing of each of the top 50 dealers. The picture shows that dealers are heterogeneous in their marginal cost of risk-bearing and that this heterogeneity varies significantly over time. Panel (a) highlights that the tail of the distribution varies over time as well. In Panels (b) and (c), we plot the respective histogram and density kernels of the cross-sectional distribution of the marginal cost of risk-bearing. These panels show the marginal cost of risk-bearing being concentrated around zero, however its distribution became fat-tailed during the Global Financial Crisis. As in [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0), many dealers act mainly as intermediaries as they cluster around zero accumulated inventories. Others dealers are decumulating inventories by relatively large amounts and thereby reducing intermediary risk-bearing capacity, while a third set of dealers provides intermediary risk-bearing capacity by accumulating credit risk. Based on the intuition described above, we expect that trades by counterparties with different positions to occur at different prices.

[Figure [4](#page-43-0) about here.]

Interdealer price dispersion also relates to the market-wide average bond yields. In Figure [4,](#page-43-0) we plot the interdealer price dispersion along with the yield spreads for investment grade and high-yield bonds.¹⁷ There is a clear pattern from the data, which is that when interdealer price dispersion is high, both investment grade and high-yield bonds trade at higher yields (lower prices). This figure shows that higher price dispersion in the dealer market coincides with periods of higher bond premia.

As discussed earlier, when dealers are more heterogeneous in their ability to take on additional credit risk, they trade the same asset at different prices. In addition, dealers being more heterogeneous and trading at dispersed prices worsen dealers' ability to reallocate risk and intermediate trades between different non-dealer financial institutions, which may result in bonds being traded at a higher premium. Consistent with this intuition, Figure [4](#page-43-0) shows that yield spreads indeed increase when interdealer price dispersion is higher.

[Figure [5](#page-43-0) about here.]

We argue that price dispersion arises from heterogeneity in dealers' marginal cost of risk-bearing. While we acknowledge that belief heterogeneity is another potential source for interdealer price dispersion, we provide evidence against this idea based on trading volume. In particular, if beliefs are heterogeneous, one would expect dealers to trade bilaterally at different prices too. However, belief and marginal cost of risk-bearing heterogeneity have opposite implications for trading volume. Belief heterogeneity increases not only price dispersion but also trading volume, and trading intensifies as investors disagree more about the value of an asset (see, for example, [Scheinkman and Xiong](#page-39-0) [\(2003b\)](#page-39-0)). On the other hand, heterogeneity in marginal costs of risk-bearing combined with trading frictions leads to higher price dispersion corresponding to lower trading volume, which is precisely what we observe in the data. Figure [5](#page-43-0) shows that interdealer price dispersion and interdealer trading volume are negatively related.

5 Empirical analysis

We conduct four empirical exercises to establish that greater interdealer price dispersion corresponds to lower bond prices, higher bond yields, and higher expected returns. We argue that this is because interdealer price dispersion results from risk misallocation within the dealer sector, and a resulting lower intermediary risk-bearing capacity. First, in Section [5.1,](#page-19-0) we estimate the relation between changes in credit spreads and changes in interdealer price dispersion by following the methodology from [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) (henceforth CDGM). Additionally, we run a series of panel regressions following the

¹⁷ICE BofA US High Yield Index Effective Yield and ICE BofA US BBB Index Effective Yield, both retrieved from FRED, Federal Reserve Bank of St. Louis.

existing specifications from the literature. In Section [5.2,](#page-22-0) we verify that changes in fair-value basis–—that is, credit spreads in excess of fair-value spreads—vary with interdealer price dispersion. Third, in Section [5.3,](#page-24-0) we follow the CDGM methodology and show that changes in interdealer price dispersion help to explain the first principal component of credit spread residuals. Finally, Section [5.4](#page-25-0) shows that change in interdealer price dispersion is priced in the cross-section of duration-times-spread and maturity-times-spread sorted portfolios of bonds. These empirical exercises combined are comprehensive evidence that interdealer price dispersion is a key factor for bond prices.

5.1 Credit spread changes and interdealer price dispersion

In this section, we document the ability of interdealer price dispersion to explain a substantial amount of the observed changes in credit spreads. We start by implementing the methodology used by CDGM, which is to run bond-by-bond time-series regressions of changes in yield spreads $(\Delta YieldSpread_{i,t})$ on various explanatory variables. In all our specifications, we control for all of the variables used by CDGM to explain changes in bond spreads, namely: (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (vii) the slope of the volatility smirk. Specifically, for each bond, we estimate the following:

$$
\Delta Yields \text{pred}_{i,t} = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D} + \beta_3^i \text{Control}_{i,t} + \varepsilon_{i,t},\tag{13}
$$

where $Controls_{i,t}$ is a vector of controls, and $\Delta \sigma_t^{D2D}$ is the change in our measure of interdealer price dispersion (Equation [10](#page-15-0) in Section [4\)](#page-14-0). Then, we report average coefficients across all estimates. The specification in Equation 13 is nearly identical to the one implemented by [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0), except for including changes in interdealer price dispersion.

Our estimation results following the CDGM methodology (Equation 13) are in Table [1.](#page-44-0) 18 In the first column, we mirror the benchmark specification in CDGM and do not include changes in interdealer price dispersion. In line with their findings, the average adjusted R^2 is 20.5%. All signs, significance, and magnitude of CDGM control coefficients are consistent with those reported in their original work. In the second column, we add changes in interdealer price dispersion. The coefficient is statistically significant and economically large—a one-basis-point increase in interdealer price dispersion is associated with yield spreads 1.36 basis points higher after controlling for the CDGM fundamental-based variables. We find

^{[1](#page-44-0)8}To improve readability, Table 1 omits the coefficients estimates for the control variables, but in the Internet Appendix, Table [A1](#page-70-0) is the full table reporting all estimated coefficients.

that the average adjusted R^2 increases to 23.7%.

[Table [1](#page-44-0) about here.]

In the remaining columns of Table [1,](#page-44-0) we control for variables that have previously been documented to explain changes in credit spreads. In Columns (3) and (4), we follow [Bessem](#page-36-0)[binder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) and include a default factor defined as the spread between long-term investment grade and treasuries yields. Consistent with [Bessembinder,](#page-36-0) [Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), we find the default factor positively relates to credit spread changes. We also find that the interdealer price dispersion coefficient remains almost unchanged after controlling for the default factor. This suggests that changes in interdealer price dispersion are not related to changes in default probabilities.

Our paper contributes to a promising stream of studies that document the importance of intermediary asset pricing factors for pricing bonds. While our study emphasizes the power of dealer heterogeneity and transaction price dispersion in explaining yield-spread changes, prior work studied dealer-sector level measures of intermediary capacity based on aggregates or averages across dealers. This distinction is important because when the marginal cost of risk-bearing is not equated across dealers, measures of the risk-bearing capacity of the intermediary sector based on simple aggregates or averages of dealer-level health are inaccurate. Indeed, the greater interdealer frictions are, and the more risk-sharing across dealers is impaired, the less appropriate it is to measure dealer-sector risk bearing capacity using average dealer health. While such aggregate measures may still contain information about intermediary risk-bearing capacity, we show that our findings are largely unchanged if we include the variables prior studies have used to measure the financial soundness of the intermediary sector. Specifically, in Columns (5) and (6), we add the capital ratio growth rate of the whole sector of primary dealers from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0). We include two risk factors from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0) in Columns (7) and (8): the dealer inventory factor and the intermediary distress factor. The significance and economic magnitude of the interdealer price dispersion coefficient are similar in Columns (2), (4), (6), and (8). Thus, our measure of intermediary risk-bearing capacity based on interdealer price dispersion captures additional information relative to existing measures of dealer-sector financial soundness, consistent with our interpretation.

Finally, we also build on important prior evidence from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0) that OTC frictions are priced in bond markets. That study constructs a comprehensive set of market-wide measures of OTC frictions by developing proxies that measure overall search and bargaining frictions, as well as aggregate inventories. In contrast, our measure of interdealer price dispersion aims to measure intermediary risk-bearing capacity by exploiting the information in dealer heterogeneity and the variation in trading prices across bilateral transactions. We argue that such price dispersion provides a useful single measure that proxies for the inability of the dealer sector to efficiently reallocate risk, thereby limiting intermediary risk-bearing capacity. In Columns (9)-(12), we verify whether interdealer price dispersion remains significant after controlling for the various measures of OTC frictions studied by [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). They analyze 11 variables split into three broad groups: inventory frictions, search frictions, and bargaining frictions. For data availability and comparison purposes, we follow their filtering approach. One of their variables is the length of the intermediation chain, which is not available for our full sample. For this reason, the sample in the last four columns is significantly reduced from 10,537 to 2,803 bonds from January 2003 to December 2013. Given the sample restriction, we first verify the previous findings in this subsample. In Columns (9) and (10), we replicate the exercises in columns (1) and (2) but using the restricted sample. We find a positive and significant coefficient for changes in interdealer price dispersion, and we also estimate a higher average adjusted R^2 . In Columns (11) and (12), we control for all the variables from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). We find that interdealer price dispersion remains positive and statistically significant. Our results indicate that interdealer price dispersion contains price-relevant information about intermediary risk-bearing capacity that is absent from measures of OTC frictions based on variables intended to capture market-wide OTC frictions.

In Table [1,](#page-44-0) we also consistently find a sizeable increase in average adjusted R^2 after including changes in interdealer price dispersion. Under the CDGM benchmark specification, the average adjusted R^2 increases by 15.6%, from 20.5% to 23.7%. In Columns (3)-(8), the average adjusted R^2 increases vary from 13.2% to 15.6%. After controlling for the OTC variables from [Friedwald and Nagler](#page-37-0) (2019) , we find that the average adjusted R^2 increases by 6.3%, from 38.3% to 40.7%.

One challenge faced by the methodology used by [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) is that the betas estimated in the time-series estimates are noisy and can potentially affect the standard errors of the average coefficient reported in the table. Although the literature has used this methodology (e.g., [Friedwald and Nagler,](#page-37-0) [2019\)](#page-37-0), we additionally estimate these coefficients in a panel regression setting, which allows us to compute standard errors clustered at bond and month levels.

Specifically, we repeat the specifications in Table [1,](#page-44-0) but in a panel regression specification with bond fixed effect. We estimate the following panel regression:

$$
\Delta Yields \text{pred}_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{\text{D2D}} + \beta_2' \text{Control}_{i,t} + \varepsilon_{i,t},\tag{14}
$$

where η_i is a bond fixed effect, $Controls_{i,t}$ is a vector of controls, and $\Delta \sigma_t^{D2D}$ is the change in our measure of interdealer price dispersion (Equation [10](#page-15-0) in Section [4\)](#page-14-0).

Table [2](#page-45-0) reports the regression estimates based on Equation $(14).^{19}$ $(14).^{19}$ In Column (1) , we report estimates for the CDGM baseline, which does not include our variable of changes in interdealer price dispersion, in a panel setting. A critical difference between this panel approach vs. the original CDGM empirical approach is that our panel specification does not feature bond-specific slopes (e.g., β_1^i in Equation [13\)](#page-19-0). Instead, we directly estimate coefficients common to all bonds (e.g., β_1 in Equation [14\)](#page-21-0). Hence, the CDGM approach of time series regressions at the bond level has a more flexible structure and therefore has a better overall fit to the data with an average R^2 of 20.5% (see Column 1 in Table [1\)](#page-44-0). Using the same control variables, the panel regression has an R^2 of 7.1% (see Column 1 in Table [2\)](#page-45-0).

[Table [2](#page-45-0) about here.]

In Column (2), we include changes in interdealer price dispersion $(\Delta \sigma_t^{D2D})$, and we find a positive and statistically significant coefficient of 0.777 with a t-statistic of 5.12, where standard errors are double clustered at month and bond levels. The estimated coefficient is economically meaningful. One basis-point increase in interdealer price dispersion is associated with credit spread increasing by 0.777 basis point on average after controlling for various fundamental-based variables.

In Columns (3) and (4) of Table [2,](#page-45-0) we add the controls for default factor (DEF) from [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), which is measured as the yield difference between long-term investment-grade corporate bonds and long-term treasuries. In Columns (5) and (6), we control for the capital ratio growth rate of the whole sector of primary dealers from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0), and in Columns (7) and (8), we control for the inventory and distress factors from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0). The interdealer price dispersion coefficient remains largely unchanged and significant. The last four columns include controls for the variables used by [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). In all specifications, the coefficient on changes in interdealer price dispersion remains significant and economically important.

5.2 Changes in fair-value basis and interdealer price dispersion

This section extends our study of interdealer price dispersion from changes in raw yield spreads to changes in fair-value bond bases. The fair-value basis is the difference between

 19 To improve readability, Table [2](#page-45-0) omits the coefficients estimates for the control variables, but in the Internet Appendix, Table [A2](#page-71-0) is the full table reporting all estimated coefficients.

bond spreads from transaction prices and fair-value spreads. The construction of fair-value spreads does not rely on bond market data; the primary inputs are data on leverage and equity volatility. Since fair-value spreads are based on equity market data, they provide a measure of credit spreads unrelated to OTC frictions since equities are not traded in overthe-counter markets. Hence, the difference between a bond spread and its fair-value spread, namely, the fair-value basis, provides one measure of the effect of OTC frictions on bond spreads, and we find that interdealer price dispersion is informative about this basis. We follow [Chang, d'Avernas, and Eisfeldt](#page-36-0) [\(2021\)](#page-36-0) to build fair value spreads (FVS) from data on equity volatility, leverage, and Moody's [\(Liu et al.,](#page-38-0) [2020;](#page-38-0) [Nazeran and Dwyer,](#page-39-0) [2015\)](#page-39-0) expected default frequencies (EDFs).

We follow the same approach as in Section [5.1](#page-19-0) and regress changes in the fair-value basis on interdealer price dispersion and various controls.²⁰ We run the following panel regression:

$$
\Delta YieldSpread_{i,t} - \Delta FVS_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D} + \beta_2' Control_{i,t} + \varepsilon_{i,t},\tag{15}
$$

where η_i is a bond fixed effect, $\Delta FVS_{i,t}$ is the change in fair value spread of bond i from month $t-1$ to t, and $\Delta \sigma_t^{D2D}$ is the change in our measure of interdealer price dispersion.

[Table [3](#page-46-0) about here.]

Table [3](#page-46-0) reports the regression estimates.²¹ In Column (1) , we control for the CDGM variables only, and in Column (2), we include changes in interdealer price dispersion $(\Delta \sigma_t^{D2D})$. The coefficient on interdealer price dispersion is positive and equal to 0.6. It is statistically significant and economically meaningful. One basis point increase in interdealer price dispersion is associated with a 0.6 basis point hike in fair-value basis.

In the remaining columns, we repeat this exercise but control for different factors. In Columns (3) and (4), we control for the default factor (DEF) from [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), which is the difference between the yields of long-term investmentgrade corporate bonds and long-term treasuries. In Columns (5) and (6), we control for the capital ratio growth rate of the whole sector of primary dealers from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0). Finally, in Columns (7) and (8), we control for both inventory and distress factors from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0).

Across these specifications, the interdealer price dispersion coefficient remains largely unchanged and significant. The coefficients on all other variables (DEF, HKM, and HKS)

²⁰In this section, we report results for panel regression specifications. However, in Internet Appendix Table [A4,](#page-73-0) we apply the same methodology as in CDGM but with fair-value basis on the left-hand side and find similar findings.

 21 To improve readability, Table [3](#page-46-0) omits the coefficients estimates for the control variables, but in the Internet Appendix, Table [A3](#page-72-0) is the full table reporting all estimated coefficients.

are insignificant. This means that neither changes in default nor changes in market-wide OTC frictions (HKM, HKS) help explaining changes in the fair-value basis. The fact that these coefficients become insignificant is consistent with the idea that, relative to changes in raw bond yields, changes in the fair value basis are more sensitive to OTC frictions. The results also support interdealer price dispersion as a measure of interdealer frictions and the resulting effects on dealer-sector risk-bearing capacity.

In the last four columns of Table [3,](#page-46-0) we control for OTC variables from [Friedwald and](#page-37-0) [Nagler](#page-37-0) [\(2019\)](#page-37-0), akin to Columns (9)-(12) in Tables [1](#page-44-0) and [2.](#page-45-0) After controlling for their variables, we find that interdealer price dispersion remains positive and significant. The coefficient decreases by nearly 40%, from 0.26 to 0.16, but it is still economically meaningful. After controlling for various fundamental-based measures from CDGM and 11 OTC-based variables, we find a positive and significant relation between interdealer price dispersion and fair-value basis.

5.3 Principal component analysis of CDGM residuals

[Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) find that their fundamental-based variables explain 20% to 25% of the changes in credit spreads observed in the data. We replicate this finding in Column (1) of Table [1,](#page-44-0) where the CDGM controls feature an average adjusted R^2 of 20.5%. A key result of their work is that the residuals from these regressions are highly cross-correlated, with the first principal component of these residuals explaining 75% of the total variation. Following the same methodology, our replication in Column (1) of Table [4](#page-47-0) depicts a similar figure in which the first principal component of the residual explains 57.2% of the variation in residuals. Panel A of Table [4](#page-47-0) contains the principal component analysis for the same set of controls used in Table [1.](#page-44-0) This first panel reports the fraction of the variance of the residuals that the first and second principal components explain, as well as the remaining unexplained variance.

[Table [4](#page-47-0) about here.]

The strong factor structure in credit spread residuals is interesting. Explaining their first principal component is crucial to understanding credit spreads' dynamics. Following [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we take the first principal component of the residuals from the benchmark CDMG specification (Column (1) in Panel A) and regress it on various factors. These results are in Panel B of Table [4,](#page-47-0) where we report R^2 , adjusted R^2 , and F-statistics for different specifications. The explanatory variables used mirror those in Panel A. In Column (2) Panel B, we find that interdealer price dispersion explains 16% of the first principal

component of CDGM residuals. Columns (3), (5), and (7) show that the default, HKM, and HKS factors have low explanatory power with R^2 of about 1%. Once we add interdealer price dispersion to these specifications, the explanatory power increases significantly, with R^2 at about 17%, as reported in Columns (4), (6), and (8). This is consistent with interdealer price dispersion providing a measure of dealer-sector risk-bearing capacity that has a common effect on all bond yields.

[Table [5](#page-48-0) about here.]

In [Friedwald and Nagler'](#page-37-0)s [\(2019\)](#page-37-0) (henceforth FN) original work, they document that their 11 OTC variables on inventory, search, and bargaining explain 23.4% of the first principal component of the CDGM residuals. Their finding suggests that OTC frictions are essential in explaining these residuals. Table [5](#page-48-0) conducts the same exercise as Table [4.](#page-47-0) However, we restrict to a subsample in which FN variables are available. We limit the sample to verify how their 11 OTC variables interplay with interdealer price dispersion in explaining the CDGM residuals. Our replication differs slightly from FN's original work. Although we followed the same procedure, our sample has 2803 bonds, and theirs has 925 bonds. These differences might be due to data availability. In Columns (1)-(3) of Table [5,](#page-48-0) we conduct our analysis following our replication, including all 2803 different bonds. As a robustness exercise, Columns $(4)-(6)$ report the same results, but we restrict the sample to the same universe of bonds used in FN's original work.

Our replication of FN findings in Column (1) of Table [5](#page-48-0) shows that FN 11 variables explain 11% of the first principal component of bond residuals. In Column (2), we find that interdealer price dispersion along with FN 11 OTC variables explain 23% over the same data sample. Finally, in Column (3), we report the results with interdealer price dispersion as the only independent variable. We find that interdealer price dispersion alone explains 12% of the first principal component of bond residuals. The results reported in Columns (4)-(6) are similar to those reported in the first three columns. Our analysis is robust to restricting the universe of bonds to those used in FN's original work. Overall, our results indicate that interdealer price dispersion explains the first principal component of bond residuals beyond a wide range of measures of OTC frictions. We expect this to be the case if interdealer price dispersion provides a measure of risk misallocation and the effective risk aversion of the dealer sector.

5.4 Price of risk

In this section, we investigate whether interdealer price dispersion is priced in the crosssection of bonds. We expect interdealer price dispersion to carry a negative price of risk.

Intuitively, interdealer price dispersion measures dealers' heterogeneity and interdealer market frictions. Thus, it measures dealers' ability to reallocate risk. When interdealer price dispersion increases, it becomes more costly for the dealer sector to reallocate risk, leading to higher yields and lower realized bond returns. This positive relation between changes in interdealer price dispersion and bond yields is what we have documented in Section [5.1.](#page-19-0)

It is crucial to note that interdealer price dispersion increases in bad states of the world, such as during the Global Financial Crisis of 2007–2008, as demonstrated in Figure [2.](#page-41-0) Consequently, a bond with a more negative exposure to interdealer price dispersion—that is, a more negative beta with respect to changes in interdealer price dispersion—pays lower returns in bad states of the world as yields increase. Such a bond is riskier as it performs poorly in bad states of the world, so it should carry a higher risk premium. On the other hand, bonds whose returns covary positively with changes in interdealer price dispersion, i.e., positive beta on interdealer price dispersion changes, are hedges against these states of the world and should carry a lower risk premium. This implies a negative price of risk for interdealer price dispersion.

To estimate the price of risk of interdealer price dispersion, we follow a two-step estimation procedure, which is a particular case of the method developed by [Fama and MacBeth](#page-37-0) [\(1973\)](#page-37-0). First, we run the following time-series regression for each portfolio i:

$$
R_{i,t} = \beta_i^0 + \beta_i^{D2D} \Delta \sigma_t^{D2D} + \beta_i^{F'} F_t + \nu_{i,t}
$$
\n(16)

where $R_{i,t}$ is the excess return on portfolio i in month t, β_i^{D2D} is the portfolio's exposure to changes in interdealer price dispersion. We also include other factors F_t . Specifically, all specifications control for the corporate bond market factor (MKTB) and the traded liquidity factor (LRF) following the work by [Dickerson, Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0).²² Additionally, in some specifications, we control for default risk from [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0), capital ratio growth rate of primary dealers from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0), or the two risk factors from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0).

Second, we run monthly cross-sectional regressions for $t = 1, 2, ..., T$ as follows:

$$
R_{i,t} = \lambda_{0,t} + \lambda_{D2D,t} \beta_i^{D2D} + \lambda_{F,t'} \beta_i^F + u_{i,t}
$$
\n(17)

 22 [Dickerson, Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0) conclude that the two priced factors in corporate bond markets are the bond market factor and the traded liquidity factor. For this reason, we use these two factors as standard controls in all our price of risk estimations. Using a novel IPCA approach, [Kelly, Palhares, and](#page-38-0) [Pruitt](#page-38-0) [\(2023\)](#page-38-0) prices bonds using time-varying bond-specific factor loadings with promising out-of-sample results. The IPCA framework may capture the effects of interdealer price dispersion, and using the IPCA framework they develop can be a fruitful direction for future research.

where γ_i 's are portfolio exposures as above and β 's are the estimated coefficients from Equa-tion [16.](#page-26-0) In this second step, we estimate the coefficient λ_t 's, and their time-series average are our estimates for the price of risk of each risk factor. In our estimations, we adjust standard error following [Shanken](#page-39-0) [\(1992\)](#page-39-0).

[Table [6](#page-49-0) about here.]

We estimate the prices of risk for different test assets, and Table [6](#page-49-0) reports our estimation results under different specifications. In Panel A, we use 10 portfolios of bonds sorted by duration times spreads as test assets, and in each row, we estimate prices of risk under different specifications. In all the rows, we control for the market factor MKTB and the traded liquidity factor LRF . In the second row, we control for the default factor (DEF) from [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0). In the third row, we control for the capital ratio growth rate of the whole sector of primary dealers [\(He, Kelly, and Manela,](#page-38-0) [2017\)](#page-38-0), and, in the fourth row, we control for inventory and distress factors [\(He, Khorrami, and Song,](#page-38-0) [2019\)](#page-38-0). In all four specifications, we find that interdealer price dispersion carries a statistically significant negative price of risk. In Panel B of Table [6,](#page-49-0) we use 25 portfolios of bonds double sorted by maturity and size.²³ Again, in all four specifications, we find that interdealer price dispersion carries a statistically significant negative price of risk, which is consistent with our intuition and previous results.

All our specifications control for two established factors in the corporate bond market: the market factor (MKTB) and the traded liquidity factor (LRF), as used in the study by [Dickerson, Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0). The key finding is that the interdealer price dispersion, when viewed as a systemic factor, is priced despite controlling for market (MKTB) and traded liquidity (LRF) factors.

Our interdealer price dispersion does not subsume MKTB and LRF but serves as an additional factor. This is consistent with extensive literature documenting the importance of liquidity for bond pricing.²⁴ Notably, our price dispersion metric exclusively uses interdealer transactions to capture heterogeneity and frictions amongst dealers. While we believe that interdealer price dispersion results from interdealer frictions, which can be interpreted as a type of illiquidity, we do not view it as a liquidity measure only. In addition to being an outcome of interdealer frictions or illiquidity, it is key for our intuition that interdealer price dispersion represents the inability of the dealer sector to efficiently reallocate risk, with the result being an effectively higher intermediary risk aversion. Thus, we view interdealer price

 23 Figures [A1](#page-68-0) and [A2](#page-69-0) in the Internet Appendix plot average bond risk premium against the predicted risk premium implied Equation [17](#page-26-0) at estimated parameters for all four specifications.

²⁴Some recent work on this topic includes [Chen et al.](#page-37-0) (2007) ; [Bao et al.](#page-36-0) (2011) ; [Jankowitsch et al.](#page-38-0) (2011) ; [De Jong and Driessen](#page-37-0) [\(2012\)](#page-37-0); [Schestag et al.](#page-39-0) [\(2016\)](#page-39-0); [Bongaerts et al.](#page-36-0) [\(2017\)](#page-36-0); [Goldberg and Nozawa](#page-38-0) [\(2021\)](#page-38-0).

dispersion as a measure of by how much intermediary risk-bearing capacity is impaired due to interdealer frictions.

6 Controlling for within-month volatility

Our measure of interdealer price dispersion consists of the cross-sectional standard deviation of all interdealer transactions' yield spreads. Within each calendar month, we first compute, for each bond, the standard deviation of yield spreads of all interdealer transactions (Equation [9\)](#page-14-0). As a second step, we average across all bonds to get the monthly time series of interdealer price dispersion (Equation [10\)](#page-15-0). One challenge to this approach is that interdealer price dispersion captures some of the within-month volatility of bond spreads because the standard deviation computed in the first step uses all interdealer trades each month. Bonds are not traded frequently, and unfortunately, we cannot compute interdealer price dispersion at a daily frequency.

We conduct two robustness exercises to control for within-month volatility. First, we construct interdealer price dispersion at a weekly frequency, which increases the frequency of our data and mitigates concerns regarding within-month volatility. However, there is still within-week volatility that is not being controlled for. In our second exercise, we control for all within-month volatility by constructing interdealer price dispersion from fair-value bases instead of bond spreads, which effectively controls for daily fundamental-based variation in bond spreads. This robustness exercise is different from our analysis in Table [3](#page-46-0) which analyzed the relation between changes in fair-value bases and interdealer price dispersion based on raw bond yield spreads. That exercise showed that our main measure of interdealer price dispersion was able to explain changes in fair value bases, consistent with interdealer price dispersion capturing a pricing effect from interdealer OTC frictions as opposed to fundamentals. In this section, we show that the dispersion in fair value bases is able to explain changes in raw yield spreads, consistent with the information in interdealer price dispersion relevant for explaining yield spread changes being unrelated to any within-month changes in bond fundamentals. Next, we discuss these two exercises in detail.

6.1 Interdealer price dispersion at weekly frequency

We construct an alternative measure of monthly interdealer price dispersion using bonds' cross-sectional standard deviation of yields of interdealer transactions within each week. This alternative measure helps control the within-month bond price volatility. In addition, we compute the volume-weighted average of week-bond dispersion, which helps to filter out weeks in which a particular bond had low trading volume.

First, for each bond i traded in week w , we compute interdealer price dispersion as:

$$
\sigma_{i,w}^{D2D} = \sqrt{\frac{\sum_{j=1}^{N_{i,w}} (yd_{j,i,w} - \overline{yd}_{i,w})^2}{N_{i,w} - 1}},\tag{18}
$$

where $N_{i,w}$ is the total number of interdealer transactions of bond i in week w, and $yd_{j,i,w}$ is the yield of interdealer transaction j.

Second, we compute the average dispersion across all bonds in a given month as our alternative measure of interdealer price dispersion:

$$
\tilde{\sigma}_t^{D2D} = \frac{1}{M_t} \sum_i \overline{\sigma}_{i,t}^{D2D} = \frac{1}{M_t} \sum_i \frac{\sum_{w \in W_t} \sigma_{i,w}^{D2D} * Q_{i,w}}{\sum_{w \in W_t} Q_{i,w}},\tag{19}
$$

where $\bar{\sigma}_{i,t}^{D2D}$ is volume-weighted average weekly interdealer price dispersion in month t, ${Q_{i,w}}_{w \in W_t}$ are bond's total trading volume in all weeks W_t within each month t, and M_t is the number of bonds traded in month t.

Then we apply this new measure of interdealer price dispersion to re-do the empirical analysis from Sections [5.1,](#page-19-0) [5.2,](#page-22-0) and [5.3.](#page-24-0) Tables [A5,](#page-74-0) [A6,](#page-75-0) [A7,](#page-76-0) [A8,](#page-77-0) and [A9](#page-78-0) in the Internet Appendix replicate Tables [1,](#page-44-0) [2,](#page-45-0) [3,](#page-46-0) [4,](#page-47-0) and [5](#page-48-0) but using the interdealer price dispersion measure controlling for weekly variation instead. We obtain results similar to those in Sections [5.1,](#page-19-0) [5.2](#page-22-0) and [5.3.](#page-24-0)

6.2 Interdealer price dispersion from fair-value bases

Another way to control for within-month variation in spreads is to match the yield spread of each transaction with its respective daily fair value spread. Fair-value spreads are a fundamental-based measure of spreads that depend on the issuers' leverage and volatility but do not rely on data from bond markets. The difference between yield spreads and fair-value spreads, the fair-value basis, captures the non-fundamental component of bond spreads and is not affected by variation in fundamentals. Hence, to control for within-month volatility in fundamentals, we construct an alternative measure of interdealer price dispersion based on fair-value basis instead of yield spreads.

Daily Fair Value Spreads We follow [Chang, d'Avernas, and Eisfeldt](#page-36-0) [\(2021\)](#page-36-0) and literature therein to build fair value spreads (FVS) but at a daily frequency.²⁵ The construction

 25 See [Liu et al.](#page-38-0) [\(2020\)](#page-38-0) and [Nazeran and Dwyer](#page-39-0) [\(2015\)](#page-39-0).

of these spreads uses no bond market data. The main inputs are data on issuers' leverage and data on daily equity price.

We apply the Vasicek-Kealhofer (VK) model to calculate, for each issuer and day, asset volatility, the market value of assets, and the issuer's distance to default (DD) . We map daily DD to obtain daily Expected Default Frequency (EDF) credit risk measure,²⁶ which is an estimate for the probability of default projected on next year. Then using the generated EDF credit risk measure, we construct a cumulative EDF (CEDF) over T years by assuming a flat term structure—that is, $CEDF_T = 1 - (1 - EDF)^T$. Then we convert our physical measure of default probabilities (CEDF) to risk-neutral default probabilities (CQDF) using the following equation:

$$
CQDF_T = N\left[N^{-1}(CEDF_T) + \lambda \rho \sqrt{T}\right],
$$

where N is the cumulative distribution function for the standard normal distribution, λ is the market Sharpe ratio, and ρ is the correlation between the underlying asset returns and market returns. Given this risk-neutral default probability measure, the fair value spread of a zero-coupon bond with duration T can be computed as

$$
FVS = -\frac{1}{T}\log(1 - CQDF_T \cdot LGD),
$$

where LGD stands for the risk-neutral expected loss given default. We set T equals bond's remaining time to maturity date, and follow [Chang, d'Avernas, and Eisfeldt](#page-36-0) [\(2021\)](#page-36-0) to set $LGD = 60\%, \lambda = 0.546, \text{ and } \rho =$ √ 0.3. We obtain series of FVS for each issuer and day.

Interdealer price dispersion based on fair-value basis. Interdealer price dispersion based on the fair-value basis is then computed monthly. We construct a monthly time series for fair-value basis dispersion by following the same methodology used in constructing interdealer price dispersion.

First, we compute the dispersion in basis for each bond in each month:

$$
\sigma_{i,t}^{basis} = \sqrt{\frac{\sum_{j=1}^{N_{i,t}} (basis_{j,i,t} - \overline{basis}_{i,t})^2}{N_{i,t} - 1}},
$$
\n(20)

where $basis_{j,i,t} = ys_{j,i,t} - FVS_{j,i,t}, ys_{j,i,t}$ is the yield spread of interdealer transaction j, $FVS_{j,i,t}$ is the corresponding daily fair-value spread of transaction j, and $N_{i,t}$ is the total number of interdealer transactions of bond i at month t . Dispersion in basis of bond i at

²⁶Our Matlab codes also refer to the following public webpage: https://fintechprofessor.com/portfolioitems/kmv-merton-distance-to-default-model-through-iterative-process-in-stata/.

month t, i.e. $\sigma_{i,t}^{basis}$, excludes the specific component of variation in yield spreads due to the fact that transactions in that particular bond may occur on different days within a given month.

Second, we compute the average dispersion across all bonds in a given month to obtain dispersion in fair-value basis over time:

$$
\sigma_t^{basis} = \frac{1}{M_t} \sum_i \sigma_{i,t}^{basis},\tag{21}
$$

where M_t is the number of bonds traded in month t.

Tables [7,](#page-50-0) [8,](#page-51-0) [9,](#page-52-0) [10,](#page-53-0) [11](#page-54-0) replicate Tables [1,](#page-44-0) [2,](#page-45-0) [3,](#page-46-0) [4,](#page-47-0) [5](#page-48-0) but using interdealer price dispersion measure constructed from fair-value bases constructed using daily data. We obtain results similar to those in Sections [5.1,](#page-19-0) [5.2](#page-22-0) and [5.3,](#page-24-0) indicating that our results are unlikely to be driven by within-month variation in volatility.

> [Table [7](#page-50-0) about here.] [Table [8](#page-51-0) about here.] [Table [9](#page-52-0) about here.] [Table [10](#page-53-0) about here.] [Table [11](#page-54-0) about here.]

6.3 Placebo tests

In this section, we conduct two placebo tests. In the first exercise, we construct two measures of interdealer price dispersion based on bonds with high and low interdealer price dispersion levels. In this placebo test, we fix all other bond characteristics by applying propensity score matching (PSM) to ensure that other bond characteristics do not confound our results. The dispersion of spreads among bonds with high interdealer price dispersion is the key measure we are interested in, while the dispersion among those with low interdealer price dispersion could be attributed to monthly volatility.

Specifically, we sort bonds monthly according to their interdealer price dispersion. We classify bonds in the top 30% as high dispersion bonds (high-D2D) and those in the bottom 30% as low dispersion bonds (low-D2D). For each month, we apply propensity score matching to create two groups of equal size from these high-D2D and low-D2D categories, matching bond-level liquidity, credit rating, duration, dealer participation, block trade proportion, and

fair value basis volatility. Then, we create monthly market-level measures of interdealer price dispersion based on either high-D2D or low-D2D bonds. Finally, we use the two versions of interdealer price dispersion as independent variables in our fixed effect models.

As expected from our mechanism and consistent with previous results, we obtain significant regression results using the high-D2D version interdealer price dispersion, as shown in Table [12.](#page-55-0) Similarly, consistent with our intuition and prior findings, the results become insignificant when using low-D2D version interdealer price dispersion, as shown in Table [13.](#page-56-0)

[Table [12](#page-55-0) about here.]

[Table [13](#page-56-0) about here.]

In our second placebo test, we conduct a similar propensity score matching analysis, but we sort bonds by value basis (FVB) instead of interdealer dispersion. A high fair-value basis suggests significant trading friction in the interdealer market. Therefore, we expect interdealer price dispersion among bonds with a high fair-value basis to better measure interdealer frictions. Consistent with our proposed mechanism and intuition, the estimated relation between changes in credit spreads and interdealer price dispersion is more pronounced when our measure of interdealer price dispersion is based on high-FVB bonds. The point estimates in Table [14](#page-57-0) are higher than in our baseline results while remaining statistically significant. Similarly, in line with our framework, the estimated relation becomes insignificant when based on low-FVB bonds, as shown in Table [15.](#page-58-0)

[Table [14](#page-57-0) about here.]

[Table [15](#page-58-0) about here.]

7 Robustness

We conduct various additional robustness exercises, which we describe next. All robustness tables are in the Internet Appendix.

(a) Volume-weighted interdealer price dispersion. In our baseline results, we construct interdealer price dispersion as an equal-weighted average of bond-level spread dispersion. To rule out the possibility that low volumed transactions drive our results, we construct a volume-weighted measure of interdealer price dispersion:

$$
\sigma_{t,vw}^{D2D} = \frac{\sum_{i} Volume_{i,t} * \sigma_{i,t}^{D2D}}{\sum_{i} Volume_{i,t}},
$$
\n(22)

where $\sigma_{i,t}^{D2D}$ is the interdealer yield dispersion of bond i in month t defined by Equation [\(9\)](#page-14-0), and $Volume_{i,t}$ is the transaction volume of bond i in month t. Tables [A10,](#page-79-0) [A11,](#page-80-0) [A12,](#page-81-0) [A13,](#page-82-0) [A14](#page-83-0) in the Internet Appendix replicate Tables [1,](#page-44-0) [2,](#page-45-0) [3,](#page-46-0) [4,](#page-47-0) [5](#page-48-0) but using volume-weighted interdealer price dispersion measure instead. We obtain results similar to those in Sections [5.1,](#page-19-0) [5.2](#page-22-0) and [5.3.](#page-24-0)

(b) Interdealer price dispersion from largest dealers only. TRACE data identify many financial institutions as dealers. Some dealers are small, while others are large. Smaller dealers are more likely to have transactions that are outliers. To verify if this is an issue for our measure, we compute interdealer price dispersion based only on transactions between the largest 50 dealers. Tables [A15,](#page-84-0) [A16,](#page-85-0) [A17,](#page-86-0) [A18,](#page-87-0) [A19](#page-88-0) in the Internet Appendix replicate Tables [1,](#page-44-0) [2,](#page-45-0) [3,](#page-46-0) [4,](#page-47-0) [5](#page-48-0) but using interdealer price dispersion measure constructed from transaction between the largest 50 dealers. We obtain results similar to those in Sections [5.1,](#page-19-0) [5.2](#page-22-0) and [5.3.](#page-24-0)

(c) Subsample excluding the Global Financial Crisis. In our sample, bond spreads and interdealer price dispersion spiked during the Global Financial Crisis (See Figure 3). This period is an outlier in our sample, but we show that our findings hold even after excluding the Global Financial Crisis period from our sample This unusual period in our sample was not a driver of our results. See Tables [A20,](#page-89-0) [A21,](#page-90-0) [A22,](#page-91-0) [A23,](#page-92-0) and [A24](#page-93-0) in the Internet Appendix replicate Tables [1,](#page-44-0) [2,](#page-45-0) [3,](#page-46-0) [4,](#page-47-0) [5](#page-48-0) but show the results for the subsample excluding the Global Financial Crisis.

(d) Liquidity: controlling for bond turnover. One could be concerned that interdealer price dispersion captures bond turnover as it could lead to changes in interdealer price dispersion. Our results hold if we control for bond turnover. See Tables [A25,](#page-94-0) [A26,](#page-95-0) and [A27](#page-96-0) in the Internet Appendix, which report the estimates of our fixed effect models discussed in Sections [5.1](#page-19-0) and [5.2](#page-22-0) but controlling for bond turnover.

(e) Nonlinear effects. To rule out nonlinear effects, we show that our results are robust to controlling for the square term of interdealer price dispersion. See Tables [A28,](#page-97-0) [A29,](#page-98-0) and [A30](#page-99-0) in the Internet Appendix, which report the estimates of our fixed effect models discussed in Sections [5.1](#page-19-0) and [5.2](#page-22-0) but controlling for the squared value of interdealer price dispersion.

(f) Market power. The market power of dealers could be a concern and a potential driver of interdealer price dispersion. As a robustness exercise, we control for dealers' market power,

measured by the Herfindahl–Hirschman index (HHI) of dealers' market share in each bond market. Our findings still hold, and interdealer price dispersion is not capturing the dealers' market power. Tables [A31,](#page-100-0) [A32,](#page-101-0) and [A33](#page-102-0) in the Internet Appendix report the estimates of our fixed effect models discussed in Sections [5.1](#page-19-0) and [5.2](#page-22-0) but controlling for the HHI of dealers' market share.

(g) Bond-specific inventory and price dispersion. In this exercise, we show that our results are robust to including bond-specific interdealer price dispersion and bond-specific changes in dealer-sector inventory as controls. This controls for the potential cross-sectional relations between yield spread change and bond-specific dealer-sector risk-bearing capacity and OTC frictions. Tables [A34,](#page-103-0) [A35,](#page-104-0) and [A36](#page-105-0) in the Internet Appendixreport the estimates of our fixed effect models discussed in Sections [5.1](#page-19-0) and [5.2](#page-22-0) but controlling for the bondspecific inventory and interdealer price dispersion.

(h) Robustness exercise for interdealer price dispersion based on fair-value basis. We repeat the previous five exercises $(c-g)$ above but replace interdealer price dispersion $\Delta \sigma_t^{D2D}$ with that from fair-value basis $\Delta \sigma_t^{D2D, bond basis}$ as well. Our results still hold: See Tables [A37](#page-106-0)[–A53](#page-122-0) in the Internet Appendix.

(i) Rating, maturity and leverage sorting. Our results are robust across bonds sorted by credit rating, maturity, and leverage. We estimate [\(13\)](#page-19-0) with all CDGM controls with and without interdealer price dispersion for different groups of bonds, as in [Collin-Dufresne,](#page-37-0) [Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0). Specifically, we consider bonds grouped by issuer's leverage, credit rating, and different maturities. Tables [A54](#page-123-0) and [A55](#page-124-0) in the Internet Appendix show that interdealer price dispersion remains consistently significant across different groups and also significantly improves the mean of adjusted R^2 relative to the CDGM specification.

(j) COVID. Finally, in Table [A56,](#page-125-0) we extend the sample until September 2022, and control for a dummy variable during the COVD period (March 2020 to April 2020). The results are nearly identical.

(k) Liquidity: price impact. Bond markets can be illiquid and transactions can potentially impact prices. To verify whether interdealer price dispersion is capturing temporary price dislocation due to price impact, we construct interdealer price dispersion based only on more liquid bonds. We identify those bonds with their average monthly Amihud ratio (throughout the whole sample period) among the top 30% of all bonds as "more liquid"

bonds. Then we use the interdealer transactions of these identified "more liquid" bonds to construct a new version of market-level interdealer price dispersion and use it as a new independent variable in our fixed effect models. We obtain a more significant effect of interdealer price dispersion both in a statistical and economic sense. See Tables [A57](#page-126-0) and [A58](#page-127-0) in the Internet Appendix, which report the estimate of our fixed effect models discussed in Sections [5.1](#page-19-0) and [5.2.](#page-22-0)

8 Conclusion

We document the explanatory power of interdealer price dispersion for corporate bond yields. When interdealer price dispersion is higher, yield spread changes are higher. Interdealer price dispersion explains a substantial fraction of the first principal component of the residuals from a bond-level regression of yield spread changes on fundamental credit-risk variables. We argue that interdealer price dispersion is a proxy for frictions in the OTC bond market. Consistent with this, we show that interdealer price dispersion explains the basis between bond spreads from the OTC bond market and bond spreads constructed using a structural model and exchange-traded equity market data on volatility and leverage. Finally, we show that interdealer price dispersion is a priced risk factor. This is consistent with the idea that systematic credit risk capacity is lower when interdealer price dispersion is greater. We argue that this is because prices in the interdealer market become more dispersed when credit risk misallocation is more severe. Credit risk misallocation reduces risk-bearing capacity and increases effective risk aversion, leading to lower prices and higher expected returns.

We offer two broad implications for future work. First, we offer a specific reason why illiquidity is priced. In our framework, trading frictions inhibit the efficient allocation of risk, impairing risk-bearing capacity. As a result, a less liquid interdealer market has a higher effective risk aversion. Second, we offer a refinement for the measure of the financial health of the intermediary sector. The ability of the dealer sector to bear risk depends not only on the average risk-bearing capacities of individual dealers, but also on how, given trading frictions, that risk is allocated in the cross section. When dealers with a higher marginal cost of risk bearing hold a greater share of credit risk, the intermediary sector as a whole is more impaired. Our measure of interdealer price dispersion offers an empirical proxy for risk misallocation.
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Figures

Figure 1: Interdealer price dispersion and risk misallocation

In our model's numerical simulation, we start with an assumed average spread of 100 basis points under ideal risk sharing $(C = 0.01)$. Risk aversion is modeled as log-normal with a mean of 2 and a standard deviation of 4. We normalize the model with $\sigma_{\varepsilon} = 1$. Building on [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0), the probability of default is set at $p = 0.0065$ and loss given default at $L = 0.6060$, resulting in a bond payout variance of $\sigma^2 = (1-p)pL^2 = 0.0024$. Our simulation involves 1 million economies, each with 25 dealers. Dealers are sorted by their risk aversion (α) to compute: (i) average risk aversion, (ii) average cross-sectional correlation between credit risk exposure $(z + \omega)$ and risk aversion (α) , (iii) average interdealer price dispersion, and (iv) average credit spread in the interdealer market. We repeat these step by varying $\rho_{\varepsilon,\alpha}$ from 0 to 1 in 41 steps (incremental steps of 0.025). Panel (a) shows a heatmap of the average risk aversion across dealers plotted against the correlation between credit risk exposure $(z + \omega)$ and risk aversion (α). Panel (b) illustrates the average interdealer price dispersion (right axis) and the average credit spread in the interdealer market (left axis), both plotted against the correlation between credit risk exposure $(z + \omega)$ and risk aversion (α) .

(a) Risk allocation (b) Avg. spread and interdealer price dispersion

Figure 2: Interdealer price dispersion and primary dealers' risk bearing capacity

This figure plots interdealer price dispersion (red solid line) and the dispersion of dealers' marginal cost of risk-bearing as proxied by their inventories (black dashed line). To compute the interdealer price dispersion, we first compute the crosssectional standard deviation of yield spreads for each bond within each month. Then, we average across all bond trades that month (see Equation [10\)](#page-15-0). Inventories are the duration-times-spread (DTS)-weighted average of cumulative bond inventory positions, and the dispersion in inventories is the cross-sectional interquartile range. See Section [4](#page-14-0) for details on the construction of these variables.

Figure 3: Risk Bearing Capacity of Dealers

In Panel (a), we plot the average inventories for the largest 50 dealers over four different sub-periods relative to the Global Financial Crisis (GFC) of 2007-2008: (i) before June 2007 (pre-GFC), (ii) from July 2007 to August 2009 (CFG), (iii) from September 2009 to February 2014 (post-CFG), and (iv) after March 2014 (Volcker). Dealer-level inventory is measured as the duration-times-spread (DTS)-weighted average of cumulative bond inventory positions. Each circle in the plot represents a different dealer. Circle size increases with the absolute value of inventory.^{[27](#page-0-0)} Circles colors were randomly chosen to differentiate dealers. In Panel (b), we plot the histogram of inventories for the largest 50 dealers for the same four periods, and, in Panel (c), we plot the density kernel. See Section [4](#page-14-0) for details on the construction of these variables.

Figure 4: Interdealer price dispersion and level of yield spreads

This figure plots interdealer price dispersion (red solid line), effective yield of BBB (blue dashed line) and high yield (green dashed line) bonds. To compute the interdealer price dispersion, we first compute the cross-sectional standard deviation of yield spreads for each bond within each month. Then, we average across all trades that month (see Equation [10\)](#page-15-0). The effective yield data are the ICE BofA US High Yield Index Effective Yield and ICE BofA US BBB Index Effective Yield, both retrieved from FRED, Federal Reserve Bank of St. Louis. See Section [4](#page-14-0) for details on the construction of these variables.

Figure 5: Interdealer price dispersion and interdealer trading volume

In Panel (a), we plot interdealer price dispersion (red solid line) and volume in the interdealer markets as a fraction of total amount outstanding (black dashed lined). We linearly detrend and standardized both series to have mean zero and variance one. In Panel (b), we plot 12-month moving average of the series in Panel (a). See Section [4](#page-14-0) for details on the construction of these variables.

Tables

Table 1: Credit Spread Changes (CDGM)

This table reports the regression estimations from Equation [\(14\)](#page-21-0):

$$
\Delta Yield Spread_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D} + \beta_2^i' Controls_t^i + \varepsilon_t^i
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne,](#page-37-0) [Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table 2: Credit Spread Changes

This table reports the regression estimations from the following equation:

$\Delta YieldSpread_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D} + \beta_2^{\prime} Control_{i,t} + \varepsilon_{i,t}$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 3: Fair-value basis changes

This table reports the regression estimations from the following equation:

 $\Delta Yields \textit{pred}_{i,t} - \Delta FVS_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D} + \beta_2^{\prime} Control_{i,t} + \varepsilon_{i,t}$

where $\Delta FVS_{i,t}$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 4: Principal components of residuals

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$$
\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D}_t + \beta^i_2' Controls^i_t + \varepsilon^i_t
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Control_i^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

Table 5: Principal components of residuals (FN sample)

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$\Delta Yields \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details.

Table 6: Prices of Risk

This table reports the estimates of the prices of the risk for interdealer price dispersion [\(Fama and MacBeth,](#page-37-0) [1973\)](#page-37-0). Exposures and prices of risk are estimated according to Equations [\(16\)](#page-26-0) and [\(17\)](#page-26-0). In Panel A, we use 10 portfolios of bonds sorted by duration times spread (DTS) as test assets. For each bond and month, we calculate bonds' average duration multiplied by its realized yield spread in that month. Then, in each month, we sort bonds based on their DTS and form 10 DTS-sorted portfolios. In Panel B, we use 25 portfolios of bonds double-sorted by maturity and size (MTS) as in [Bai, Bali, and Wen](#page-36-0) [\(2019\)](#page-36-0). These 25 value-weighted test portfolios are formed by independently sorting corporate bonds into 5×5 quintiles portfolios based on size (amount outstanding) and maturity. Each row refers to an estimation with different controls. In all specifications, we control for the market factor MKTB and the traded liquidity factor LRF as used in the study by [Dickerson, Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0). Rows (1) and (5) include only the baseline controls of bond market factor and traded liquidity factor. In Rows (2) and (6), we control for the default factor (DEF) from [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), and, in Rows (3) and (7), we control for the capital ratio growth rate of the whole sector of primary dealers [\(He, Kelly, and Manela,](#page-38-0) [2017\)](#page-38-0). Finally, in Rows (4) and (8), we control for inventory and distress factors [\(He, Khorrami, and Song,](#page-38-0) [2019\)](#page-38-0) See Section [5.4](#page-25-0) for details. We adjust standard errors following [Shanken](#page-39-0) [\(1992\)](#page-39-0).

Table 7: Credit spread changes and fair-value basis dispersion (CDGM)

This table reports the regression estimations from Equation [\(14\)](#page-21-0):

$\Delta YieldS \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D, \text{ fair-value basis}} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta \sigma_t^{D2D}$, fair-value basis is the *alternative* measure of monthly change in dealer market price dispersion controlling for daily fair value spread (fvs), and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table 8: Credit spread changes and fair-value basis dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pred}_t^i = \beta_1 \Delta \sigma_t^{D2D, \text{ fair-value basis}} + \beta_2' Controls_t^i + \eta^i + \varepsilon_t^i$

where $\Delta \sigma_t^{D2D}$, fair-value basis is the *alternative* measure of monthly change in dealer market price dispersion controlling for daily fair value spread (fvs), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free ra slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 9: Fair-value basis and fair-value basis dispersion

This table reports the regression estimations from the following equation:

 $\Delta YieldSpread_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D, \text{ fair-value basis}} + \beta_2' Control_s^i + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$, fair-value basis is the alternative measure of monthly change in dealer market price dispersion controlling for daily fair value spread (fvs), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 10: Principal components of residuals using fair-value basis dispersion

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$\Delta YieldS \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D, \text{ fair-value basis}} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta \sigma_t^{D2D}$, fair-value basis is the *alternative* measure of monthly change in dealer market price dispersion controlling for daily fair value spread (fvs), and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

Table 11: Principal components of residuals using fair-value basis dispersion (FN sample)

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

 $\Delta YieldS \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D, \text{ fair-value basis}} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta\sigma_t^{D2D}$, fair-value basis is the *alternative* measure of monthly change in dealer market price dispersion controlling for daily fair value spread (fvs), and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details.

Table 12: Credit spread changes and high-D2D interdealer price dispersion

This table reports the regression estimations from the following equation:

$\Delta YieldS \textit{pread}_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, High-D2D} + \beta_2^{\prime} Controls_{i,t} + \varepsilon_{i,t}$

where $\Delta \sigma_t^{D2D, High-D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with high bond-level interdealer price dispersion controlling for bond-level liquidity, credit rating, duration, proportion of dealer participation, proportion of block trades and bond-level fair value basis volatility, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 13: Credit spread changes and low-D2D interdealer price dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pred}_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, Low-D2D} + \beta_2' Controls_{i,t} + \varepsilon_{i,t}$

where $\Delta\sigma_t^{D2D, Low-D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with low bond-level interdealer price dispersion controlling for bond-level liquidity, credit rating, duration, proportion of dealer participation, proportion of block trades and bond-level fair value basis volatility, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 14: Credit spread changes and high-FVB interdealer price dispersion

This table reports the regression estimations from the following equation:

$\Delta YieldS pred_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, High-FVB} + \beta_2' Control_{i,t} + \varepsilon_{i,t}$

where $\Delta \sigma_t^{D2D, High-FVB}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with high bond-level fair value basis (FVB) controlling for bond-level liquidity, credit rating, duration, proportion of dealer participation, proportion of block trades and bond-level fair value basis volatility, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table 15: Credit spread changes and low-FVB interdealer price dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pred}_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, Low-FVB} + \beta_2^{\prime} Controls_{i,t} + \varepsilon_{i,t}$

where $\Delta\sigma_t^{D2D, Low-FVB}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with low bond-level fair value basis (FVB) controlling for bond-level liquidity, credit rating, duration, proportion of dealer participation, proportion of block trades and bond-level fair value basis volatility, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Internet Appendix to "Interdealer Price Dispersion"

Andrea L. Eisfeldt¹, Bernard Herskovic², Shuo Liu³

A Risk misallocation model

In this section, we develop a tractable theoretical framework to highlight how misallocation frictions relate to interdealer price dispersion and average credit spreads. Our model builds on the OTC network model of [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0), but the two frameworks differ in important aspects. Ours features risk-aversion heterogeneity and a continuum of agents. Also, we explicitly model the interdealer corporate bond market instead of all credit-default swaps contracts' transactions. Given that all dealers actively trade with one another, we assume a complete trading network in which all bilateral trades are allowed.

There is a continuum of agents indexed by $i \in [0, 1]$, one asset representing credit risk exposure (e.g., a corporate bond) with an average payoff of μ and variance of σ^2 . Agents are heterogeneous regarding their initial endowment of credit risk exposure (ω_i) and risk aversion (α_i) . Agent i's optimization problem is given by:

$$
\max_{z_i, \{\gamma_{ij}\}_{j=1}^n} \omega_i \mu + \int_0^1 \gamma_{ij} (\mu - P_{ij}) dj - \frac{\alpha_i}{2} (\omega_i + z_i)^2 \sigma^2 - \frac{1}{2} \int_0^1 \phi \gamma_{ij}^2 dj
$$

s.t. $z_i - \int_0^1 \gamma_{ij} dj = 0$,

where γ_{ij} is the number of bonds agent i buying from agents j, α_i is the risk aversion of agent i, ϕ is the bilateral trading cost as in [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0). We interpret ϕ as a misallocation parameter, as it curbs trade and makes it harder for agents to share risk with one another.

From the first-order conditions, we can solve agent i's optimization problem for agents' bilateral and net positions:

$$
\gamma_{ij} = \frac{1}{\phi} \left[\mu - P_{ij} - \alpha_i (\omega_i + z_i) \sigma^2 \right], \tag{A1}
$$

where

$$
z_i = \int_0^1 \gamma_{ij} dj = \frac{\int_0^1 (\mu - P_{ij}) dj - \alpha_i \omega_i \sigma^2}{\phi + \alpha_i \sigma^2}.
$$
 (A2)

As in [Eisfeldt et al.](#page-37-0) [\(2023\)](#page-37-0), the market clearing conditions are given by:

$$
\gamma_{ij} + \gamma_{ji} = 0 \qquad \forall i, j \in [0, 1], \tag{A3}
$$

and we also assume no transaction costs between any two counterparties:

$$
P_{ij}=P_{ji}.
$$

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We can combine Equations [\(A1\)](#page-59-0) and [\(A3\)](#page-59-0), and find that, in equilibrium, agents i and j trade at a price given by:

$$
\mu - P_{ij} = \left[\frac{\alpha_i(\omega_i + z_i) + \alpha_j(\omega_j + z_j)}{2} \right] \sigma^2, \tag{A4}
$$

and if we substitute the contract premium (Equation A4) into the agents' first-order condition (Equation [A1\)](#page-59-0), then:

$$
\gamma_{ij} = \frac{1}{\phi} \left[\mu - P_{ij} - \alpha_i (\omega_i + z_i) \sigma^2 \right] = \frac{1}{2\phi} \left[\alpha_j (\omega_j + z_j) - \alpha_i (\omega_i + z_i) \right] \sigma^2.
$$

which means that i buys credit risk from j (i.e., $\gamma_{ij} > 0$) if, and only if, agent j is more exposed to credit risk than agent i after trading and correcting for differences in risk aversion, that is, $\alpha_i(\omega_i + z_i) > \alpha_i(\omega_i + z_i)$. The trade volume between two counterparties depends on the difference of their post-trade exposures scaled by risk aversion and by the misallocation parameter, ϕ .

The net positions, $\{z_i\}_i$, are determined in equilibrium. We can use Equations [\(A2\)](#page-59-0) and (A4), and solve for equilibrium net positions. From Equation (A4), we have:

$$
\mu - P_{ij} = \sigma^2 \left[\frac{\alpha_i}{2} (\omega_i + z_i) + \frac{\alpha_j}{2} (\omega_j + z_j) \right]
$$

and

$$
\int_0^1 (\mu - P_{ij}) dj = \sigma^2 \int_0^1 \left[\frac{\alpha_i}{2} (\omega_i + z_i) + \frac{\alpha_j}{2} (\omega_j + z_j) \right] dj
$$

$$
= \frac{1}{2} \sigma^2 \alpha_i (z_i + \omega_i) + \frac{1}{2} \sigma^2 \int_0^1 \alpha_j (z_j + \omega_j) dj
$$

We can rewrite Equation [\(A2\)](#page-59-0) as follows:

$$
z_i = \frac{\int_0^1 (\mu - P_{ij}) dj - \alpha_i \omega_i \sigma^2}{\phi + \alpha_i \sigma^2}
$$

$$
\int_0^1 (\mu - P_{ij}) dj = z_i (\phi + \alpha_i \sigma^2) + \alpha_i \sigma^2 \omega_i
$$

and have:

$$
z_i \left(\phi + \alpha_i \sigma^2\right) + \alpha_i \sigma^2 \omega_i = \frac{1}{2} \sigma^2 \alpha_i (z_i + \omega_i) + \frac{1}{2} \sigma^2 \int_0^1 \alpha_j (z_j + \omega_j) dj
$$

$$
z_i \left(1 + \frac{\phi}{\alpha_i \sigma^2}\right) + \omega_i = \frac{1}{2} (z_i + \omega_i) + \frac{1}{2} \int_0^1 \frac{\alpha_j}{\alpha_i} (z_j + \omega_j) dj
$$

$$
\alpha_i z_i \left(1 + \frac{2\phi}{\alpha_i \sigma^2}\right) = -\alpha_i \omega_i + \int_0^1 (\alpha_j z_j + \alpha_j \omega_j) dj \qquad \forall i \in [0, 1].
$$

The system above then becomes:

$$
\alpha_i z_i + \alpha_i \omega_i = (1 - \lambda_i) \alpha_i \omega_i + \lambda_i \int_0^1 \alpha_j (z_j + \omega_j) d j \qquad \forall i \in [0, 1]
$$
 (A5)

$$
\alpha_i z_i = -\lambda_i \alpha_i \omega_i + \lambda_i \int_0^1 \alpha_j (z_j + \omega_j) dj \qquad \forall i \in [0, 1].
$$
 (A6)

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where

$$
\lambda_i = \frac{1}{1 + \frac{2\phi}{\alpha_i \sigma^2}}\tag{A7}
$$

The system of equations in $(A6)$ holds in equilibrium, and it pins down the equilibrium net positions scaled by risk aversion.

Equation $(A5)$ is intuitive. It states that the post-trade credit risk exposure of agent i scaled by her risk averse (i.e., $\alpha_i z_i + \alpha_i \omega_i$) is an convex combination of her risk-aversion-scaled pre-trade exposure (i.e., $\alpha_i \omega_i$) and the average risk-aversion-scaled post-trade exposure of her trading partners (i.e., $\int_0^1 \alpha_j (z_j + \omega_j) d_j$). The weight used in this convex combination is $\lambda_i \in (0, 1)$, misallocation (ϕ), risk aversion (α_i) , and credit risk (σ^2) . When trading costs are higher or risk aversion is lower, there is less risk sharing, and post-trade credit exposure is closer to agents' pre-trade credit risk exposure.

A.1 No-Misallocation Benchmark

$$
\int_0^1 \int_0^1 \mu - P_{ij} \, di\,ij} = \mu - \overline{P} = \sigma^2 \overline{\omega} \frac{1}{1/\alpha},\tag{A8}
$$

where $\frac{1}{1/\alpha} \equiv \frac{1}{\int_0^1 1/\alpha_i di}$ is the harmonic average of agents' risk aversion.

As a frictionless benchmark, let us consider the case in which there is no misallocation, that is, $\phi = 0$. In this case, we have $\lambda_i = \frac{1}{1 + \frac{2\phi}{\alpha_i \sigma^2}}$ $= 1$, and Equation [\(A6\)](#page-60-0) becomes:

$$
\alpha_i z_i + \alpha_i \omega_i = \int_0^1 \alpha_j (z_j + \omega_j) dj \tag{A9}
$$

Solving for $\int_0^1 \alpha_j (z_j + \omega_j) dj = \overline{\alpha z} + \overline{\alpha \omega}$:

$$
z_i + \omega_i = \frac{1}{\alpha_i} \int_0^1 \alpha_j (z_j + \omega_j) dj \tag{A10}
$$

integrating over i from 0 to 1

$$
\overline{\omega} = \overline{1/\alpha}(\overline{\alpha z} + \overline{\alpha \omega})
$$
 (A11)

$$
\overline{\alpha z} + \overline{\alpha \omega} = \frac{\overline{\omega}}{1/\alpha},\tag{A12}
$$

which is the average pre-trade exposure divided by the harmonic average of risk aversion.

Hence, in the no-misallocation benchmark optimal post-trade exposure is given by

$$
z_i + \omega_i = \frac{1}{\alpha_i} \int_0^1 \alpha_j (z_j + \omega_j) dy = \frac{1}{\alpha_i} \times \frac{\overline{\omega}}{\overline{1/\alpha}} = \frac{1}{\alpha_i} \times \frac{\int \omega_j dj}{\int 1/\alpha_j dj}
$$
(A13)

The average premium in the Walrasian Benchmark:

$$
\mu - P_{ij} = \sigma^2 \frac{\overline{\omega}}{1/\alpha} \tag{A14}
$$

In the no-misallocation benchmark, the average credit premium is the average pre-trade exposure multiplied by the harmonic average of risk aversion. The constant term used in the main text is

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therefore

$$
C = \frac{\overline{\omega}}{1/\alpha} = \frac{\int_0^1 \omega_i di}{\int_0^1 \frac{1}{\alpha_i} di}
$$
 (A15)

A.2 Misallocation Benchmark

Let us introduce misallocation by assuming $\phi > 0$. In this case, we have $\lambda_i = \frac{1}{1 + \frac{2\phi}{\alpha_i \sigma^2}}$ $\in (0,1)$, and Equation [\(A6\)](#page-60-0) becomes:

$$
\alpha_i z_i + \alpha_i \omega_i = (1 - \lambda_i) \alpha_i \omega_i + \lambda_i \int_0^1 \alpha_j (z_j + \omega_j) dij \tag{A16}
$$

Solving for $\int_0^1 \alpha_j (z_j + \omega_j) dj = \overline{\alpha z} + \overline{\alpha \omega}$:

$$
\alpha_i z_i = -\lambda_i \alpha_i \omega_i + \lambda_i (\overline{\alpha z} + \overline{\alpha \omega})
$$
\n(A17)

$$
z_i + \lambda_i \omega_i = \frac{\lambda_i}{\alpha_i} \left(\overline{\alpha z} + \overline{\alpha \omega} \right) \tag{A18}
$$

integrating over i from 0 to 1

$$
\overline{\lambda\omega} = \overline{\lambda/\alpha} \left(\overline{\alpha z} + \overline{\alpha \omega} \right) \tag{A19}
$$

$$
\overline{\alpha z} + \overline{\alpha \omega} = \frac{\lambda \omega}{\overline{\lambda/\alpha}}.\tag{A20}
$$

Hence, substituting into Equation A16, the misallocation benchmark optimal post-trade exposure is given by

$$
z_i + \omega_i = (1 - \lambda_i)\omega_i + \lambda_i \frac{\int \alpha_j (z_j + \omega_j) d\mathbf{j}}{\alpha_i} = (1 - \lambda_i)\omega_i + \lambda_i \frac{\int \lambda_j \omega_j d\mathbf{j}}{\alpha_i} \tag{A21}
$$

The average premium in the Complete Network Benchmark:

$$
\int_0^1 \int_0^1 \mu - P_{ij} \, di \, dj = \mu - \overline{P} = \sigma^2 \frac{\overline{\lambda \omega}}{\overline{\lambda/\alpha}} \tag{A22}
$$

A.3 Comparative statistics

Let us assume that $\alpha_i \sim U[\alpha_l, \alpha_h]$, and $\omega_i \sim U[\omega_l, \omega_h]$ where $\omega_i \perp \alpha_i$. Under these assumptions along with $\phi > 0$, the average credit premium is:

$$
\mu - \overline{P} = \sigma^2 \frac{\overline{\lambda \omega}}{\overline{\lambda/\alpha}} \tag{A23}
$$

$$
= \sigma^2 \frac{\int_0^1 \lambda_i \omega_i di}{\int_0^1 \lambda_i / \alpha_i di}
$$
\n(A24)

$$
= \sigma^2 \frac{\frac{1}{\alpha_h - \alpha_l} \int_{-0.5}^{0.5} \int_{\alpha_l}^{\alpha_h} \frac{1}{1 + \frac{2\phi}{\alpha \sigma^2}} (\overline{\omega} + A \varepsilon) d\alpha d\varepsilon}{\frac{1}{\alpha_h - \alpha_l} \int_{\alpha_l}^{\alpha_h} \frac{1}{\alpha + \frac{2\phi}{\sigma^2}} d\alpha}
$$
(A25)

$$
= \sigma^2 \frac{\overline{\omega} \int_{\alpha_l}^{\alpha_h} \frac{1}{1 + \frac{2\phi}{\alpha \sigma^2}} d\alpha}{\int_{\alpha_l}^{\alpha_h} \frac{1}{\alpha + \frac{2\phi}{\sigma^2}} d\alpha}
$$
(A26)

$$
= \sigma^2 \overline{\omega} \frac{\int_{\alpha_l}^{\alpha_h} \frac{\alpha}{\alpha + \frac{2\phi}{\sigma^2}} d\alpha}{\int_{\alpha_l}^{\alpha_h} \frac{1}{\alpha + \frac{2\phi}{\sigma^2}} d\alpha} \tag{A27}
$$

$$
= \sigma^2 \overline{\omega} \frac{\alpha_h - \alpha_l - \frac{2\phi}{\sigma^2} \log \left(\alpha_h + \frac{2\phi}{\sigma^2} \right) + \frac{2\phi}{\sigma^2} \log \left(\alpha_l + \frac{2\phi}{\sigma^2} \right)}{\log \left(\alpha_h + \frac{2\phi}{\sigma^2} \right) - \log \left(\alpha_l + \frac{2\phi}{\sigma^2} \right)}
$$
(A28)

and the following proposition shows how the average credit spread depends on the misallocation parameter.

Proposition A1. Trading frictions increase average bond spreads whenever $\phi > 0$, that is,

$$
\frac{d}{d\phi}\left(\mu - \overline{P}\right) > 0. \tag{A29}
$$

Proof. The proof consists of showing that

$$
\frac{d}{d\phi} \left(\sigma^2 \overline{\omega} \frac{\alpha_h - \alpha_l - \frac{2\phi}{\sigma^2} \log \left(\alpha_h + \frac{2\phi}{\sigma^2} \right) + \frac{2\phi}{\sigma^2} \log \left(\alpha_l + \frac{2\phi}{\sigma^2} \right)}{\log \left(\alpha_h + \frac{2\phi}{\sigma^2} \right) - \log \left(\alpha_l + \frac{2\phi}{\sigma^2} \right)} \right) > 0
$$

Step 1: For $\alpha_h > \alpha_l$:

$$
\frac{\partial}{\partial \alpha_h} \left[- (\alpha_h - \alpha_l) + \frac{\alpha_h + \alpha_l}{2} \log \left(\frac{\alpha_h}{\alpha_l} \right) \right] = -1 + \frac{1}{2} \log \left(\frac{\alpha_h}{\alpha_l} \right) + \frac{1}{\alpha_h} \left(\frac{\alpha_h + \alpha_l}{2} \right) \tag{A30}
$$

$$
-1 + \frac{1}{2}\log\left(\frac{\alpha_l}{\alpha_l}\right) + \frac{1}{\alpha_l}\left(\frac{\alpha_l + \alpha_l}{2}\right) = 0 \tag{A31}
$$

<u>Step 2</u>: Let $\varphi = \frac{2\phi}{\sigma^2} > 0$. We have that:

$$
\frac{\partial}{\partial \varphi} \left[\log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right) \frac{\alpha_h + \alpha_l}{2} + \varphi \log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right) \right] < 0
$$

Step 3:

$$
\frac{\partial}{\partial \varphi} \left[\log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right)^2 (\alpha_h + \varphi) (\alpha_l + \varphi) \right]
$$
\n(A32)

$$
=2\log\left(\frac{\alpha_h+\varphi}{\alpha_l+\varphi}\right)\left(\frac{1}{\alpha_h+\varphi}-\frac{1}{\alpha_l+\varphi}\right)(\alpha_h+\varphi)(\alpha_l+\varphi)+\log\left(\frac{\alpha_h+\varphi}{\alpha_l+\varphi}\right)^2(\alpha_h+\alpha_l+2\varphi)
$$
(A33)

$$
=2\log\left(\frac{\alpha_h+\varphi}{\alpha_l+\varphi}\right)\left[-\left(\alpha_h-\alpha_l\right)+\log\left(\frac{\alpha_h+\varphi}{\alpha_l+\varphi}\right)\frac{\alpha_h+\alpha_l}{2}+\varphi\log\left(\frac{\alpha_h+\varphi}{\alpha_l+\varphi}\right)\right],\tag{A34}
$$

using Step 2 and evaluating the last two terms at $\varphi \to 0$, we get the following inequality:

$$
> 2\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right) \left[-(\alpha_h - \alpha_l) + \frac{\alpha_h + \alpha_l}{2} \log\left(\frac{\alpha_h}{\alpha_l}\right) \right],\tag{A35}
$$

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using Step 1, we get the following inequality:

$$
> 2\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right) \left[-(\alpha_l - \alpha_l) + \frac{\alpha_l + \alpha_l}{2} \log\left(\frac{\alpha_l}{\alpha_l}\right) \right] = 0 \tag{A36}
$$

Step $4\mathrm{:}$

$$
\lim_{\varphi \to \infty} \log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right)^2 (\alpha_h + \varphi) (\alpha_l + \varphi) = \lim_{\varphi \to \infty} \frac{\log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right)^2}{(\alpha_h + \varphi)^{-1} (\alpha_l + \varphi)^{-1}}
$$
(A37)

$$
= \lim_{\varphi \to \infty} \frac{-2\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right) \frac{\alpha_h - \alpha_l}{(\alpha_h + \varphi)(\alpha_l + \varphi)}}{-\frac{1}{(\alpha_h + \varphi)^2(\alpha_l + \varphi)^1} - \frac{1}{(\alpha_h + \varphi)^1(\alpha_l + \varphi)^2}}
$$
(A38)

$$
= \lim_{\varphi \to \infty} \frac{2 \log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi} \right) (\alpha_h - \alpha_l)}{\frac{1}{(\alpha_h + \varphi)} + \frac{1}{(\alpha_l + \varphi)}}
$$
(A39)

$$
= \lim_{\varphi \to \infty} \frac{-2 \frac{\alpha_h - \alpha_l}{(\alpha_h + \varphi)(\alpha_l + \varphi)} (\alpha_h - \alpha_l)}{-\frac{1}{(\alpha_h + \varphi)^2} - \frac{1}{(\alpha_l + \varphi)^2}}
$$
(A40)

$$
= \lim_{\varphi \to \infty} \frac{2(\alpha_h + \varphi)(\alpha_l + \varphi)(\alpha_h - \alpha_l)^2}{(\alpha_h + \varphi)^2 + (\alpha_l + \varphi)^2}
$$
 (A41)

$$
= \lim_{\varphi \to \infty} \frac{2\left(\frac{\alpha_h}{\varphi} + 1\right) \left(\frac{\alpha_l}{\varphi} + 1\right) (\alpha_h - \alpha_l)^2}{\left(\frac{\alpha_h}{\varphi} + 1\right)^2 + \left(\frac{\alpha_l}{\varphi} + 1\right)^2}
$$
(A42)

$$
=\frac{2(\alpha_h - \alpha_l)^2}{1+1} = (\alpha_h - \alpha_l)^2
$$
\n(A43)

Step 5: We can write the average bond spreads as follows

$$
\mu - \overline{P} = \frac{\alpha_h - \alpha_l - \varphi \log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right)}{\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right)} \tag{A44}
$$

and its derivative with respect to φ is given by:

$$
\frac{d}{d\varphi}\left(\mu - \overline{P}\right) = -1 - \frac{\alpha_h - \alpha_l}{\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right)^2} \left(\frac{1}{\alpha_h + \varphi} - \frac{1}{\alpha_l + \varphi}\right)
$$
\n(A45)

$$
= -1 + \frac{(\alpha_h - \alpha_l)^2}{\log\left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right)^2 (\alpha_h + \varphi) (\alpha_l + \varphi)},\tag{A46}
$$

using Step 4 and taking the limit as $\varphi \to \infty$, we get the following inequality:

$$
> -1 + \frac{(\alpha_h - \alpha_l)^2}{\lim_{\varphi \to \infty} \log \left(\frac{\alpha_h + \varphi}{\alpha_l + \varphi}\right)^2 (\alpha_h + \varphi) (\alpha_l + \varphi)},
$$
\n(A47)

using Step 5, we get the following equality:

$$
= -1 + 1 = 0. \tag{A48}
$$

 \Box

Why do trading frictions increase credit spreads? When ϕ increases, bilateral trading costs are higher, and overall trading is reduced. We can see this from Equation $(A2)$:

$$
z_i = \frac{\mu - \overline{P} - \alpha_i \omega_i \sigma^2}{\phi + \alpha_i \sigma^2}.
$$

The equation above shows that if we hold the average prices fixed—that is, keep \overline{P} unchanged—then z_i shrinks towards zero for both net buyers and net sellers of credit risk as ϕ increases. Moreover, when ϕ increases, less risk-averse agents, who are net credit risk buyers on average, reduce their overall risk exposure by buying fewer bonds. At the same time, more risk-averse agents, who are net sellers of credit risk on average, optimally choose to sell fewer bonds. Hence, both sellers and buyers of credit risk reduce their positions when ϕ increases; however, the magnitude of the reduction in net position across agents depends nonlinearly on risk aversion. In fact, less risk-averse agents respond more aggressively to changes in bilateral trading costs. Less risk-average agents are typically willing to take extreme positions and are more responsive to trading conditions. As a result, the aggregate reduction in demand for credit risk by less risk-averse agents is not offset by the fact that higher risk-averse agents sell fewer bonds. If bond prices do not adjust, there will be an excess surplus of bonds in the market. Hence, in order to clear the bond market, bond prices must fall and credit spreads increase.

To see how the aggregate demand for credit risk depends on ϕ in the model equations, we can start from the following equilibrium condition: $\int_0^1 z_i di = 0$. Then, take the total derivative with respect to ϕ : $\frac{d}{d\phi}$ $\frac{d}{d\phi} \int_0^1 z_i di = 0$. To evaluate this object, notice that the total derivative of z_i with respect to ϕ is given by:

$$
\frac{d}{d\phi}z_i = \frac{\partial z_i}{\partial \phi} + \frac{\partial z_i}{\partial (\mu - \overline{P})} \frac{\partial (\mu - \overline{P})}{\partial \phi},
$$

which implies:

$$
\frac{d}{d\phi} \int_0^1 z_i di = 0 \implies \frac{\partial}{\partial \phi} \int_0^1 z_i di = -\int_0^1 \underbrace{\frac{\partial z_i}{\partial (\mu - \overline{P})}}_{>0} \underbrace{\frac{\partial (\mu - \overline{P})}{\partial \phi}}_{>0} di < 0. \tag{A49}
$$

When ϕ increases but bond spreads are held fixed, the aggregate demand for credit risk decreases, leading to a corporate bond surplus if prices do not adjust. That is, ϕ curbs overall trade across all agents: buyers of credit risk buy fewer bonds, and sellers sell fewer bonds. However, net buyers of credit risk— low-risk aversion agents—are more sensitive to changes in ϕ . As a result, the aggregate effect is a surplus of credit risk, with the supply of bonds for net sellers being greater than the demand from net buyers. In equilibrium, bond spreads have to increase to incentive more purchases of credit risk and clear the corporate bond market.

Proposition [A1](#page-63-0) formalizes the intuition behind the relationship between the misallocation parameter and average credit spreads. Moreover, ϕ reduces trading volume and increases the crosssectional dispersion of spreads. Next, we map our misallocation risk model to the simplied version discussed in the main text.

A.4 Simplified misallocation model

From Equation [1,](#page-8-0) we have that misallocation is defined as:

$$
\varepsilon_i = \frac{1}{\sigma_{\varepsilon}} \left[\omega_i + z_i - OptExp_i \right]. \tag{A50}
$$

The term $OptExp_i$ is dealer i's optimal exposure under perfect risk sharing (i.e., $\phi = 0$) discussed in Section [A.1.](#page-61-0) From Equation [A13,](#page-61-0) we have:

$$
OptExp_i = \frac{1}{\alpha_i} \times \underbrace{\int \omega_j dj}_{\equiv C} = \frac{C}{\alpha_i}.
$$
\n(A51)

The term $\omega_i + z_i$ in Equation A50 is given by the optimal post-trade exposure when there is misallocation (i.e., $\phi = 0$), which was discussed earlier in Equation [A21:](#page-62-0)

$$
z_i + \omega_i = (1 - \lambda_i) \omega_i + \lambda_i \frac{\int \lambda_j \omega_j dj}{\alpha_i},
$$

where $\lambda_i = \frac{1}{1 + \frac{2\phi}{\alpha_i \sigma^2}}$ $\in (0, 1)$.

The variance of misallocation, namely σ_{ε}^2 , is the cross sectional variace of $\omega_i + z_i - OptExp_i$:

$$
\sigma_{\varepsilon}^{2} = \int \left[(1 - \lambda_{i}) \omega_{i} + \lambda_{i} \frac{\frac{\int \lambda_{j} \omega_{j} d\mathbf{j}}{\int \lambda_{j} / \alpha_{j} d\mathbf{j}}}{\alpha_{i}} - \frac{C}{\alpha_{i}} \right]^{2} di. \tag{A52}
$$

In the following proposition, we confirm that there is no misallocation when $\phi = 0$.

Proposition A2. If $\phi = 0$, we have no misallocation

$$
\varepsilon_i = 0 \text{ for every } i.
$$

Proof. When $\phi = 0$, we have $\lambda_i = 1$ for every dealer, and therefore,

$$
z_i + \omega_i = (1 - \lambda_i)\omega_i + \lambda_i \frac{\int \lambda_j \omega_j dj}{\alpha_i} = \frac{\int \omega_j dj}{\alpha_i} = OptExp_i
$$

Hence,

$$
\varepsilon_i = \frac{1}{\sigma_{\varepsilon}} \left[\omega_i + z_i - OptExp_i \right] = \frac{1}{\sigma_{\varepsilon}} \left[OptExp_i - OptExp_i \right] = 0, \text{ for every } i. \tag{A53}
$$

 \Box

Next, in Propositions A3 and [A4,](#page-67-0) we show two important properties of misallocation.

Proposition A3. Misallocation is mean zero,

$$
\int \varepsilon_i di = 0.
$$

Proof. From Equation [A3,](#page-59-0) which states that $\gamma_{ij} = -\gamma_{ji}$ for every i and j, and that fact that $z_i = \int \gamma_{ij} dj$, we have that $\int z_i di = 0$. Thus,

$$
\int \varepsilon_i di = \frac{1}{\sigma_{\varepsilon}} \int \left[\omega_i + z_i - OptExp_i \right] di \tag{A54}
$$

$$
= \frac{1}{\sigma_{\varepsilon}} \left[\int \omega_i di - \int OptExp_i di \right] \tag{A55}
$$

$$
= \frac{1}{\sigma_{\varepsilon}} \left[\int \omega_i di - \int \omega_i di \right] = 0. \tag{A56}
$$

(A57)

 \Box

The last step used Equation [A51,](#page-66-0) which implies $\int OptExp_i di = \int \omega_i di$.

Proposition A4. If $\phi > 0$, then misallocation covaries positively with risk aversion,

$$
Cov(\alpha_i, \varepsilon_i) > 0.
$$

Proof. Note that $Cov(\alpha_i, \varepsilon_i) = \int \alpha_i \varepsilon_i di$, because from Proposition [A3,](#page-66-0) we have $\int \varepsilon_i di = 0$.

Also, note that the equilibrium credit spread in a transaction between dealers i and j is given by:

$$
\mu - P_{ij} = \frac{\sigma^2}{2} \left[\alpha_i \left(\omega_i + z_i \right) + \alpha_j \left(\omega_j + z_j \right) \right],\tag{A58}
$$

and therefore, the average spread across all transactions is given by

$$
\mathbb{E}\left(\mu - P_{ij}\right) = \mu - \overline{P} = \int \int \mu - P_{ij} didj \tag{A59}
$$

$$
= \frac{1}{2}\sigma^2 \int \int \left[\alpha_i \left(\omega_i + z_i\right) + \alpha_j \left(\omega_j + z_j\right)\right] di d\!j \tag{A60}
$$

$$
= \sigma^2 \int \alpha_i \left(\omega_i + z_i\right) di \tag{A61}
$$

$$
= \sigma^2 C + \sigma_{\varepsilon} \int \alpha_i \varepsilon_i di \tag{A62}
$$

$$
= \sigma^2 C + \sigma_{\varepsilon} \text{Cov}(\alpha_i, \varepsilon_i)
$$
\n(A63)

From Proposition [A1,](#page-63-0) we know that the average spread increases with the misallocation parameters ϕ , that is, $\frac{d}{d\phi}(\mu - \overline{P}) > 0$. When $\phi = 0$, we have that Cov $(\alpha_i, \varepsilon_i) = 0$ as a direct implication of Proposition A4. Since, nomisallocation benchmark spreads do not depend on ϕ , that is, $\frac{d}{d\phi}(\sigma^2 C) = 0$, we have that

$$
\frac{d}{d\phi} \left[\sigma_{\varepsilon} \text{Cov} \left(\alpha_i, \varepsilon_i \right) \right] > 0,
$$

which implies, for $\phi > 0$, that

 $Cov(\alpha_i, \varepsilon_i) > 0,$

because $\sigma_{\varepsilon} > 0$ whenever $\phi > 0$ and σ_{ε} Cov $(\alpha_i, \varepsilon_i) = 0$ when $\phi = 0$. The term σ_{ε} Cov $(\alpha_i, \varepsilon_i)$ is an increasing function of ϕ starting at zero, thus when $\phi > 0$, we have $\sigma_{\varepsilon} \text{Cov}(\alpha_i, \varepsilon_i) > 0$. \Box

Figures

Figure A1: Real v.s. fitted 10 DTS-portfolio average excess return across all months

This table reports the fitted and realized expected returns based on the second-stage estimates of the prices of the risk for interdealer price dispersion reported in Table [6.](#page-49-0) Exposures and prices of risk are estimated according to Equations [\(16\)](#page-26-0) and [\(17\)](#page-26-0). The estimates reported in this figure refer to those in Panel A of Table [6,](#page-49-0) where we use 10 portfolios of bonds sorted by duration times spread (DTS) as test assets. In each panel, we plot the risk premium of each bond portfolio as predicted by our price of risk estimate, i.e., the models' fitted value, in the y-axis against the actual average return of the bond portfolio observed in the data in the x-axis. Each panel refers to an estimation with different controls. In all specifications, we control for the market factor MKTB and the traded liquidity factor LRF as used in the study by [Dickerson, Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0). The upper-left panel (D2D) includes only the baseline controls of bond market factor and traded liquidity factor. In the upper-right panel (D2D+DEF), we control for the default factor (DEF) from [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), and, in the lower-left panel (D2D+HKM), we control for the capital ratio growth rate of the whole sector of primary dealers [\(He, Kelly, and Manela,](#page-38-0) [2017\)](#page-38-0). Finally, in the lower-right panel (D2D+HKS), we control for inventory and distress factors [\(He,](#page-38-0) [Khorrami, and Song,](#page-38-0) [2019\)](#page-38-0)

Figure A2: Real v.s. fitted 25 MTS-portfolio average excess return across all months

This table reports the fitted and realized expected returns based on the second-stage estimates of the prices of the risk for interdealer price dispersion reported in Table [6.](#page-49-0) Exposures and prices of risk are estimated according to Equations [\(16\)](#page-26-0) and [\(17\)](#page-26-0). The estimates reported in this figure refer to those in Panel B of Table [6,](#page-49-0) where we use 25 portfolios of bonds double-sorted by maturity and size (MTS) as test assets [\(Bai, Bali, and Wen,](#page-36-0) [2019\)](#page-36-0). In each panel, we plot the risk premium of each bond portfolio as predicted by our price of risk estimate, i.e., the models' fitted value, in the y-axis against the actual average return of the bond portfolio observed in the data in the x -axis. Each panel refers to an estimation with different controls. In all specifications, we control for the market factor $MKTB$ and the traded liquidity factor LRF as used in the study by [Dickerson,](#page-37-0) [Mueller, and Robotti](#page-37-0) [\(2023\)](#page-37-0). The upper-left panel (D2D) includes only the baseline controls of bond market factor and traded liquidity factor. In the upper-right panel (D2D+DEF), we control for the default factor (DEF) from [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0), and, in the lower-left panel (D2D+HKM), we control for the capital ratio growth rate of the whole sector of primary dealers [\(He, Kelly, and Manela,](#page-38-0) [2017\)](#page-38-0). Finally, in the lower-right panel (D2D+HKS), we control for inventory and distress factors [\(He, Khorrami, and Song,](#page-38-0) [2019\)](#page-38-0)

Tables

Table A1: Credit spread changes (CDGM), full table

This table reports estimates identical to those in Table [1,](#page-44-0) including all committed coefficients. See Table [1](#page-44-0) for details.

Table A2: Credit spread changes, full table

This table reports estimates identical to those in Table [2,](#page-45-0) including all committed coefficients. See Table [2](#page-45-0) for details.

This table reports estimates identical to those in Table [3,](#page-46-0) including all committed coefficients. See Table [3](#page-46-0) for details.

Table A4: Fair-value basis changes (CDGM)

This table reports the regression estimations from Equation [\(15\)](#page-23-0):

$$
\Delta Yields \text{pred}_{t}^{i} - \Delta FVS_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i}\Delta \sigma_{t}^{D2D} + \beta_{2}^{i}/Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t , and $Controls_t^i$ contains different combinations of bondand market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared riskfree rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A5: Credit spread changes (CDGM), controlling for weekly variation

This table reports the regression estimations from the following equation:

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \tilde{\sigma}_{t}^{D2D, week} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \tilde{\sigma}_t^{D2D,week}$ is the *alternative* measure of monthly change in dealer market price dispersion controlling for weekly variation within each bond, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A6: Credit spread changes, controlling for weekly variation

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i = \beta_1 \Delta \tilde{\sigma}_t^{D2D, week} + \beta_2' Control_s^i_t + \eta^i + \varepsilon_t^i,$

where $\Delta \tilde{\sigma}_t^{D2D,week}$ is the *alternative* measure of monthly change in dealer market price dispersion controlling for weekly variation within each bond, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yieldcurve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder,](#page-36-0) [Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A7: Fair-value basis changes, controlling for weekly variation

This table reports the regression estimations from the following equation:

$\Delta YieldS \textit{pread}^i_t - \Delta FVS^i_t = \beta_1 \Delta \tilde{\sigma}^{D2D,week}_t + \beta_2' Controls^i_t + \eta^i + \varepsilon^i_t$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \tilde{\sigma}_t^{D2D, week}$ is the *alternative* measure of monthly change in dealer market price dispersion controlling for weekly variation within each bond, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A8: Principal components of residuals, controlling for weekly variation

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations:

$\Delta Yields \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \tilde{\sigma}_t^{D2D,week} + \beta_2^i' Control_s^i + \varepsilon_t^i$

where $\Delta \tilde{\sigma}_t^{D2D,week}$ is the *alternative* measure of monthly change in dealer market price dispersion controlling for weekly variation within each bond, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

Table A9: Principal components of residuals (FN sample), controlling for weekly variation

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations:

$$
\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \tilde{\sigma}^{D2D, week}_t + \beta^i_2' Controls^i_t + \varepsilon^i_t
$$

where $\Delta \tilde{\sigma}_t^{D2D,week}$ is the *alternative* measure of monthly change in dealer market price dispersion controlling for weekly variation within each bond, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details.

Table A10: Credit spread changes (CDGM), volume-weighted interdealer price dispersion

This table reports the regression estimations from Equation [\(14\)](#page-21-0):

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \sigma_{t}^{D2D, vol-w} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \sigma_t^{D2D, vol-w}$ is the volume-weighted average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A11: Credit spread changes, volume-weighted interdealer price dispersion

This table reports the regression estimations from the following equation:

$$
\Delta Yields \textit{pred}^i_t = \beta_1 \Delta \sigma^{D2D, vol-w}_t + \beta_2{}'Controls^i_t + \eta^i + \varepsilon^i_t
$$

where $\Delta\sigma_t^{D2D, vol-w}$ is the volume-weighted average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A12: Fair-value basis changes, volume-weighted interdealer price dispersion

This table reports the regression estimations from the following equation:

$$
\Delta Yields \textit{pred}^i_t - \Delta FVS^i_t = \beta_1 \Delta \sigma^{D2D, vol-w}_t + \beta_2{}'Controls^i_t + \eta^i + \varepsilon^i_t
$$

where ΔFVS_t^i is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D, vol-w}$ is the volume-weighted average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A13: Principal components of residuals, volume-weighted interdealer price dispersion

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$$
\Delta Yields \textit{predd}_t^i = \beta_0^i + \beta_1^i\Delta\sigma_t^{D2D, vol-w} + \beta_2^{i\,\prime} Controls_t^i + \varepsilon_t^i
$$

where $\Delta \sigma_t^{D2D, vol-w}$ is the volume-weighted average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

Table A14: Principal components of residuals (FN sample), volume-weighted interdealer price dispersion

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \sigma_{t}^{D2D, vol-w} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta\sigma_t^{D2D, vol-w}$ is the volume-weighted average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details.

Table A15: Credit spread changes (CDGM), interdealer price dispersion based on largest dealers

This table reports the regression estimations from the following equation:

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \sigma_{t}^{D2D, top50} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \sigma_t^{D2D, top50}$ is the *alternative* measure of monthly change in dealer market price dispersion constructed using transactions completed by the top 50 dealers, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A16: Credit spread changes, interdealer price dispersion based on largest dealers

This table reports the regression estimations from the following equation:

$$
\Delta YieldS\textit{pread}_{t}^{i} = \beta_{1}\Delta\sigma_{t}^{D2D,\textit{top50}} + \beta_{2}^{\prime}Controls_{t}^{i} + \eta^{i} + \varepsilon_{t}^{i}
$$

where $\Delta\sigma_t^{D2D,top50}$ is the *alternative* measure of monthly change in dealer market price dispersion constructed using transactions completed by the top 50 dealers (we calculate series $\{\Delta \sigma_t^{D2D,top50}\}$ using academic version of TRACE data which is available until March 2018), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A17: Fair-value basis changes, interdealer price dispersion based on largest dealers

This table reports the regression estimations from the following equation:

$$
\Delta Yields \textit{pred}^i_t - \Delta FVS^i_t = \beta_1 \Delta \sigma_t^{D2D, top50} + \beta_2{}'Controls^i_t + \eta^i + \varepsilon^i_t
$$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D, top50}$ is the *alternative* measure of monthly change in dealer market price dispersion constructed using transactions completed by the top 50 dealers, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A18: Principal components of residuals, interdealer price dispersion based on largest dealers

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

 $\Delta Yields \text{pred}^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma_t^{D2D, top50} + \beta^i_2' Control_{}s^i_t + \varepsilon^i_t$

where $\Delta\sigma_t^{D2D,top50}$ is the *alternative* measure of the monthly change in dealer market price dispersion constructed using transactions completed by the top 50 dealers, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

Table A19: Principal components of residuals (FN sample), interdealer price dispersion based on largest dealers

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations::

$$
\Delta Yields \textit{predi}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D, top50} + \beta_2^i 'Controls_t^i + \varepsilon_t^i
$$

where $\Delta\sigma_t^{D2D,top50}$ is the *alternative* measure of monthly change in dealer market price dispersion constructed using transactions completed by the top 50 dealers, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details.

Table A20: Credit spread changes (CDGM), subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period):

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \sigma_{t}^{D2D} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Control_i^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne,](#page-37-0) [Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A21: Credit spread changes, subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period):

$\Delta Y \text{} = \beta_1 \Delta \sigma_t^{D2D} + \beta_2' \text{Controls}_t^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A22: Fair-value basis changes, subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period):

$$
\Delta Yields \text{pred}_{t}^{i} - \Delta FVS_{t}^{i} = \beta_{1}\Delta \sigma_{t}^{D2D} + \beta_{2}^{\prime}Controls_{t}^{i} + \eta^{i} + \varepsilon_{t}^{i}
$$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A23: Principal components of residuals, subsample excluding GFC

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations (excluding GFC period):

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{0}^{i} + \beta_{1}^{i} \Delta \sigma_{t}^{D2D} + \beta_{2}^{i} 'Controls_{t}^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

The sample used in these estimates excludes the GFC period.

Table A24: Principal components of residuals (FN sample), subsample excluding GFC

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations (excluding GFC period):

$$
\Delta Yields \textit{pred}^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D}_t + \beta^i_2' Controls^i_t + \varepsilon^i_t
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details. The sample used in these estimates excludes the GFC period.

Table A25: Credit spread changes (CDGM), controlling for turnover

This table reports the regression estimations from the following equation:

$\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D}_t + \beta^i_2 \Delta \overline{turnover}_t + {\beta^i_3}^{\prime} Controls^i_t + \varepsilon^i_t$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, Δ turnover_t is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A26: Credit spread changes, controlling for turnover

This table reports the regression estimations from the following equation:

$$
\Delta Yields \text{pred}_{t}^{i} = \beta_{1} \Delta \sigma_{t}^{D2D} + \beta_{2} \Delta \overline{turnover}_{t} + \beta_{3}' Controls_{t}^{i} + \eta^{i} + \varepsilon_{t}^{i}
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, Δ turnover_t is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A27: Fair-value basis changes, controlling for turnover

This table reports the regression estimations from the following equation:

 $\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D} + \beta_2 \Delta \overline{turnover}_t + \beta_3' Controls_t^i + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month t − 1 to month t, $\Delta \overline{turnover}$ is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A28: Credit spread changes (CDGM), controlling for nonlinear effects

This table reports the regression estimations from the following equation:

$$
\Delta Yields \textit{predd}_t^i = \beta_0^i + \beta_1^i\Delta\sigma_t^{D2D} + \beta_2^i(\Delta\sigma_t^{D2D})^2 + {\beta_3^i}^{\prime}Controls_t^i + \varepsilon_t^i
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne,](#page-37-0) [Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A29: Credit spread changes, controlling for nonlinear effects

This table reports the regression estimations from the following equation:

 $\Delta YieldS \textit{pread}_t^i = \beta_1 \Delta \sigma_t^{D2D} + beta_2 (\Delta \sigma_t^{D2D})^2 + \beta_3' Control_s^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A30: Fair-value basis changes, controlling for nonlinear effects

This table reports the regression estimations from the following equation:

 $\Delta Yield Spread^i_t - \Delta FVS^i_t = \beta_1 \Delta \sigma_t^{D2D} + \beta_2 (\Delta \sigma_t^{D2D})^2 + \beta_3' Control_{t} + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A31: Credit spread changes (CDGM), controlling for market power

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D} + \beta_2^i HHII_t + \beta_3^i'Controls_t^i + \varepsilon_t^i$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, HHI_t is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004

Table A32: Credit spread changes, controlling for market power

This table reports the regression estimations from the following equation:

$$
\Delta YieldS\text{pread}^i_t = \beta_1 \Delta \sigma_t^{D2D} + \beta_2 H H I_t + \beta_3' Controls^i_t + \eta^i + \varepsilon^i_t,
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, $\Delta \sigma_t^{FVS}$ is the simple average change in fair-value-spread (FVS) dispersion across all bonds from month t – 1 to month t, HHI_t is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A33: Fair-value basis changes, controlling for market power

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D} + \beta_2 HHI_t + \beta_3' Control_s^i_t + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t - 1$ to month t, HHI_t is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A34: Credit spread changes (CDGM), controlling for inventory and bond-level price dispersion

This table reports the regression estimations from the following equation:

$$
\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1\Delta\sigma^{D2D}_t + \beta^i_2\sigma^{D2D}_{i,t} + \beta^i_3Inventory_{i,t} + \beta^i_4'Controls^i_t + \varepsilon^i_t
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, $\sigma_{i,t}^{D2D}$ is bond-specific dealer market price dispersion in month t, Inventory_{i,t} is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne,](#page-37-0)

Table A35: Credit spread changes, controlling for inventory and bond-level price dispersion

This table reports the regression estimations from the following equation:

 $\Delta Yields \textit{pred}_t^i = \beta_1 \Delta \sigma_t^{D2D} + \beta_2 \sigma_{i,t}^{D2D} + \beta_3 \textit{Inventory}_{i,t} + \beta_4{}' \textit{Controls}_t^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, $\sigma_{i,t}^{D2D}$ is bond-specific dealer market price dispersion in month t, Inventory_{i,t} is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A36: Fair-value basis changes, controlling for inventory and bond-level price dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1\Delta\sigma_t^{D2D} + \beta_2\sigma_{i,t}^{D2D} + \beta_3 \textit{Inventory}_{i,t} + \beta_4' \textit{Controls}_t^i + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, $\sigma_{i,t}^{D2D}$ is bond-specific dealer market price dispersion in month t, Inventory_{i,t} is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and

Table A37: Credit spread changes and fair-value basis interdealer price dispersion (CDGM), subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period):

$$
\Delta Yields \textit{pred}^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D,\text{fair-value basis}}_t + \beta^{i}_2 / Controls^i_t + \varepsilon^i_t
$$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A38: Credit spread changes and fair-value basis interdealer price dispersion, subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period):

 $\Delta YieldS \text{}pred_t^i = \beta_1 \Delta \sigma_t^{D2D, \text{fair-value basis}} + \beta_2' Control_t^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A39: Fair-value basis changes and fair-value basis interdealer price dispersion, subsample excluding GFC

This table reports the regression estimations from the following equation (excluding GFC period)::

$$
\Delta Yields \textit{pred}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2' Controls_t^i + \eta^i + \varepsilon_t^i
$$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D, \text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t , η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details. The sample used in these estimates excludes the GFC period.

Table A40: Principal components of residuals and fair-value basis interdealer price dispersion, subsample excluding GFC

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations (excluding GFC period):

 $\Delta YieldSpread_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor. Panel A reports the fraction of the variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1 specification) on the various controls considered in Panel B. In all model specifications (Columns 1-8), we use the sample from January 2004 to December 2019. See Section [5.1](#page-19-0) for details.

The sample used in these estimates excludes the GFC period.

Table A41: Principal Components of residuals (FN sample) and fair-value basis interdealer price dispersion, subsample excluding GFC

This table reports principal component analysis of the residuals from Equation [\(14\)](#page-21-0) regression estimations (excluding GFC period):

$\Delta YieldS \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2^i' Controls_t^i + \varepsilon_t^i$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. Panel A reports the friction of variance of residuals explained by the first and second principal components and the level of the remaining unexplained variance. Panel B reports R^2 , adjusted R^2 , and F-statistics of the regression of the first principal component of CDGM residual (Column 1) specification) on the various controls considered in Panel B. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), in Columns 1-3, we follow their filtering approach to construct a new data sample from January 2003 to December 2013 and use the new sample to do regression only for model specification with FN controls. In Columns 4-6, we use the sample of bond from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0). See Section [5.1](#page-19-0) for details. The sample used in these estimates excludes the GFC period.

Table A42: Credit spread changes and fair-value basis interdealer price dispersion (CDGM), controlling for turnover

This table reports the regression estimations from the following equation:

$\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D,\text{fair-value basis}}_t + \beta^i_2 \Delta \overline{turnover}_t + \beta^i_3' Controls^i_t + \varepsilon^i_t$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, $\Delta \overline{turnover_t}$ is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), and $Control_i^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A43: Credit spread changes and fair-value basis interdealer price dispersion, controlling for turnover

This table reports the regression estimations from the following equation:

$$
\Delta YieldS \textit{pread}_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2 \Delta \overline{turnover}_t + \beta_3{}'Controls_t^i + \eta^i + \varepsilon_t^i
$$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, $\Delta \overline{turnover_t}$ is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A44: Fair-value basis changes and fair-value basis interdealer price dispersion, controlling for turnover

This table reports the regression estimations from the following equation:

ΔY ieldSpread $i_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2 \Delta \overline{turnover}_t + \beta_3' Controls_t^i + \eta^i + \varepsilon_t^i$

where ΔFVS_i^i is the change in fair value spread of bond i from month $t-1$ to $t, \Delta \sigma_t^{D2D, \text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t , $\Delta \overline{turnover}$ is the change in the average level (in cross section of bonds) of bond's monthly turnover rate (monthly trading amounts divided by outstanding amount), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A45: Credit spread changes and fair-value basis interdealer price dispersion (CDGM), controlling for nonlinear effects

This table reports the regression estimations from the following equation:

$\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D,\text{fair-value basis}}_t + \beta^i_2 (\Delta \sigma^{D2D,\text{fair-value basis}}_t)^2 + \beta^i_3' Controls^i_t + \varepsilon^i_t$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December

Table A46: Credit spread changes and fair-value basis interdealer price dispersion, controlling for nonlinear effects

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i = \beta_1 \Delta \sigma_t^{D2D, \text{fair-value basis}} + \beta_2 (\Delta \sigma_t^{D2D, \text{fair-value basis}})^2 + \beta_3' Controls_t^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A47: Fair-value basis changes and fair-value basis interdealer price dispersion, controlling for nonlinear effects

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2 (\Delta \sigma_t^{D2D,\text{fair-value basis}})^2 + \beta_3' Controls_t^i + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t, $\Delta \sigma_t^{D2D, \text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t , η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami,](#page-38-0) [and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A48: Credit Spread Changes and fair-value basis interdealer price dispersion (CDGM), controlling for market power

This table reports the regression estimations from the following equation:

 $\Delta Yield Spread_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2^i HHI_t + \beta_3^i'Controls_t^i + \varepsilon_t^i$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t , HHI_t is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t , and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. See Section [5](#page-18-0) for details.

Table A49: Credit spread changes and fair-value basis interdealer price dispersion, controlling for market power

This table reports the regression estimations from the following equation:

$\Delta Yields \text{pred}_t^i = \beta_1 \Delta \sigma_t^{D2D, \text{fair-value basis}} + \beta_2 H H I_t + \beta_3' Control_s^i + \eta^i + \varepsilon_t^i,$

where $\Delta \sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month $t, \Delta \sigma_t^{FVS}$ is the simple average change in fair-value-spread (FVS) dispersion across all bonds from month $t-1$ to month t , HHI_t is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald](#page-37-0) [and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A50: Fair-value basis changes and fair-value basis interdealer price dispersion, controlling for market power

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2 HHI_t + \beta_3' Control_s^i + \eta^i + \varepsilon_t^i$

where $\Delta F V S_t^i$ is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D, \text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t - 1$ to month t, HHIt is the simple average of bond-specific market share concentration (measured by Herfindahl–Hirschman Index of dealers' market shares) across all bonds in month t, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A51: Credit Spread Changes and fair-value basis interdealer price dispersion (CDGM), controlling for inventory and bond-level fair-value basis dispersion

This table reports the regression estimations from the following equation:

 $\Delta YieldS \textit{pread}_t^i = \beta_0^i + \beta_1^i \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2^i \sigma_{i,t}^{D2D,\text{basis}} + \beta_3^i \textit{Inventory}_{i,t} + \beta_4^i' \textit{Controls}_t^i + \varepsilon_t^i$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month $t, \sigma_{i,t}^{D2D, basis}$ is bond-specific dealer market fair-value basis dispersion in month t, Inventory_{i,t} is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and](#page-36-0) [Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December

Table A52: Credit spread changes and fair-value basis interdealer price dispersion, controlling for inventory and bond-level fair-value basis dispersion

This table reports the regression estimations from the following equation:

$$
\Delta YieldS \textit{pread}^i_t = \beta_1 \Delta \sigma^{D2D,\text{fair-value basis}}_t + \beta_2 \sigma^{D2D,\text{basis}}_{i,t} + \beta_3 Inventory_{i,t} + \beta_4{}'Controls^i_t + \eta^i + \varepsilon^i_t,
$$

where $\Delta\sigma_t^{D2D,\text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, $\sigma_{i,t}^{D2D, basis}$ is bond-specific dealer market fair-value basis dispersion in month t, Inventor $y_{i,t}$ is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A53: Fair-value basis changes and fair-value basis interdealer price dispersion, controlling for inventory and bond-level fair-value basis dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pread}_t^i - \Delta FVS_t^i = \beta_1 \Delta \sigma_t^{D2D,\text{fair-value basis}} + \beta_2 \sigma_{i,t}^{D2D,\text{basis}} + \beta_3 \textit{Inventory}_{i,t} + \beta_4{}^\prime \textit{Controls}_t^i + \eta^i + \varepsilon_t^i$

where ΔFVS_i^i is the change in fair value spread of bond i from month $t-1$ to $t, \Delta\sigma_t^{D2D, \text{fair-value basis}}$ is the simple average change in dealer market fair-value basis dispersion across all bonds from month $t-1$ to month t, η^i is bond fixed effect, $\sigma_{i,t}^{D2D, basis}$ is bond-specific dealer market fair-value basis dispersion in month t, Inventory_{i,t} is bond-specific dealer inventory in month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019.

Table A54: Credit spread changes by leverage and maturity (CDGM)

This table reports the regression estimations from Equation [\(14\)](#page-21-0):

$$
\Delta Yields \textit{pred}^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D}_t + \beta^i_2{}'Controls^i_t + \varepsilon^i_t,
$$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month t − 1 to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls from [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0), including changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, and (viii) slope of Volatility Smirk). We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. The sample is from January 2004 to December 2019, and we report the estimates of β_1^i for various subsamples based on bond characteristics. Each column in each panel reports results for a different subsample. In Panel A, we create subsamples based on the issuer's average monthly leverage ratio. In Panels B and C, we repeat this exercise but within a subsample of short-maturity (less than 9 years) and long-maturity (more than 12 years) bonds, respectively.

Panel A: Leverage Groups and All maturities

Panel B: Leverage Groups and Short Maturities (<= 9 years)

Panel C: Leverage Groups and Long Maturities (>= 12 years)

Table A55: Credit spread changes by credit rating and maturity (CDGM)

This table reports the regression estimations from Equation [\(14\)](#page-21-0):

 $\Delta Yield Spread^i_t = \beta^i_0 + \beta^i_1 \Delta \sigma^{D2D}_t + \beta^i_2' Control^{i}_t + \varepsilon^i_t,$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t, and $Controls_t^i$ contains different combinations of bond- and market-level controls from [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0), including changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, and (viii) slope of Volatility Smirk). We follow [Collin-Dufresne, Goldstein, and Martin](#page-37-0) [\(2001\)](#page-37-0) estimation procedure. The sample is from January 2004 to December 2019, and we report the estimates of β_1^i for various subsamples based on bond characteristics. Each column in each panel reports results for a different subsample. In Panel A, we create subsamples based on the credit rating of the bond. In Panels B and C, we repeat this exercise but within a subsample of short-maturity (less than 9 years) and long-maturity (more than 12 years) bonds, respectively.

Panel A: Credit Rating Groups and All maturities

Panel B: Credit Rating Groups and Short Maturities (<= 9 years)

Panel C: Credit Rating Groups and Long Maturities (>= 12 years)

Table A56: Credit spread changes, during COVID

This table reports the regression estimations from the following equation:

$\Delta Yield Spread_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D} + \beta_2 \Delta \sigma_t^{D2D} \times Dum_{Covid} + \beta_3' Control_{i,t} + \varepsilon_{i,t}$

where $\Delta \sigma_t^{D2D}$ is the simple average change in dealer market price dispersion across all bonds from month t − 1 to month t, Dum_{Covid} is the dummy variable for COVID period (Mar 2020 - Apr 2020), η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; The sample is from January 2004 to September 2022. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A57: Credit spread changes and high-liquidity interdealer price dispersion

This table reports the regression estimations from the following equation:

 $\Delta YieldSpread_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, High-Liquidity} + \beta_2' Control_{i,t} + \varepsilon_{i,t}$

where $\Delta \sigma_t^{D2D, High-Liquidity}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with higher liquidity identified by low Amihud ratio, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle, Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

Table A58: Fair-value basis changes and high-liquidity interdealer price dispersion

This table reports the regression estimations from the following equation:

$\Delta Yields \textit{pred}_{i,t} - \Delta FVS_{i,t} = \eta_i + \beta_1 \Delta \sigma_t^{D2D, High-Liquidity} + \beta_2' Controls_{i,t} + \varepsilon_{i,t}$

where $\Delta FVS_{i,t}$ is the change in fair value spread of bond i from month $t-1$ to t , $\Delta \sigma_t^{D2D,High-Liquidity}$ is the simple average change in dealer market price dispersion across all bonds from month $t-1$ to month t using bonds with higher liquidity identified by low Amihud ratio, η^i is bond fixed effect, and $Controls_t^i$ contains different combinations of bond- and market-level controls as follows: (1) CDGM controls (changes in (i) issuer-firm leverage, (ii) risk-free rate, (iii) squared risk-free rate, (iv) yield-curve slope, (v) VIX, (vi) S&P500 return, (viii) slope of Volatility Smirk); (2) a default factor (DEF) similar to [Bessembinder, Kahle,](#page-36-0) [Maxwell, and Xu](#page-36-0) [\(2008\)](#page-36-0) which is the difference between the yields of long-term investment-grade corporate bonds and long-term treasuries; (3) the capital ratio growth rate of the whole sector of primary dealers (HSM) from [He, Kelly, and Manela](#page-38-0) [\(2017\)](#page-38-0); (4) two risk factors (HKS) from [He, Khorrami, and Song](#page-38-0) [\(2019\)](#page-38-0): the dealer inventory factor and the intermediary distress factor; (5) three groups of over-the-counter market frictions (FN) from [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0): inventory frictions, search frictions and bargaining frictions. To compare with regression results in [Friedwald and Nagler](#page-37-0) [\(2019\)](#page-37-0), we follow their filtering approach to construct a new data sample from January 2003 to December 2013, and use the new sample to do regression only for model specification with FN controls. For all other model specifications (Columns 1-8), we use the sample of January 2004 to December 2019. These are panel regression estimates and standard errors are clustered at bond and month levels. See Section [5](#page-18-0) for details.

