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Abstract

We link bond market functioning to future economic activity through a new measure, the Corporate Bond Market Distress Index (CMDI). The CMDI coalesces metrics from primary and secondary markets in real time, offering a unified measure to capture access to debt capital markets. The index correctly identifies periods of distress and predicts future realizations of commonly used measures of market functioning, while the converse is not the case. We show that disruptions in access to corporate bond markets have an economically material, statistically significant impact on the real economy, even after controlling for standard predictors including credit spreads.

Key words: credit conditions, primary and secondary corporate bond market, dimension reduction, financial conditions, real activity

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1 Introduction

The financial system and the real economy are linked through corporate bond markets, which fund more than two-thirds of American corporate debt. In this paper, we introduce a new measure of corporate bond market conditions – the U.S. Corporate bond Market Distress Index (CMDI) – that aims to capture access to corporate bond markets. If access to debt markets is impaired, productive borrowers are unable to obtain financing and are forced to reduce their activities. Widespread market access freezes have the potential to propagate shocks and weaken aggregate economic activity, as formalized in the "financial accelerator" channel.[1] This paper adds empirical support for this channel, documenting that impaired corporate bond market functioning predicts deterioration in future real economic activity, a result that holds especially when both primary and secondary markets are distressed.

Even in normal times, bond market issuance is lumpy and changes with issuer risk. While this variability makes it hard to construct a timely measure of market functioning, primary markets contain important information about access to debt capital. We make use of primary market data from Mergent FISD to quantify corporate bond market functioning in real time. Grounded in the theoretical literature,[2] primary market metrics are added to a broad set of metrics from secondary market trading data from the supervisory version of the Trade Reporting and Compliance Engine (TRACE) and data on the pricing of non-traded bonds from ICE – Bank of America corporate bond indices.[3] We then use insights from the image recognition literature to coalesce these metrics into a unified measure of distress – the CMDI. This "preponderance of metrics" approach differs fundamentally from more commonly-used

[1]See e.g. Bernanke and Gertler (1989); Carlstrom and Fuerst (1997); Kiyotaki and Moore (1997) and subsequent papers which link vulnerabilities in credit availability to the future evolution of the real economy.

[2]Indications of impaired access to the corporate debt market include: (i) primary market issuance slows down (e.g. Bebchuk and Goldstein, 2011); (ii) secondary market prices decrease and liquidity dries up (e.g. Dang et al., 2015; Benmelech and Bergman, 2018); and (iii) secondary market trading volume may or may not increase (e.g. Benmelech and Bergman, 2018).

[3]Secondary market measures rely on the substantial academic literature on pricing and measures of secondary market liquidity in the corporate bond market (e.g., Collin-Dufresne et al., 2001, Geske and Delianedis, 2001, Longstaff et al., 2005, Chen et al., 2007, Dick-Nielsen et al., 2012, Friewald et al., 2012, Helwege et al., 2014, Chen et al., 2017, and Friewald and Nagler, 2019).

aggregation methods as it explicitly recognizes the degree of correlation between different signals instead of just maximizing the explained overall signal variance.

We document that the CMDI identifies commonly-accepted periods of market distress, peaking during the global financial crisis in late 2008 and early 2009 and with the next largest peak during the COVID-19-related market stress in March 2020. Comparing the evolution of the CMDI with that of indices focused separately on primary and secondary markets, we show that the CMDI is particularly high when conditions in both markets appear stressed. In other words, the CMDI downweights periods when only a subset of indicators signal market stress.

Market stress measured by a higher level of CMDI is associated with reduced real economic activity over the next year. We find that this effect is both economically and statistically significant, with a one standard deviation increase in the CMDI corresponding to, for example, a 3.1 percentage point (p.p.) decrease in annual industrial production growth and a 0.8 p.p. increase in unemployment in 12 months' time. These results are significant even after controlling for alternative metrics of credit market conditions, such as the commonly-used predicted credit spread and excess bond premium (EBP) of Gilchrist and Zakrajšek (2012). Furthermore, we document that the CMDI predicts downside risks to real activity. These results suggest the importance of financial market functioning, more broadly, to the real economy.

A key contribution of the paper and a feature of the CMDI is that it combines both primary market and secondary market measures to offer a full picture of corporate bond market functioning. These primary market measures appear to capture information about credit conditions for non-financial borrowers not being revealed by secondary market trading. The CMDI approach also allows for the integration of different dimensions of market functioning, eliminating the need to run a horse-race among metrics (see, for example, Schestag et al., 2016).

Three principles guide the index. First, while information on prices and price volatility is included, changing prices in either the primary or the secondary market are not by themselves a sufficient statistic to measure market disruptions: price changes are consistent with functioning markets when risk and risk tolerance change. Second, market liquidity – both in the primary market, capturing the ability of issuers to issue new debt, and in the secondary market, capturing the ability of market participants on both sides of the market to transact – plays a key role in the index. Third, the standardized metrics take into account the real-time historical properties of market conditions, so that the index can be back-tested and measured in a historical context. The CMDI serves as a template in terms of how to measure stress in a particular market and the predictive power of that stress for real economic output.

This paper is related to the literature on measuring financial distress. Starting with the seminal paper of Illing and Liu (2006), a number of indices of financial market distress at the economy level have been proposed for developed economies across the world. For the U.S.,[4] examples include Nelson and Perli (2007) ("financial fragility indicator"), Hakkio and Keeton (2009) ("Kansas City Financial Stability Indicator"), Kliesen and Smith (2010) ("St. Louis Fed's Financial Stress Index"), Brave and Butters (2011) ("National Financial Conditions Index"), and Oet et al. (2011) ("Cleveland Financial Stress Index"). The approach is inspired by measures developed to aggregate information on economic stress, specifically, the Composite Indicator of Systemic Stress (CISS, Hollo et al., 2012), but adapted to the empirical constraints of capturing the systematic distress of a market.

In addition to these and other economy-wide measures of market distress, the literature after the financial crisis has proposed a number of distress measures for individual financial institutions. Adrian and Brunnermeier (2016) and Acharya et al. (2017) both propose measures of risks at financial institutions that contribute to financial instability at the economy level and thus serve as a complement for the aggregate indices of financial conditions. The CMDI represents an intermediate level of aggregation – more focused than the aggregate indices of financial conditions but broader than measures of individual financial institutions'

[4]See the literature review in Hollo et al. (2012) for a discussion of indices developed for other advanced economies.

distress – capturing functioning of debt capital markets.

In a related work categorizing market distress, Pasquariello (2014) measures aggregate, time-varying intensity of arbitrage parity violations across assets and constructs a monthly market dislocation index (MDI), capturing episodes in which financial markets cease to price assets correctly on a *relative* basis. While this approach is informative about aggregate conditions, it does not have the CMDI's ability to measure whether an individual market (or markets) is in distress. In fact, we show that (i) contemporaneous movements in the CMDI are only weakly related to arbitrage violations between CDS and corporate bond markets, and between corporate bond ETFs and the underlying securities; (ii) the CMDI predicts future arbitrage violations in these markets but not vice versa; and (iii) arbitrage violations are not correlated with primary market activity. This is important context to studies that use arbitrage violations to signal dysfunction in the bond market, by offering a measure that can identify if the dislocations may be instead in the derivatives markets, and thus a different concern than access to market funding.

While our focus in this paper is the corporate bond market, the methodology can be used to measure distress in other markets. Since the global financial crisis and the onset of the pandemic-related market distress, central banks around the world are increasingly instituting programs to support market functioning (see, for example, the BIS's "Market dysfunction and central bank tools" which lays out backstop principles for market interventions), making robust measures of market dislocations particularly salient. The methodology is particularly advantageous when multiple volatile signals exist and the information in each signal is important.

The rest of the paper is organized as follows. We begin by laying out the challenges of recognizing market distress. Then we summarize the data used in the paper and the properties of the raw market conditions indicators in Section 3. Section 4 describes the construction of the CMDI, and documents how the index evolves over time. We investigate the predictive information in the CMDI for future real outcomes in Section 5. We examine the differential information from primary market metrics in Section 6. Section 7 concludes. Technical details, additional results and robustness exercises can be found in the Appendix.

2 What is corporate bond market distress?

While academics, policymakers and practitioners likely know market distress when they see it, generally the extent of distress is defined based on the impairment of market functioning. Borio (2004) defines a functioning *secondary* market as one in which transactions can take place rapidly and with little impact on price, volume that can be absorbed without undue influence on prices, execution is immediate, and prices return quickly to "normal" after temporary order imbalances. Episodes of market distress – or "liquidity black holes" in practitioner parlance – are marked by heavily one-sided order flow, rapid price changes, and financial distress on the part of many market participants. As noted in Morris and Shin (2004), large price changes alone are not sufficient to characterize a liquidity black hole as large price changes can instead indicate a smoothly functioning market that incorporates new information quickly.

Policymakers' interest in market functioning often arises from an interest in functioning in the primary market. Indeed, the Emergency Relief and Construction Act of 1932, which specifies the so-called 13(3) authority of the Federal Reserve, states that in order to supply backstop lending that

> ...the Federal Reserve Bank shall obtain evidence that such individual, partnership, or corporation is *unable to secure adequate credit accommodations from other banking institutions.*

That is, from a U.S. statutory perspective, distress of a market is characterized by a shutdown of the primary market itself, not by challenges in executing secondary market transactions.[5]

[5]Similarly, the BIS Markets Committee ("Market dysfunction and central bank tools") highlights the

As is apparent from the many aspects of market functioning, market distress is inherently multi-faceted. Thus, to measure distress, we need a methodology that aggregates information from a variety of sources and differentiates periods when we observe a coincident deterioration in multiple metrics of market functioning. Similar to the challenge of image recognition, we interpret this problem as recognizing the "features" of an episode of market distress. Just as individual features do not allow for image recognition, market distress is hard to pin down with only one aspect of market functioning, such as secondary market credit spreads.

3 Data

3.1 Primary market measures

Data on the U.S. primary corporate bond market is obtained from Mergent FISD. From the overall set of fixed income securities reported in Mergent FISD, we select securities that are identified as corporate securities, excluding convertible securities. Starting with the bond-level information on issuance by non-financial corporations, we construct two sets of weekly metrics of primary market functioning, with additional details available in Appendix A.4.

Measures of primary market issuance We construct three metrics of primary market issuance. Two metrics are volume-based: dollar amount issued relative to the average issuance in the same week of the year over the previous five years, and dollar amount issued relative to the amount outstanding maturing in the next year. Considering issuance relative to historical issuance allows us to account for both the overall positive time trend in bond issuance as well as seasonality in the timing of corporate bond issuance, while issuance relative to maturing within the next year captures the ability of companies to satisfy their re-financing needs. Figure 1a shows that while the two volume metrics mostly co-move together, with the rate

importance of flow of credit to borrowers, stating "[m]arket dysfunction has the potential to disrupt the flow of credit to the economy, thereby impacting real activity and price stability and, as a result, attainment of central banks' monetary policy goals."

of issuance declining during periods of distress, the information they provide is not identical. The third metric is the number of sequential weeks without at least 20 individual issuers to account for the fact that there is information in the (endogenous) decision of issuers coming to the market.

Measures of primary market spread We use offering yields to construct average default-adjusted offering spreads and offering spreads volatility (time series standard deviation). To keep the index interpretable as a real-time index of market conditions, we estimate the predictive regression for the primary market default-adjusted spread on an expanding window basis, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. We then compute the average spread and spread volatility from an ARCH-in-mean model (Engle et al., 1987) estimated on an expanding window, using again the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. Figure 1b shows that the primary-secondary spread is positive and relatively small during "normal" periods, but it becomes negative and large during periods of distress. That is, while during normal times primary market pricing reflects a positive spread to prevailing secondary market prices and issuers are freely able to access the market, market access during downturns is restricted to better-performing issuers, and the average price in the primary market is above the average price in the secondary market.

3.2 Secondary market measures

We use corporate bond transactions data from a regulatory version of TRACE, which contain price, uncapped trade size, and counterparties' identities[6] as well as other trade terms. Transactions are required to be reported in real-time, with 15 minutes delay, with occasional cancelled or corrected trades. In the regulatory version of TRACE, cancelled and corrected records are linked with a control number, so we keep the most up to date record of the trade.

[6]Registered FINRA dealers are identified by a designated Market Participant Identifier (MPID), and non-FINRA members are identified either as C (for client), or as A (for a non-member affiliate).

We also account for multiple reporting of interdealer trades and trades that were executed through a non-exempt Alternative Trading System (ATS). Additional details on cleaning of TRACE data are available in Appendix A.2.

After applying these cleaning steps, we keep secondary-trades only, and exclude trades with price and size outliers, trades on weekends and SIFMA holidays, and special-processing trades. The remaining dataset includes 171,194,725 bond-trade level observations, corresponding to 151,642 unique CUSIPs or 19,563 unique issuers. We then combine the trading activity data with bond and firm characteristics from Mergent FISD, and construct bond-date level measures of liquidity and secondary market spreads. It is important to note that although we use the regulatory version of Corporate TRACE, in the construction of the liquidity measures we do not use any measure that depends on dealers' identities. This is to show that the CMDI can be re-produced by non-regulatory TRACE users. Even using standard TRACE, which includes capped trade sizes, and calculating liquidity measures based on approximated trade size (based on the historical relationship between capped and uncapped trade sizes; MarketAxess, for example, offers their users such an approximation) results in very similar levels of CMDI as that calculated using TRACE uncapped trade size.

We construct five sets of weekly metrics of secondary market functioning, capturing secondary volume, liquidity, duration-matched spreads, default-adjusted spreads and conditions for non-traded bonds. These measures are described qualitatively in this section, and with greater detail in Appendix A.3.

Measures of volume We use four metrics of trading volume in the secondary market: dealer-to-customer volume as a fraction of gross trading volume (which we dub "intermediated volume"), average dealer-to-customer trade size, ratio of customer buy volume to customer sell volume (which we dub "customer buy-sell pressure ratio"), and turnover. Intermediated volume captures how easily customer volume can be absorbed by dealers in the market, with a lower intermediated volume indicating that the same dealer-to-customer volume generates a greater dealer-to-dealer volume. Turnover measures the fraction of amount outstanding that trades every day. Figure 1c plots the time series of the measures of secondary market volume. Turnover tends to be high and intermediated volume, average trade size and customer buy-sell pressure ratio all tend to be low during periods of market stress, as customers re-balance portfolios and dealers require a greater volume of interdealer trading before finding the ultimate customer buyers to offset customer sales.

Measures of liquidity We construct four standard metrics of market liquidity for corporate bonds: effective bid-ask spread, Thompson and Waller (1987) spread, Amihud (2002) price impact, and imputed round-trip cost. Figure 1d plots the time series of these four metrics. Figure 1d shows that, although the absolute level of each metric is different, with imputed round-trip cost generally the lowest measure of illiquidity and the Thompson and Waller spread the highest, the four spreads co-move tightly together, rising during periods of market distress. Indeed, the first principal component of the four spreads explains 88% of the variation.

Measures of duration-matched spreads To capture information about the pricing of the corporate bond market relative to Treasuries, we compute duration-matched spreads as in Gilchrist and Zakrajšek (2012) at the bond-level, and construct time series of average spreads, spread volatility (time series standard deviation), and interquartile range of spreads (cross-sectional standard deviation). To keep the index interpretable as a real-time index of market conditions, we compute the average spread and spread volatility from an ARCH-in-mean model (Engle et al., 1987) estimated on an expanding window, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. Figure 1e plots the time series of the three moments of duration-matched spreads. Though all three metrics increase during periods of broad market distress, such as the 2008-2009 financial crisis and March 2020, spread volatility tends to normalize much more quickly and does not increase as much during less significant periods of disruptions, such as the European debt crisis and the 2015–2016 manufacturing recession.

Measures of default-adjusted spreads Duration-matched spreads capture the pricing of corporate bonds relative to similar duration Treasuries, reflecting both expected default rates and default risk premia. To isolate the latter, we construct default-adjusted spreads at the bond-level, and construct time series of average spreads, spreads volatility (time series standard deviation), and interquartile range of spreads (cross-sectional standard deviation). As with the offering spreads, to keep the index interpretable as a real-time index of market conditions, we estimate the predictive regression for the default-adjusted spread on an expanding window basis, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. As with the duration-matched spreads, we further compute the average spread and spread volatility from an ARCH-in-mean model (Engle et al., 1987) estimated on an expanding window, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. Figure 1f plots the time series of the three moments of default-adjusted spreads. As with the duration-matched spreads, all three metrics increase during periods of broad market distress, with spreads volatility normalizing much quicker than the other two measures.

Measures of conditions for non-traded bonds While TRACE provides a wealth of information on market conditions for bonds that are actually traded on the secondary market, TRACE does not capture information about market conditions for bonds which are not regularly traded. Instead, we use price quotes from ICE - BAML for bonds included in ICE - BAML U.S. corporate bond indices to construct average default-adjusted spreads, spreads volatility (time series standard deviation), and interquartile range of spreads (cross-sectional standard deviation).[7] As with the traded spreads, we compute the average spread

[7] As with the default-adjusted spread index based on TRACE trades, to keep the index interpretable as a real-time index of market conditions, we estimate the predictive regression for the quoted default-adjusted spread on an expanding window basis, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample.

and spread volatility from an ARCH-in-mean model (Engle et al., 1987) estimated on an expanding window, using the first two years of the sample (January 1, 2005 – December 31, 2006) as the initial sample. Figure 1g shows that the quoted-traded spread increases during periods of market stress, such as the 2008-09 financial crisis and March 2020 market disruption, so that conditions for non-traded bonds deteriorate even more than those for traded bonds during periods of market stress.

4 Corporate Bond Market Distress Index

To combine these measures into an index, we follow the machine learning literature which studies the problem of identifying the similarity of features (e.g. image recognition and language processing). From a theoretical perspective, Lin (1998) derives a "similarity theorem" that states that the similarity between two features A and B is measured as the information needed to convey the commonalities between A and B relative to the information needed to describe A and B fully.[8] While, in practice, measuring similarity is complicated by variations in how features are observed, we follow the prescription advocated in the machine learning literature (see e.g. Deng et al., 2005) for our implementation.

4.1 Aggregating to an index

Armed with weekly time series of primary and secondary market conditions metrics, we follow the procedure in Hollo et al. (2012) to construct a weekly index of corporate bond market distress. We summarize here the steps involved in this procedure. Note that we have normalized the "sign" of all series so that a high value of each standardized metric corresponds to a period of stress identified by that metric.

Standardizing each metric We begin by standardizing each individual metric using the empirical cumulative distribution function of the metric. The appeal of this transformation

[8] For example, if A and B are identical, the similarity between A and B is exactly 1.

is that it allows us to combine variables with different "natural" units by imposing a common support without assuming a particular parametric transformation, as would, for example, be the case with a z-score transformation. More specifically, given a time series $\{x_{it}\}_{t=1}^{T}$ of the i^{th} metric and a corresponding ranked sample $\left(x_{i[1]}, \ldots, x_{i[T]}\right)$, with $x_{i[1]} \leq x_{i[2]} \leq \ldots \leq x_{i[T]}$, the standardized times series $\{z_{it}\}_{t=1}^{T}$ of the i^{th} metric is then given by:

$$z_{it} = \hat{F}_{iT}\left(x_{it}\right) = \begin{cases} \frac{r}{T} & \forall x_{i[r]} \leq x_{it} < x_{i[r+1]}, \quad r = 1, 2, \ldots, T-1 \\ 1 & \forall x_{it} \geq x_{i[T]} \\ 0 & \forall x_{it} < x_{i[1]} \end{cases} \tag{1}$$

As observations get added to the sample, so that T grows, the shape of the empirical CDF can change, as shown in the comparison between the full-sample and the expanding sample empirical CDFs plotted in Figure A.3.

We use the expanding sample transformation in our construction of the index as it corresponds more closely to the objective of monitoring market conditions in real time and allowing a true test of the approach with historical data. We use the first two years of the data (January 2, 2005 – December 30, 2006) as the initial sample, and add one week at a time to create the transformed series.

Creating sub-indices We group metrics into 7 categories: secondary market volume, secondary market liquidity, secondary market duration-matched spreads, secondary market default-adjusted spreads, traded-quoted spreads, primary market issuance, and primary-secondary market spreads. For each category, we construct the category-specific sub-index as the equal-weighted average of the standardized constituent series. Figure 2 plots the time series of all 7 sub-indices. Although each individual sub-index is quite noisy, as we will see in the next figure, the combined index is not. In addition, Figure 2 hints that a simple average across the sub-indices may omit important information about time-varying co-movement across the sub-indices without eliminating the noise of the individual sub-indices.

Time-varying correlation weights The final step in the construction of the CMDI is to combine the sub-indices using time-varying correlation weights, corresponding to cosine-similarity weighting across features of the market. To that end, as in Hollo et al. (2012), we estimate time-varying correlations ρ_{ij} between our 7 sub-indices on a recursive basis using an exponentially-weighted moving average approach:

$$\sigma_{ij,t} = \lambda\sigma_{ij,t-1} + (1-\lambda)\,\tilde{s}_{it}\tilde{s}_{jt}, \quad i,j = 1,\ldots,7 \tag{2}$$

$$\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}\sigma_{jj,t}}}, \tag{3}$$

where $\sigma_{ij,t}$ is the estimate of the time-varying covariance between sub-indices i and j (and $\sigma_{ii,t}$ is the estimate of the time-varying variance of sub-index i), and $\tilde{s}_{it} = (s_{it} - 0.5)$ is the deviation of the value s_{it} of sub-index i from its theoretical mean of 0.5.[9] The exponentially-weighted moving average assigns relatively more weight to the recent history and relatively less weight to more distant observations. For our baseline results, we choose $\lambda = 0.9$ so that observations more than one year in the past receive essentially no weight in the index. As with the empirical CDF, we use the first two years of the data to initialize the covariance matrix in the recursion (2). In Appendix C, we present a number of robustness checks to the construction of the CMDI.

Figure 3 plots the estimated time-varying correlation matrix across the 7 sub-indices. A few features are worth noting. First, the exponentially-weighted moving average accommodates meaningful time-variation in correlations without excessive high-frequency fluctuations. Second, for a number of sub-index pairs, the sign of the correlation switches over time, so that series that were positively correlated in the past can become negatively correlated and vice versa. Figure 3 thus demonstrates the importance of taking into account time variation in the co-movement between even closely-related sub-indices. For example, even the correlation between the secondary market duration-matched and default-adjusted spread indices

[9]Note that, for a continuous random variable x, with CDF F, the standardized variable $F(x)$ has a standard uniform distribution with mean 0.5.

is almost never 1 and, moreover, dips below 0.5 during both the 2008-09 financial crisis and the European debt crisis. Importantly, we see that toward the end of our sample, the sign of the correlation switches for a number of sub-index pairs, a feature that might be missed by alternative weighting schemes.

Given the estimated time-varying correlation matrix $\mathcal{R}_t$, with (i,j) element given by $\rho_{ij,t}$, we construct the CMDI as

$$\mathrm{CMDI}_t = \frac{\sqrt{s_t' \mathcal{R}_t s_t}}{7}, \tag{4}$$

where s_t is the column-vector of the seven sub-indices $s_t = [s_{1t}, \ldots, s_{7t}]'$. In the special case when all the sub-indices are perfectly correlated, so that $\mathcal{R}_t$ is the $7{\times}7$ matrix of ones, the CMDI collapses to the equally-weighted average across the sub-indices: $\sum_{i,j=1}^{7} s_{it}s_{jt} = \left(\sum_{i=1}^{7} s_{it}\right)^2$, so that $\mathrm{CMDI}_t = \frac{1}{7}\sum_{i=1}^{7} s_{it}$. In all other cases, $\mathcal{R}_t$ is not identically equal to a matrix of ones and thus the time-varying correlations between the sub-indices play an important role in the level and the dynamics of the CMDI.

To gain intuition on how this aggregation approach differs from those more commonly used, we can consider a simple analytical example and compare the CMDI to what one would obtain using a principal components (PCs) approach. Consider the very simple (static) case where all the sub-indices have the same pairwise correlations $\rho \in (0, 1]$, so that $\mathcal{R}$ is a matrix with 1's on the diagonal and ρ in all other elements. When $\rho = 1$, both the first PC and the CMDI put equal weight on each sub-index. However, even when ρ is not equal to 1, the first PC continues to put equal weight on each sub-index, no matter how close to 0 or 1 ρ is. In contrast, the CMDI will take on higher values when ρ is higher for the same realizations of the sub-indices. This is the sense in which the CMDI construction captures the commonality of signals not just the average signal. We provide full details in Appendix B and also show that this simple intuition extends to an arbitrary correlation matrix $\mathcal{R}_t$, which may have different pairwise correlations across sub-indices: the first PC is invariant to changes in the correlation matrix that keep the ratio between any two pairwise correlations the same.

4.2 Results

We begin by examining the time series of the CMDI, plotted in Figure 4. Starting with the overall sample, we see that the CMDI peaks in the fall of 2008 and remains elevated beyond the end of the Great Recession (first gray shaded area). The CMDI then has a local peak at the height of the European debt crisis (first peach shaded area), and then a smaller peak in the middle of the 2015 – 2016 manufacturing recession (second peach shaded area). The final pre-2020 peak is at the end of 2018, corresponding to market turmoil in both equity and credit markets, which was ameliorated by the Federal Open Market Committee pausing its cycle of interest rate increases. In addition to plotting the index, which varies from 0 to 1, we show the percentile of the pre-2020 CMDI distribution on the right axis, which offers a more intuitive context, as well as highlighting the historically extreme levels of distress reached in 2020.

Turning to the more recent period, we see that, prior to the start of the COVID-19-related disruptions to asset markets in March 2020, the CMDI was noticeably below the pre-2020 historical median. The CMDI rose above the historical 90th percentile – estimated based on data prior to January 2020 – the week ending on March 21. This was the first time it had reached that percentile since the financial crisis. The announcement of Federal Reserve interventions on March 22 halted any further increases in the level of the CMDI, but the index remained above this historical benchmark until the week ending on April 11, which coincided with the announced expansion of the Corporate Credit Facilities in both size and scope. Over the course of April and May, the CMDI continued its gradual decline and was modestly below the historical median by the end of July 2020. Interestingly, the commencement of ETF purchases by the Secondary Market Corporate Credit Facility on May 12 did not immediately accelerate the pace of improvement of the index; indeed, the index did not drop below the historical 75th percentile until after the start of purchases of cash bonds on June 16. This is consistent with the larger impact of cash bond purchases on secondary market pricing and liquidity documented in Boyarchenko et al. (2022).

We expand the understanding of how conditions in primary and secondary markets enter into the overall index in Figure 5, which shows a decompositon of the square of the CMDI into the underlying sub-indices.[10] Note that, unlike the index itself, the square of the index is additive in these components, making a linear decomposition feasible.

Increases in the secondary-market-related sub-indices tend to somewhat lead increases in the primary-market-related sub-indices, consistent with the conventional wisdom that trading-activity-based measures react more quickly. Moreover, since corporate bond issuances take a relatively long time to "come to market", intuitively, we would expect primary market deteriorations to be more sluggish.

For example, while the secondary market measures were already elevated starting in the second half of 2007, the primary market conditions only deteriorated to historical highs in Fall 2008. Consistent with the fluctuating sign of pairwise correlations we see in Figure 3, the sign of the contribution from both primary and secondary market volume measures fluctuates over time. What characterizes periods of broad market distress (financial crisis, European debt crisis, 2015 – 2016 manufacturing recession, end of 2018 market turmoil, 2020 recession) is rapid deterioration in both secondary market measures accompanied by a deterioration in the primary-secondary spread and primary market issuance volumes. That is, during periods of broad market distress, conditions across both the primary and secondary markets deteriorate, amplifying the individual contribution of each market to the overall index. In contrast, outside these periods of market distress, the contribution from the interaction terms is either negligible or negative, suggesting that, during normal times, this secondary-primary market amplification spiral does not arise. This decomposition also adds intuition as to how the index methodology can add more information than a simple average or principal components approach.

[10] More specifically, the contribution from index i is $s_{it} \sum_{j=1}^{7} \rho_{ij,t} s_{jt}/49$.

Prior literature (see e.g. Adrian et al., 2017; Bessembinder et al., 2018) has argued that dealer balance sheet constraints play an important role in shaping corporate bond market conditions. We begin by examining the predictive content of a commonly-used proxy for dealer balance sheet constraints – the average 5-year CDS spread for the so-called "G14" dealers[11] – for future extreme realizations of the CMDI. We estimate a probit regression for the probability of future CMDI realization in the historical 75th percentile as a function of the current level of CMDI and the G14 dealers CDS spread:

$$\mathbb{P}_t\left(\text{CMDI}_{t+h} \in \text{P75}\right) = \alpha_0 + \beta_0 CMDI_t + \beta_M \text{Avg. dealer CDS}_t + \epsilon_{h,t}. \quad (5)$$

Table 1 reports the estimated coefficients from regression (5). Higher dealer CDS spreads predict higher probability of the CMDI rising above its historical 75th percentile, up to a quarter ahead. This relationship is both economically and statistically significant: a 100 bps increase in the average 5-year CDS spread of G14 dealers increases the probability of CMDI rising above its historical 75th percentile by 2 percentage points within a week, by 1.6 p.p. within a month, and by 1.3 p.p. within a quarter.

Turning next to how individual contributions to the CMDI are related to dealer balance sheet constraints, we estimate the following predictive regression for h period ahead metric:

$$\text{Contribution}_{i,t} = \alpha_i + \beta_i \text{Avg. dealer CDS}_t + \varphi_i \text{Contribution}_{i,t-1} + \epsilon_{i,t}. \quad (6)$$

When β_i is positive, the contribution of sub-index i is greater when dealer balance sheets are more impaired.[12]

Table 2 reports the estimated coefficients from regression (6). The average dealer 5-year CDS spread is significantly associated with contributions to the CMDI (squared) from secondary market credit spreads (both the duration-matched and default-adjusted spread),

[11] See e.g. Ang et al. (2011).

[12] We include 13 additional lags in the weekly regressions. Results are robust to alternative lag choices.

secondary-market liquidity, the quoted prices, and primary market spreads. In particular, when the 5-year CDS spread is higher, so that dealer balance sheets are more likely to be constrained, contributions from these sub-indices are larger.[13]

Finally, in Appendix D we show that the CMDI predicts future realizations of commonly-used measures of corporate bond market distress, highlighting the timeliness of the information contained in the CMDI.

5 Bond market distress and real outcomes

5.1 Bond market conditions and expected real outcomes

Several papers (see e.g. Gilchrist and Zakrajšek, 2012; López-Salido et al., 2017; Krishnamurthy and Muir, 2017) have identified the predictive content of credit spreads for future real activity. We now investigate whether incorporating information about corporate bond market distress more broadly contains additional predictive information for real outcomes over and above that contained in credit spreads. More formally, similar to Gilchrist and Zakrajšek (2012), we estimate the following predictive regression for cumulative one-year-ahead growth rates in real outcomes as a function of lagged real outcomes, risk-free interest rates and credit market conditions:

$$\Delta y_{t,t+H} = \alpha + \varphi \Delta y_{t-H,t} + \beta_{\text{FF}} \text{Real eff. FFR}_t + \beta_{\text{Slope}} \text{10y/1y TSY slope}_t + \gamma' \text{CS}_t + \epsilon_{t+H}, \tag{7}$$

where Real eff. FFR_t is the real effective federal funds rate, 10y/1y TSY slope_t is the difference between the 10 year and the 1 year constant maturity Treasury yields, and CS_t is the vector of credit conditions variables.[14] For inference, we utilize a lag-augmentation ap-

[13] In unreported results, we also show that these relationships are not driven by either the Global Financial Crisis (GFC) or the COVID-19 pandemic related market dislocations.

[14] We construct the real effective federal funds rate as the difference between the effective federal funds rate (FRED series FEDFUNDS) and the 12 month change in the core CPI (FRED series CPILFESL).

proach. As shown in Montiel Olea and Plagborg-Møller (2021), this augmentation implies that standard inference can be conducted based on heteroskedasticity robust standard errors, despite the persistence of both the dependent and independent variables in the regression. In contrast, HAC estimators have been shown to substantially over-reject the null hypothesis of no predictability in the environment of persistent predictors and overlapping outcome variables (e.g., Wei and Wright (2013), Crump and Gospodinov (2024)).[15] Here, $\Delta y_{t,t+H}$ is the 12 month change ($H = 12$) in the monthly real outcome variable of interest. We estimate this regression on the sample excluding observations in 2020 to ensure that our estimates are not driven by the unprecedentedly large movements in economic conditions during the pandemic.

Consider first the predictive relationship between aggregate credit market conditions and future real outcomes (coefficient γ in predictive regression (7)). Column (1) in each of the subtables of Table 3 report the estimated coefficient when credit market conditions are measured using the market-level CMDI.[16]

Across all measures of real activity, a higher level of CMDI – more distressed corporate bond market – is associated with reduced real economic activity over the next year. This effect is both economically and statistically significant, with a 0.1 point change in the CMDI corresponding to a 1.9 percentage point (p.p.) decrease in annual industrial production growth, a 1.4 p.p. decrease in durable goods expenditures over a 12 month period, a 48 bps increase in the unemployment rate over a 12 month period, and a 58 bps decline in the rate of private employment.

Turning to the second column in each subpanel, we see that these results are robust to controlling for the real-time analogues to the commonly-used predicted "G-Z" spread and excess bond premium (EBP) (Gilchrist and Zakrajšek, 2012), which measure the predictable and unpredictable components of average duration-adjusted credit spreads. Unlike the imple-

[15] Just as with HAC estimators, the lag-augmentation procedure requires a user-inputted tuning parameter (the number of lags). To ensure that our results are not sensitive to this choice we have confirmed that our conclusions are robust to alternative lag choices in all of our empirical results.

[16] We include 1 additional lag in the monthly regressions. Results are robust to alternative lag choices.

mentation in Gilchrist and Zakrajšek (2012), we estimate the predictable and unpredictable components using real-time information only, putting these measures on the same footing as the CMDI and avoiding potential look-ahead bias inherent in estimating the full sample predictive relationship between default probabilities and credit spreads.

For almost all our measures of real outcomes, except for private employment, the CMDI remains statistically (at least the 10% significance level) and economically significant. The real-time EBP, instead, is only a statistically significant predictor for private employment once the CMDI is included. Consistent with the results in Gilchrist and Zakrajšek (2012), the real-time predicted G-Z spread is also almost never significant. In particular, the real-time predicted G-Z spread is a statistically significant predictor only of industrial production growth but has a counterintuitive positive sign.

Finally, the third column in each subpanel in Table 3 compares the predictive information contained in the CMDI relative to an alternative weighting scheme across the seven sub-indices. More specifically, we use the full sample first principal component (PCA) of these sub-indices. The table shows that weighing corporate bond market distress measures according to the "preponderance of metrics" approach provides significantly better predictive information for future real outcomes than by weighing the same metrics using PCA. In fact, the estimated coefficients on the PCA are never significant and almost always have the wrong sign. That is, the choice of the approach for aggregating information across a broad set of metrics is not inconsequential for the information content of the final measure.

Overall, the results in Table 3 suggest that corporate bond market functioning, over and above the information contained in credit spreads alone, has predictive information about future real outcomes. Although we have a relatively short sample (15 years) for which we can construct the CMDI, the predictive relationship between CMDI and a variety of real outcome variables provides reassurance about the robustness of these results.

5.2 Bond market conditions and downside risk to growth

We conclude this section by investigating the relationship between bond market conditions and downside risk to real activity. More specifically, we estimate quantile regressions of the form

$$Q_\tau\left(\Delta y_{t,t+H}\right) = \alpha_\tau + \varphi_\tau \Delta y_{t-H,t} + \beta_{\tau,\mathrm{FF}}\text{Real eff. FFR}_t + \beta_{\tau,\mathrm{Slope}}\text{10y/1y TSY slope}_t + \gamma_\tau' \mathrm{CS}_t + \epsilon_{\tau,t+H}.$$

Table 4 reports the estimated quantile coefficients for the 0.1 quantile of 12 month industrial production growth, growth in durable goods expenditure, and growth in private employment, and the 0.9 quantile of 12 month unemployment growth. We also report the t-statistics using the IVX approach of Lee (2016), which is robust to highly persistent predictors. The first column of each panel shows that higher CMDI is associated with greater downside risk to future real activity, with higher levels of CMDI associated with a more negative 0.1 quantile and a more positive 0.9 quantile. The second column of each panel further controls for the real-time predicted G-Z spread and EBP. Even in the presence of these additional predictors, the predictability of the left tails of growth in industrial production and durable goods expenditures by the CMDI remains strongly statistically significant. Moreover, although the EBP is also statistically significant it enters the regression with the wrong sign. For example, higher levels of EBP are associated with a *smaller* 0.1 quantile for future industrial production growth. For the labor market variables, the presence of these additional predictors diminishes the statistical significance of the CMDI; however, it is important to emphasize that the estimated coefficient associated with the CMDI remains large in magnitude and the coefficients on both the G-Z spread and the EBP have the wrong sign.

6 Information in primary market metrics

Since one key contribution of the approach is to include information on primary market conditions, we turn to the question of whether the primary market metrics included in the CMDI provide distinct information about the state of the corporate bond market itself and future real outcomes than the secondary market metrics. We follow the same procedure as for the CMDI to construct a primary corporate bond market conditions index (PM-CMDI) and a secondary corporate bond market conditions index (SM-CMDI), as well as the correlation between primary and secondary market conditions. The PM-CMDI uses only the primary market issuance and the primary-secondary spread sub-indices as components, while the SM-CMDI uses secondary market volume, secondary market liquidity, duration-matched spread, default-adjusted spread, and quoted-traded spread sub-indices. While the PM-CMDI captures measures of ease of access to the corporate bond market contemporaneously, the SM-CMDI captures conditions in the secondary market and thus potentially future primary market conditions. Finally, the correlation between primary and secondary market conditions (PM-SM correlation) can be obtained as

$$\text{PM-SM correlation}_t = \text{CMDI}_t^2 - \left(\frac{2}{7}\text{PM CMDI}_t\right)^2 - \left(\frac{5}{7}\text{SM CMDI}_t\right)^2.$$

Figure 6 plots the time series of the PM-CMDI (in black) and the SM-CMDI (in green), together with the full market index (in blue). The figure highlights that the information in primary market conditions is distinct from the information in secondary market conditions, with slowdowns in the primary market sometimes occurring without slowdowns in the secondary market and vice versa. The overall index is highest when both the PM-CMDI and the SM-CMDI signal market distress.

We now revisit the results in Table 4, decomposing the overall CMDI into these three components. Table 5 shows that downside to future real activity is particularly high when the primary-secondary market correlation measure is high. That is, real activity is particularly fragile when conditions in both the primary and secondary corporate bond markets deteriorate. These results illustrate the advantages of the CMDI as this interaction term captures the specific aggregation approach and would be absent in conventional approaches (e.g. principal components as discussed in Section 4).

We conclude by considering the relationship between access to credit and measures of corporate bond market conditions. Table 6 reports the estimated contemporaneous and predictive relationships between measures of credit market conditions and changes in nonfinancial corporate bond amount outstanding. In column (1), we also report results using quarterly net issuance as the proxy for contemporaneous primary market conditions. Starting with the top panel, we see that, contemporaneously, there is no relationship between EBP and net issuance and amount outstanding growth. In columns (3) and (4), there is a statistically significant relationship between EBP and changes in amount outstanding, but with the wrong sign: increases in EBP today predict increases in amount outstanding in the future, over the same horizons that they predict decreases in economic activity. These results once again suggest that, while linked, conditions in primary and secondary markets are potentially asynchronous. Results are similar when estimated for shorter time horizons with measures of secondary market distress such as the CDS-bond basis.

The bottom panel of Table 6 instead uses the primary and second market CMDI as metrics of corporate bond market conditions. We see that while the PM-CMDI has a statistically significant relationship with net issuance and current quarter amount outstanding growth, with higher levels of PM-CMDI corresponding to lower issuance and declines in amount outstanding, the SM-CMDI is unrelated to primary market conditions. That is, while secondary market conditions may affect *future* willingness of dealers to underwrite corporate debt as well as the willingness of firms to borrow at higher rates, secondary market conditions do not appear to have an immediate impact on primary market conditions.

Taken together, this suggests that, as a whole, the corporate bond market is in distress when both the primary and secondary markets are struggling. These are times when borrowers cannot access the primary market and the secondary market experiences increases in bid-ask spreads, decreases in market depth, declines in the speed of immediacy, and a decline of market resilience to temporary order imbalances. Thus, market distress is multifaceted and is unlikely to be captured by a proxy for any of its facets alone.

7 Conclusion

Market commentators and policy makers value indexes for many reasons. As early as 1884, Charles Dow sought to summarize stock market conditions averaging stock returns of a dozen companies for his newsletter. Indexes reduce dimensionality by combining multiple measures into a single measure. Moreover, indexes of market distress are particularly valuable for policy makers as they can both summarize conditions and facilitate the implementation of market interventions. The CMDI presents a unified measure of corporate bond market conditions broadening market distress measurement away from just identifying periods of high credit spreads or periods of increased illiquidity in secondary markets. Together with the real-time nature of the index, this makes the CMDI a valuable summary metric of market distress and functioning. While market participants are likely to know market distress when they see it, formalizing that perception is valuable. The CMDI thus has clear value to inform policy makers at times like March 2020, when corporate bond markets across the world experienced severe distress related to the COVID-19 pandemic.

Another benefit of indexes is that they can be more than the sum of their parts. The broad range of indicators that underlie the CMDI, spanning both primary and secondary market activity, in both price and quantity terms, reduce the risk that the index increases without a corresponding episode of market stress. In predictive regressions, we find that the CMDI predicts real activity over the subsequent year. Moreover, the predictive power of the CMDI remains economically and statistically significant for a number of real activity metrics even after controlling for standard predictors, such as the term spread and credit spreads. This means that stress in the corporate bond market appears to have meaningful consequences for economic outcomes more broadly. Said differently, corporate credit market conditions beyond just the credit spread may matter for real activity, providing additional stylized facts that can be targeted by structural macro-finance models.

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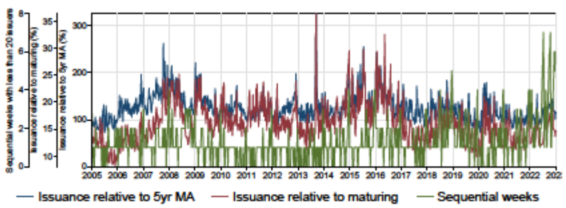
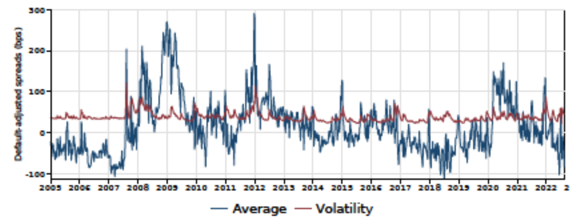
Figure 1. Time series of raw market conditions indicators. This figure plots the raw time series of measures of secondary and primary market functioning.

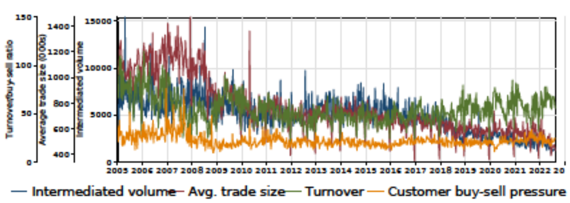
(a) Primary market volume



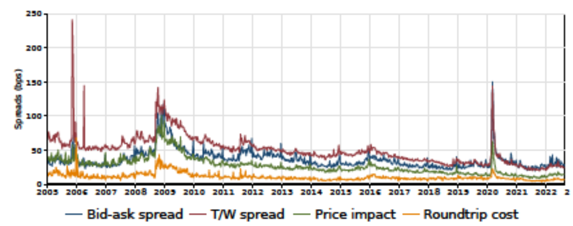
(b) Offering D-spread



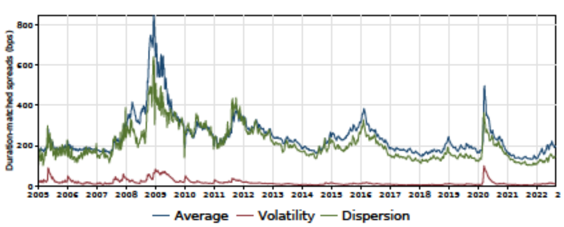
(c) Secondary market volume



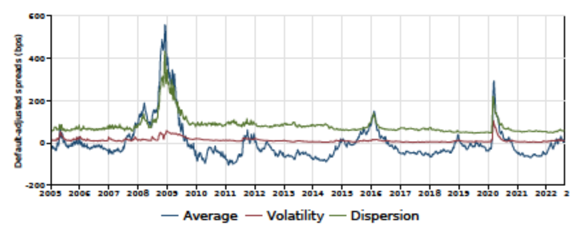
(d) Secondary market liquidity



(e) Secondary market Z-spread



(f) Secondary market D-spread



(g) Quoted D-spread

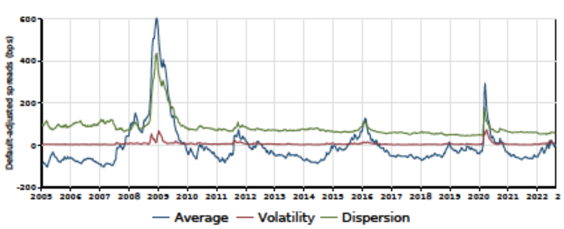
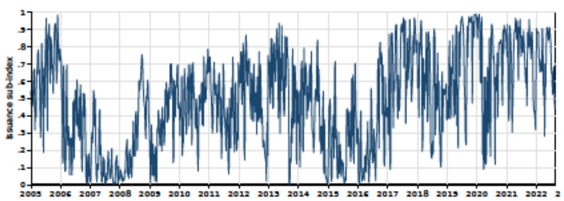
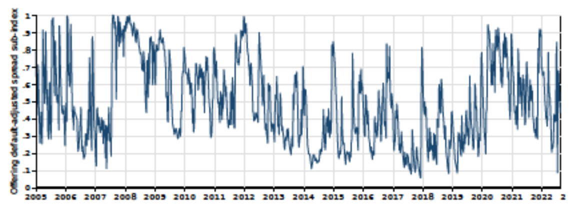


Figure 2. Category-level sub-indices. This figure plots the time series of category-level sub-indices of the corporate market distress index. Each sub-index is constructed as the equal-weighted average of the constituent individual measures.

(a) Primary market volume



(b) Offering spread



(c) Secondary market volume

(d) Secondary market liquidity

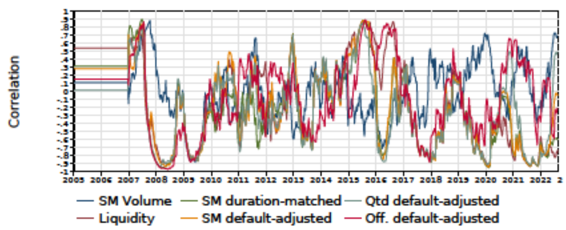
(e) Secondary market Z-spread

(f) Secondary market D-spread

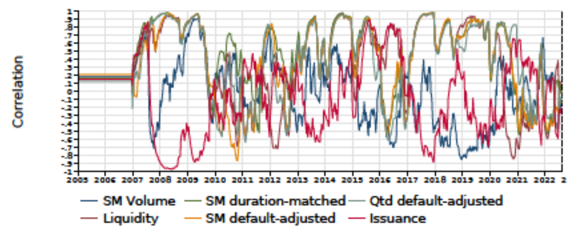
(g) Quoted spread

Figure 3. Time-varying correlations between market indicators. This figure plots the time series of estimated time-varying pairwise correlations between the category-level sub-indices. Time-varying variance-covariance matrix estimated using an exponentially-weighted moving average with smoothing parameter $\lambda = 0.9$.

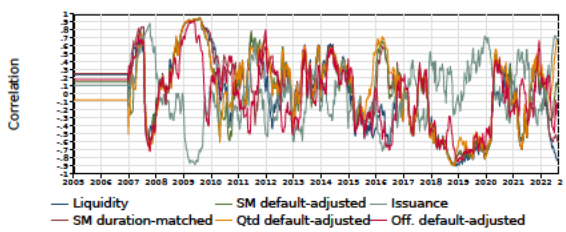
(a) Primary market volume



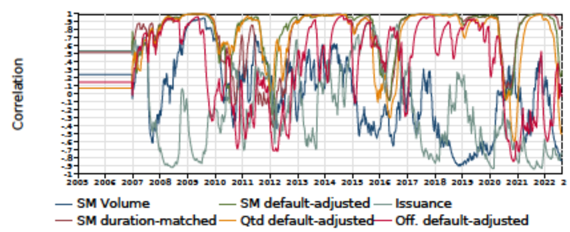
(b) Offering spread



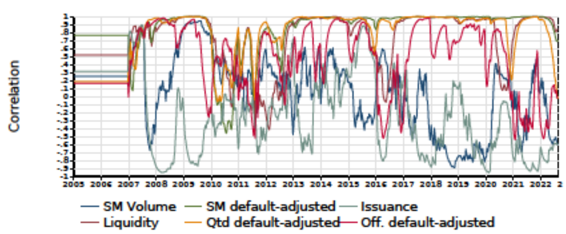
(c) Secondary market volume



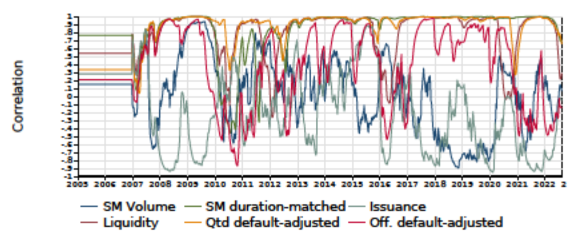
(d) Secondary market liquidity



(e) Secondary market Z-spread



(f) Secondary market D-spread



(g) Quoted spread

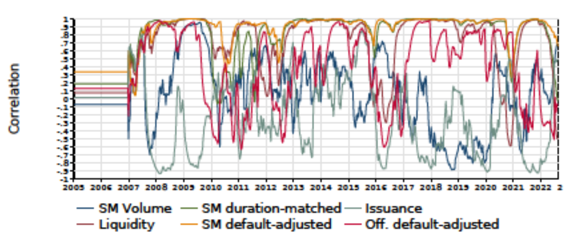


Figure 4. Corporate bond market distress index. This figure plots the time series of the corporate market distress index. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). For reference, the right y-axis presents selected percentiles of the pre-2020 CMDI distribution.

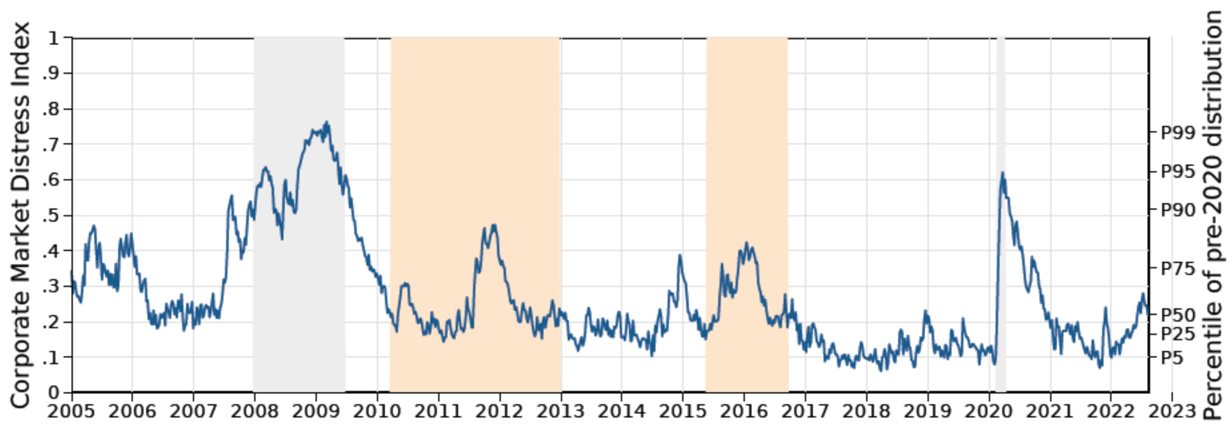


Figure 5. Contributions to the CMDI. This figure plots the time series of the sub-index contributions to the corporate market distress index (squared).

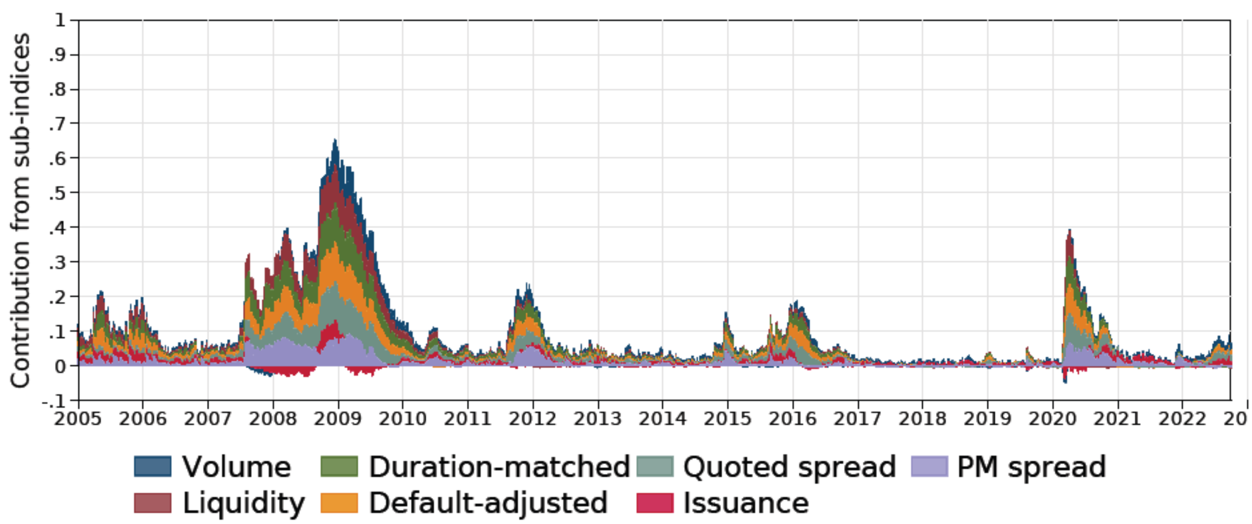


Figure 6. Primary and secondary bond market distress index. This figure plots the time series of the primary and secondary corporate market distress indices. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). For reference, the right y-axis presents selected percentiles of the pre-2020 CMDI distribution.

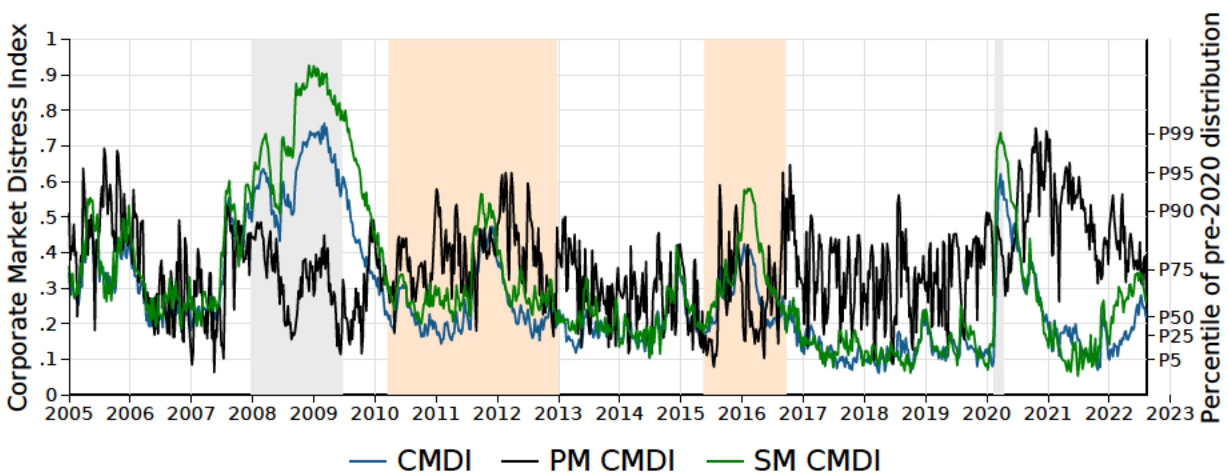


Table 1: Dealer balance sheets and extreme CMDI realizations. This table reports the estimated coefficients from the predictive probit of the CMDI h weeks ahead being in the 75^{th} historical quantile on a constant, the contemporaneous level of the CMDI, and the average 5-year CDS spread on "G14" dealers. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	1W	4W	1Q	2Q
CMDI	28.96	18.52	7.21	4.34
	(4.38)***	(3.31)***	(2.22)***	(1.96)**
G14 5y CDS spread	509.84	197.57	93.88	36.03
	(129.46)***	(68.10)***	(50.29)*	(48.45)
Pseudo R-sqr.	0.85	0.70	0.45	0.33
N. of obs	910	910	901	888

Table 2: Contributions to CMDI and dealer balance sheets. This table reports the estimated coefficients from the contemporaneous regression of contributions to the CMDI (squared) on a constant, one week lag of the dependent variable, and the average 5-year CDS spread on "G14" dealers. Lag-augmented (Montiel Olea and Plagborg-Møller, 2021) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	Volume	Liquidity	Dur. match. spd	Def. adj. spd	Qtd spd	PM vol	PM spd
G14 5y CDS spread	-0.06	0.87	0.53	0.62	0.74	-0.36	0.35
	(0.25)	(0.28)***	(0.15)***	(0.21)***	(0.27)***	(0.32)	(0.20)*
Adj. R-sqr.	0.90	0.97	0.98	0.98	0.99	0.81	0.94
N. of obs	910	910	910	910	910	910	910

Table 3: CMDI and real activity. This table reports the estimated coefficients from the predictive regression of one-year ahead industrial production, durable goods expenditure, unemployment, and private employment growth on a constant, one year lag of the dependent variable, the contemporaneous real effective federal funds rate, the contemporaneous 10 year - 1 year constant maturity Treasury slope, and corporate bond market conditions metrics. Lag-augmented (Montiel Olea and Plagborg-Møller, 2021) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Industrial production

	(1)	(2)	(3)
Market CMDI	-18.89	-27.37	-19.97
	(9.35)**	(9.39)***	(11.29)*
Real-time EBP		-0.24	
		(1.39)	
Real-time Predicted G-Z spread		15.89	
		(5.03)***	
PCA			0.44
			(3.49)
Adj. R-sqr.	0.43	0.57	0.43
N. of obs	157	157	157

(b) Durable goods expenditure

	(1)	(2)	(3)
Market CMDI	-13.61	-18.61	-21.36
	(7.50)*	(6.25)***	(8.41)**
Real-time EBP		1.70	
		(1.03)	
Real-time Predicted G-Z spread		-3.14	
		(5.42)	
PCA			3.47
			(2.69)
Adj. R-sqr.	0.66	0.71	0.66
N. of obs	133	133	133

(c) Unemployment rate

	(1)	(2)	(3)
Market CMDI	4.82	3.44	6.87
	(1.98)**	(1.82)*	(2.41)***
Real-time EBP		0.57	
		(0.35)	
Real-time Predicted G-Z spread		-1.23	
		(1.61)	
PCA			-0.82
			(0.72)
Adj. R-sqr.	0.67	0.70	0.66
N. of obs	157	157	157

(d) Private employment

	(1)	(2)	(3)
Market CMDI	-5.79	-3.49	-8.38
	(2.92)**	(2.74)	(3.34)**
Real-time EBP		-0.86	
		(0.49)*	
Real-time Predicted G-Z spread		1.83	
		(2.35)	
PCA			1.03
			(0.99)
Adj. R-sqr.	0.70	0.72	0.70
N. of obs	157	157	157

Table 4: CMDI and tails of real activity. This table reports the estimated coefficients from the quantile predictive regression of one-year ahead industrial production, durable goods expenditure, unemployment, and private employment growth on a constant, one year lag of the dependent variable, the contemporaneous real effective federal funds rate, the contemporaneous 10 year - 1 year constant maturity Treasury slope, and corporate bond market conditions metrics. t-statistics reported in parentheses below point estimates using the IVX approach of Lee (2016). *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Q10 Industrial production

	(1)	(2)
Market CMDI	-45.44	-76.11
	(-11.57)***	(-5.36)***
Real-time EBP		7.08
		(-4.23)***
Real-time Predicted G-Z spread		16.51
		(0.76)
Pseudo R-sqr.	0.41	0.48
N. of obs	158	158

(b) Q10 Durable goods expenditure

	(1)	(2)
Market CMDI	-30.06	-41.04
	(-2.08)**	(-2.62)***
Real-time EBP		2.88
		(2.06)**
Real-time Predicted G-Z spread		-4.47
		(0.24)
Pseudo R-sqr.	0.58	0.66
N. of obs	134	134

(c) Q90 Unemployment rate

	(1)	(2)
Market CMDI	8.30	12.49
	(2.41)**	(0.88)
Real-time EBP		-0.46
		(4.73)***
Real-time Predicted G-Z spread		-2.28
		(2.34)**
Pseudo R-sqr.	0.59	0.65
N. of obs	158	158

(d) Q10 Private employment

	(1)	(2)
Market CMDI	-14.69	-19.55
	(-4.70)***	(-1.19)
Real-time EBP		1.01
		(-3.52)***
Real-time Predicted G-Z spread		3.06
		(-1.49)
Pseudo R-sqr.	0.63	0.68
N. of obs	158	158

Table 5: Primary and secondary market CMDI and tails real activity. This table reports the estimated coefficients from the quantile predictive regression of one-year ahead industrial production, durable goods expenditure, unemployment, and private employment growth on a constant, one year lag of the dependent variable, the contemporaneous real effective federal funds rate, the contemporaneous 10 year - 1 year constant maturity Treasury slope, and primary and secondary corporate bond market conditions metrics. t-statistics reported in parentheses below point estimates using the IVX approach of Lee (2016). *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	Q10 Industrial production	Q10 Dur. goods expenditure	Q90 Unemployment	Q10 Private employment
PM CMDI	20.74	1.29	-1.53	2.26
	(1.97)*	(0.49)	(-3.50)***	(2.75)***
SM CMDI	-17.74	-14.96	4.20	-7.84
	(-6.11)***	(-0.58)	(2.29)**	(-0.81)
PM-SM correlation	-121.44	-69.81	14.40	-27.08
	(-6.01)***	(-3.69)***	(3.43)***	(-3.08)***
Pseudo R-sqr.	0.56	0.58	0.63	0.67
N. of obs	158	134	158	158

Table 6: Credit conditions and primary market activity. This table reports the estimated coefficients from the contemporaneous regression of net corporate bond issuance and contemporaneous and predictive regressions of annualized corporate bond amount outstanding growth rate on a constant, lags of the dependent variable, the contemporaneous real effective federal funds rate, the contemporaneous 10 year - 1 year constant maturity Treasury slope, and corporate bond market conditions metrics. Corporate bond amount outstanding from Financial Accounts of the United States, Table L.103 (non-financial corporations) and Table L.110 (Depository Institutions). Corporate bond net issuance from Financial Accounts of the United States, Table F.103 (non-financial corporations) and Table F.110 (Depository Institutions). Lag-augmented (Montiel Olea and Plagborg-Møller, 2021) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

(a) Secondary market spreads

	Net issuance	Current Q	1Q ahead	1Y ahead
Default-adjusted spread	-1.34	-0.75	1.76	1.17
	(29.86)	(1.04)	(0.85)**	(0.71)
Predicted spread	-61.07	-1.96	2.90	1.31
	(37.38)	(1.38)	(1.15)**	(1.19)
Adj. R-sqr.	0.41	0.40	0.42	0.46
N. of obs	183	183	183	180

(b) PM and SM CMDI

	Net issuance	Current Q	1Q ahead	1Y ahead
PM CMDI	-764.17	-18.06	3.21	1.92
	(256.58)***	(6.25)***	(5.74)	(3.52)
SM CMDI	-279.46	-8.94	3.29	1.72
	(351.63)	(8.10)	(5.47)	(3.46)
PM-SM correlation	994.06	33.70	25.16	12.06
	(1154.07)	(27.46)	(21.56)	(9.98)
Adj. R-sqr.	0.35	0.29	0.15	0.24
N. of obs	55	55	55	52

A Internet Appendix

A.1 Sample selection

Choosing the universe of corporate bonds to be included in the CMDI poses a tension between capturing a wider spectrum among heterogeneous bonds and constructing a cohesive time-series of prices and spreads. From the universe of corporate bonds with issue and issuer information in Mergent FISD, we exclude bonds issued in foreign currency, bonds issued as either Yankee or Canadian bonds, 144A bonds, convertible and asset backed bonds, as well as bonds that remain unrated more than 2 weeks after the initial offering date. We only retain senior and senior secured bonds issued by issuers domiciled in the U.S. For spreads in both the secondary and the primary markets, we further restrict the sample to only include fixed-coupon bonds as pricing of floating rate and zero coupon bonds behaves differently from the pricing of the much more prevalent fixed-coupon bonds. In addition, for both spreads and measures of secondary market volume and liquidity, we exclude bonds that have less than one year remaining time to maturity – as the clientele for such bonds usually consists of money market funds and these bonds trade differently than longer duration bonds – and bonds that were issued in the previous 30 days – as trading for such bonds reflects the initial offering and differs from typical trading patterns. As mentioned before, we limit our sample to the common TRACE – Mergent FISD sample, with a start date of January 2, 2005, after TRACE was completely phased-in. Restricting to the common sample mitigates any concerns that the standardized series are incompatible with each other because they are standardized on disparate sample periods. That is, selecting a common sample ensures that all metrics have "experienced" the same set of economic and financial conditions.

Our final sample thus has 34,074,792 unique bond-trade observations in the secondary market, corresponding to 31,018 unique CUSIPs, or 2,711 unique issuers. In the primary market, we have 58,381 unique issues, corresponding to 2,913 unique issuers. The disparity between the traded and the issued number of CUSIPs reflects the relatively low percentage of corporate bonds that are regularly traded.

A.2 TRACE data cleaning

In our analysis, we use TRACE data provided by FINRA at the end of each business day. Starting in July 2002, each registered FINRA member that is a party to a reportable transaction in a TRACE-eligible security has a reporting obligation. The reporting is done in real-time. The set of TRACE-eligible securities has changed throughout the years. We start our sample in 2005, when all investment-grade and high-yield U.S. corporate bonds were included in the TRACE-eligible securities definition (except for 144A). A trade report includes the security identifier, date, time, size (par value), and price of the transaction. A report also identifies the member firm's side of the transaction (buy or sell), their capacity as a principal or agent, and the other parties to the transaction. The required reporting time varies between categories of TRACE-eligible securities. Member firms must report a secondary corporate bond transaction as soon as practicable, no later than within 15 minutes of the time of execution. There a few issues that need to be addressed:

1. **Correction and Cancellations.** A trade record that is corrected or cancelled at a later time because of misreporting remains on the tape, and additional records indicate its current status.

   What do we do? We keep the most recent status of each trade record based on the system control number and the record type.

2. **Interdealer Trades.** The reporting requirements require all registered broker-dealers (BDs) to report to TRACE. Hence, a trade between two BDs is reported twice, while a trade between a client and a BD is reported once.

   What do we do? To keep one record of each trade, we keep the sell side of an interdealer trade.

3. **Non-Member Affiliates.** While BDs are identified in trade records, clients' identities are masked, and all clients are reported as "C". Effective on November 2, 2015, firms are required to identify transactions with non-member affiliates , entering "A" instead of "C" if the affiliate is a non-FINRA member.

   The reporting rule amendment also requires firms to use an indicator to identify certain trades that typically are not economically distinct and, as such, would not provide investors useful information for pricing, valuation or risk evaluation purposes if disseminated publicly. Specifically, FINRA is requiring firms to identify trades with non-member affiliates that occur within the same day and at the same price as a trade between the firm and another contra-party in the same security. Thus, firms are required to use "non-member affiliate—principal transaction indicator" when reporting a transaction to TRACE in which both the member and its non-member affiliate act in a principal capacity, and where such trade occurs within the same day, at the same price and in the same security as a transaction between the member and another counterparty. A firm is not required to append the indicator if it does not reasonably expect to engage in a same day, same price transaction in the same security with another counterparty as with a non-member affiliate.

   What do we do? We exclude records where the field SPCL_PRCSG_CD is non-missing. In addition, for volume calculations, we break down dealer-to-client (DC) and dealer-to-affiliate (DA) trading activity. We exclude non-member affiliate trades with the same price and the same size that happen within 60 seconds of each other.

4. **Trades on Electronic Platforms.** With the growth of electronic trading platforms, we see more transactions being executed through such platforms. Electronic platforms may or may not have a reporting obligation. The reporting obligation of an electronic platform is dependent on whether the platform is a party to the trade, and a registered alternative trading system (ATS) with the SEC. An ATS platform is a party to all transactions executed through its system, and therefore has a reporting obligation. An electronic platform that is not an ATS is not necessarily a party to all trades executed through its system so may not always have a reporting obligation.

   Trades on an electronic platform which also has a reporting obligation increases the number of observations in the TRACE data. For example, a trade between two member firms on an electronic platform with a reporting obligation results in four observations in the TRACE data: a sell by the first member firm to the platform, a purchase by the platform from the first member firm, a sell by the platform to the second member firm, and a purchase by the second member firm from the platform. This needs to be addressed to avoid an upward-bias of trading activity, and a downward bias of price-based liquidity measures.

What do we do? Depending on the analysis, one might want to flag such trades. We use the counterparties identities and FINRA's TRACE ATS identifiers list to flag such trades. We also construct an additional trade size variable that reset to 0 if the seller is an ATS platform. For trading volume calculations, for example, we use the ATS-adjusted volume variable. If we do not account for multiple trade reports, then we would include some trades more than once depending on whether the counterparties are FINRA members and whether an electronic platform also had a reporting obligation. This would result in an overestimation of the trading activity on electronic platforms with a reporting obligation (e.g., non-6732 ATSs), and an inaccurate comparison of the trading activity between platforms with different reporting obligations (e.g., 6732 ATSs and non-6732 ATSs). Overall, the filter that we apply to the TRACE data ensures that we include each trade only once in our sample.

A.3 Secondary market metrics definitions

Metrics of volume

- *Intermediated volume*: is defined as the ratio between the total volume across all trades between dealers and either customers or affiliates ("D2CA") and the total volume across all trades in-between dealers ("D2D"). When intermediated volume is low, a lot of interdealer trades are necessary to reallocate bonds across end holders, and the market is more likely to be stressed. We compute the intermediated volume at the week-cusip level, then aggregate to either the market or the credit-rating level by taking the median across corresponding bonds. As electronic trading became more prevalent, intermediated volume has trended down, as can be seen in the blue line in Figure A.1a. We thus only use the most recent 2 years of data in computing the empirical CDF standardization for intermediated volume.

- *Customer buy-sell pressure ratio*: is defined as the ratio between the buy flow of customers and the sell flow of customers. When the ratio is low, there is more one-sided selling of customer and the market is more likely to be stressed. We compute customer buy-sell pressure ratio at the day-cusip level, and then we take the weekly average to get to the week-cusip level. We aggregate to either the market or the credit rating level by taking the mean across all bonds.

- *Average trade size*: is the average D2CA trade size across all bonds traded within the week. When average trade size is smaller, customers have to split their trades to make the transaction more palatable to dealers, indicating less willingness to intermediate. As with the intermediated volume, average trade size (blue line in Figure A.1b) has traded down since the advent of electronic trading. We thus only use the most recent 2 years of data in computing the empirical CDF standardization for average trade size.

- *Turnover*: is the total volume as a fraction of the remaining amount outstanding in the bond as of the trade date. When turnover is high, a large fraction of amount outstanding is re-allocated across end holders, and the market is more likely to be stressed. We compute turnover at the week-cusip level, then aggregate to either the market or the credit-rating level by taking the median across corresponding bonds. We only use the most recent 2 years of data in computing the empirical CDF standardization for average trade size.

  Figure A.1c shows that turnover is particularly low the last week of each month and the first week of every quarter, as the market prepares itself for monthly rebalancing by fund managers at the start of each month. We correct for this seasonality by replacing the turnover in those weeks with the four-week moving average (red line in Figure A.1c).

Metrics of secondary market liquidity

- *Effective bid-ask spread*: the (effective) bid-ask spread is the difference between the trade-size-weighted average price of the trades where customers buy from dealers and the trade-size-weighted average price of the trades where customers sell to dealers. Negative observations are set to zero to maintain the intuition of the measure as a transaction cost:

$$bas_{b,t} = \sum_{n=1}^{N_{b,t}} \frac{P^B_{n,b} V^B_{n,b}}{\sum_{n=1}^{N_{b,t}} P^B_{n,b} V^B_{n,b}} - \sum_{m=1}^{M_{b,t}} \frac{P^S_{m,b} V^S_{m,b}}{\sum_{m=1}^{M_{b,t}} P^S_{m,b} V^S_{m,b}},$$

  where $N_{b,t}$ is the number of customer buy trades in bond b in date t, $M_{b,t}$ is the number of customer sell trades, $P_{\cdot,b}$ is the traded price and $V_{\cdot,b}$ the traded volume in each trade. We compute the effective bid-ask spread at the week-bond level, and compute the volume-weighted average to aggregate the bid-ask spread to either the market or the credit rating level.

- *TW spread*: the Thompson and Waller (1987) bid-ask spread estimator is the average of non-zero price changes throughout the day. This estimator works well in settings where trades but no quotes are available, and is computed as

$$tw_{b,t} = \frac{1}{N_{b,t}} \sum_{n=1}^{N_{b,t}} \left| \Delta P_{n,b} \right|,$$

  where $N_{b,t}$ is the number of non-zero price changes on bond b in date t. We compute the TW bid-ask spread at the week-bond level, and compute the volume-weighted average to compute the TW spread at either the market or the credit rating level.

- *Price impact*: the Amihud (2002) price impact is defined as the absolute return of consecutive transactions per million of trade volume, averaged across all the D2C trades in a day:

$$\text{Price impact}_{b,t} = \frac{1}{N_{b,t}} \sum_{n=1}^{N_{b,t}} \frac{|r_{n,b}|}{V_{n,b}} \times 10^6.$$

We compute the price impact at the week-bond level, and compute the volume-weighted average to construct the price impact at either the market or the credit rating level.

- *Imputed round trip cost*: to compute the Dick-Nielsen et al. (2012) imputed round trip cost, we identify transactions in a given bond with the same trade size occurring on the same day. For each set of imputed round-trip trades, the imputed round-trip cost is:

$$IRC_{b,t} = 100 \times \frac{P_{max,b} - P_{min,b}}{P_{min,b}},$$

where $P_{max,b}$ is the highest price within an imputed round-trip trade set, and $P_{min,b}$ is the lowest price within an imputed round-trip trade set. We aggregate to the weekly-credit rating level by taking the median across bonds within a week.

Secondary market credit spread metrics We begin by computing duration-matched spreads at the bond-trade level. As in Gilchrist and Zakrajšek (2012), define the Treasury-implied yield $y^f_{b,t}$ on bond b on trade date t as

$$\sum_{s=1}^{2T} \frac{C_b}{2} Z_t\left(\frac{s}{2}\right) + 100 Z_t\left(T\right) = \sum_{s=1}^{2T} \frac{\frac{C_b}{2}}{\left(1 + \frac{y^f_{b,t}}{2}\right)^s} + \frac{100}{\left(1 + \frac{y^f_{b,t}}{2}\right)^{2T}},$$

where T is the time-to-maturity of the bond, C_b is the coupon on the bond, and $Z_t\left(s\right)$ is the Treasury zero-coupon bond price for time-to-maturity s. The trade-level duration-matched spread on bond b on trade date t is then

$$z_{b,k,t} = y_{b,k,t} - y^f_{b,t},$$

where $y_{b,k,t}$ is the yield on bond b priced in trade k on trade date t. We aggregate to the bond-trade day level by averaging using trading volume weights:

$$z_{b,t} = \frac{\sum_{k \in \mathcal{K}_{b,t}} z_{b,k,t} V_{b,k,t}}{\sum_{k \in \mathcal{K}_{b,t}} V_{b,k,t}},$$

where $\mathcal{K}_{b,t}$ is the set of all trades in bond b in on trading day t and $V_{b,k,t}$ is the volume of the k^{th} trade in bond b on trade date t.

Duration-matched spreads measure the spread differential between corporate bonds and Treasuries with similar duration, capturing risk premia for both the differential credit and liquidity risk between Treasuries and corporate bonds. To separate these two components, similar to Gilchrist and Zakrajšek (2012), we estimate the duration-matched spread that would be predicted based on bond and issuer characteristics using the following regression

$$\log z_{b,t} = \alpha + \beta \text{EDF}_{b,t} + \vec{\gamma} F_{b,t} + \epsilon_{b,t},$$

where $\text{EDF}_{b,t}$ is the one year expected default probability for bond b on day t estimated by Moody's KMV,[17] and $F_{b,t}$ is a vector of bond and issuer characteristics: log duration, log amount outstanding, log age of the bond, log coupon rate, a dummy for call provision, and a 3-digit NAICS industry fixed effect.[18] When bond-level EDFs are not available, we use the issuer-level EDF instead and include a dummy variable for whether bond- or issuer-level EDF is used in the specification. EDFs measure the probability of a firm's bond experiencing a credit event (failure to make a scheduled principal or interest payment) over the following year, constructed from a Merton (1974)-style model. EDFs thus provide a timely measure of the credit worthiness of both the firm as a whole and the firm's individual bonds, for both private and public firms.

We estimate this regression on an expanding-window basis, using the first 2 years of the sample (January 1, 2005 – December 31, 2006) to initialize, separately for each credit rating category, allowing different credit ratings to have a different relationship between expected duration-matched spreads and bond characteristics.[19] The default-adjusted spread for bond b on date t is then calculated as the difference between the priced and the predicted duration-matched spread on bond b on date t

$$d_{b,t} = z_{b,t} - \exp\left\{\alpha + \beta \text{EDF}_{b,t} + \vec{\gamma} F_{b,t} + \frac{\sigma^2}{2}\right\},$$

where σ^2 is the estimated variance of the idiosyncratic error $\epsilon_{b,t}$. Figure A.2a plots the time series of the expanding-window and the full-sample estimate of the market-level default-adjusted spread. With the benefit of hindsight, the full-sample estimates the default-adjusted spread to have been negative in the run-up to the financial crisis, but the real-time estimate of the spread during that period is positive.

For both the duration-matched and default-adjusted spread measures, we calculate the following.

- *Spread mean and volatility*: for average and volatility of spreads, we average the bond-level daily metric to market/credit rating × week level using volume weights. We then estimate an "ARCH-in-mean" model (see e.g. Engle et al., 1987) for the weekly time series at the market/credit rating level, and use the predicted mean and volatility from that model as our measure of weekly average spread and volatility:

$$\begin{aligned} \text{Spread}_{r,t} &= \alpha_r + \varphi_r \text{Spread}_{r,t-1} + \theta_r h_{r,t} + \epsilon_{r,t} \\ h_{r,t} &= \delta_r + \beta_r \epsilon^2_{r,t-1} + \vartheta_r h_{r,t-1}. \end{aligned}$$

[17] See `https://www.moodysanalytics.com/-/media/products/edf-expected-default-frequency-overview.pdf`.

[18] The full-sample version of the regression also includes rating fixed effects.

[19] Table A.1 reports the estimated coefficients for the above regression for the full sample January 1, 2005 – November 28, 2020.

We estimate the ARCH-in-mean model on an expanding window basis, using the first 2 years of the sample (January 1, 2005 – December 31, 2006) to initialize. Figures A.2c–A.2f plot the real-time and expanding sample estimated mean and volatility of the duration-matched and default-adjusted market spreads. As a longer history becomes available, the ARCH-in-mean model has sufficient observations to estimate the time-varying volatility component of the model, and fits a constant volatility otherwise.

- *Interquartile range*: we compute the difference between the 25th and 75th percentile of bond-week level spreads for trading week.

Conditions for non-traded bonds

- *Quoted default-adjusted spread*: we compute equal-weighted average default-adjusted spreads for bonds with quotes in the ICE-BAML database, at either the market or credit rating category level, as well the interquartile range. For the market (credit rating category) level spread, we estimate an "ARCH-in-mean" model (see e.g. Engle et al., 1987) for the weekly time series at the market/credit rating level, and use the predicted mean and volatility from that model as our measure of weekly average spread and volatility.

A.4 Primary market metrics definitions

Primary market volumes We construct two metrics of primary market issuance: dollar amount issued relative to the average issuance in the same week of the year over the previous five years and dollar amount issued relative to the amount outstanding maturing in the next year. Considering issuance relative to historical issuance allows us to account for both the overall positive time trend in bond issuance as well as seasonality in the timing of corporate bond issuance, while issuance relative to maturing within the next year captures the ability of companies to satisfy their re-financing needs.[20] Figure A.1e shows that, at a weekly level, these primary market volume metrics are quite volatile, reflecting the relatively long time-to-market of corporate bond issuance. We smooth these series by first averaging offering amounts across weeks until we observe issuance from at least 20 individual issuers, and then estimating an exponential "ARCH-in-mean" model for the ratio of the smoothed offering amount relative to 5 year average and for the ratio of the smoothed offering amount relative to maturing amount outstanding. The corresponding predicted means are plotted in red in Figures A.1e.

Primary market pricing As with the secondary market, we construct two measures of primary market credit spreads: duration-matched offering spread and default-adjusted offering spread.[21] We use offering-amount-weighted averaging to construct the time series of

[20]See e.g. Almeida et al. (2012).

[21]As with the secondary market, we estimate the explanatory regression for duration-matched spreads on expanding-window basis, using the first 2 years of the sample (January 1, 2005 – December 31, 2006) to initialize, separately for each credit rating category, allowing different credit ratings to have a different relationship between expected duration-matched spreads and bond characteristics. Table A.3 reports the

market-level primary default-adjusted spreads, averaging across all fixed coupon bonds that satisfy the sample inclusion criteria outlined in Section A.1. As with primary market volumes, we average across weeks until we observe issuance from at least 20 individual issuers. We estimate an "ARCH-in-mean" model (see e.g. Engle et al., 1987) for the weekly time series at the market/credit rating level, and use the predicted mean and volatility from that model as our measure of weekly average spread and volatility, as plotted in Figure A.1f.

A.5 Common measures of financial stress

ETF-NAV basis We collect daily price per share, net asset value (NAV), and assets under management (AUM) data on the largest 48 investment-grade and the largest 68 high-yield bond exchange traded funds (ETFs) from Bloomberg. A bond ETF is considered to be "investment grade" if it specializes in investing in investment-grade-rated corporate securities, and "high yield" if it specializes in investing in high-yield-rated corporate securities. For each day-ETF observation, we compute the ETF-NAV basis as the basis point relative difference between the price per share and the fund's NAV:

$$\text{ETF-NAV basis}_{f,t} = 100 \times 100 \times \frac{P_{f,t} - \text{NAV}_{f,t}}{\text{NAV}_{f,t}}.$$

When the ETF-NAV basis is positive, a share in the ETF costs more than the replicating basket of individual bonds. Given the panel of fund-level ETF-NAV basis, we construct the time series of the credit rating category level absolute ETF-NAV basis as the AUM-weighted average of fund-level ETF-NAV bases across funds in each rating category at each date:

$$\text{ETF-NAV basis}_{IG,t} = \frac{\sum_{f \in IG} \text{AUM}_{f,t} \, |\text{ETF-NAV basis}_{f,t}|}{\sum_{f \in IG} \text{AUM}_{f,t}}$$
$$\text{ETF-NAV basis}_{HY,t} = \frac{\sum_{f \in HY} \text{AUM}_{f,t} \, |\text{ETF-NAV basis}_{f,t}|}{\sum_{f \in HY} \text{AUM}_{f,t}}.$$

We then average each basis time series within the week to obtain a week-credit rating category ETF-NAV basis.

A.6 Credit rating categories

To construct credit-rating-level indices, we first coalesce bond-level ratings by multiple rating agencies into a single number based on the plurality rule: if a bond is rated by more than one agency, we use the rating agreed upon by at least two rating agencies and use the lowest available rating otherwise. For secondary market measures, we use the bond-level ratings contemporaneous with the trade date. For primary market measures, we use ratings closest to the bond's offering date, restricting that each rating is issued no less than 7 days prior to the offering date and no more than 30 days after the offering date. Bonds rated BBB- or

estimated coefficients for the primary market duration-matched spreads regression for the full sample January 1, 2005 – November 28, 2020.

above are considered to be "investment grade". Bonds rated below BBB- but above DDD are considered to be "high yield".

B Comparison to principal components analysis

In this Section, we provide further intuition on the difference between the CMDI construction and the PC approach. Suppose we are in the simple (static) case where the correlation matrix is all ones, i.e.,

$$C_0 = \iota_N \iota_N',$$

where ι_N is an $N \times 1$ vector of ones. This is a rank-one, symmetric matrix and so the only non-zero eignenvalue is $\lambda_{\max}(\iota_N \iota_N') = \operatorname{trace}(\iota_N \iota_N') = N$. The corresponding eigenvector is $v_0^* = \frac{\iota_N}{\sqrt{N}}$ since,

$$C_0 v_0^* = \iota_N \iota_N' \frac{\iota_N}{\sqrt{N}} = N \cdot \frac{\iota_N}{\sqrt{N}}.$$

Thus, when the correlation matrix is all ones, then the first principal component will weight all sub-indices equally and so, in this special case, PCA and the "preponderance of metrics" approach coincide: the CMDI is the sample average of the sub-indices (as discussed in Section 4). However, this is a knife-edge case and is not true in general. To see this, suppose that the correlation matrix is of the form,

$$C_{1-\rho} = \rho C_0 + (1-\rho)\,\mathsf{I}_N, \qquad 0 < \rho < 1$$

where I_N is the $N \times N$ identity matrix. In words, we have that all series are positively correlated with a common correlation coefficient. Then,

$$C_{1-\rho} v_0^* = (\rho C_0 + (1-\rho)\,\mathsf{I}_N)\, v_0^* = \rho N v_0^* + (1-\rho)\, v_0^* = (\rho N + (1-\rho))\, v_0^*.$$

Since C_0 is rank one and $(1-\rho) > 0$ then $\lambda_{\max}(C_{1-\rho}) = (\rho N + (1-\rho))$ and so v_0^* continues to be the loadings on the first principal component (PC). In other words, the first PC does not change with ρ no matter if it is very close to zero or very close to one. In contrast, the CMDI will tend to be higher, all else equal, when ρ is high than when it is low. This is the sense in which CMDI is grounded by the idea that distress is reflected in commonality of signals – not just the individual signals themselves.

It is important to note that the simple analytical example above generalizes further and the conclusions do not rest on the assumption of a common ρ. To see this let C be an arbitrary correlation matrix (i.e., a positive semi-definite matrix with all diagonal elements equal to one). Assume that the maximum eigenvalue of C, $\lambda_{\max}(C)$ is unique so that the first PC can be unambiguously defined. Let v^* be the eigenvector associated with $\lambda_{\max}(C)$ and let $a > 0$ be a constant. Then, we can rescale the correlations in C by considering $\tilde{C}$ defined as

$$\tilde{C} = aC + (1-a)\mathsf{I}_N.$$

We restrict a only to be positive and take on values that ensure $\tilde{C}$ remains positive semi-definite. Then, since $Cv^* = v^* \lambda_{\max}(C)$ we have that

$$\tilde{C}v^* = (aC - a\mathsf{I}_N)\, v^* = av^* \lambda_{\max}(C) - av^* = a\left(\lambda_{\max}(C) - 1\right) v^* = \lambda_{\max}\big(\tilde{C}\big) v^*.$$

Thus, even when we rescale the correlations in an arbitrary correlation matrix to be stronger (larger a) or weaker (smaller a), the loadings on the first principal component remain v^*.

C Robustness

We conduct a number of robustness checks to ensure that the overall CMDI is not unduly affected by any particular implementation choice.

Full-sample vs expanding sample ECDF We begin by comparing the baseline CMDI to one constructed from the individual metrics standardized using the full-sample ECDF. This alternative index would, of course, be un-available in real time but provides a useful point of reference in assessing the timeliness of the CMDI in identifying periods of distress.[22] Figure A.4 shows both series for the full sample. Note that, by construction, the two series converge to each other by the end of the sample. Strikingly, both the CMDI and its infeasible counterpart provide very similar signals of market distress. Indeed, the full-sample "hindsight" primarily manifests in a higher level of the index during the latter half of the financial crisis and the subsequent initial recovery, highlighting just how extreme market dislocations were at that time. Thus, Figure A.4 demonstrates that the CMDI provides a timely measure of market distress in real time that performs well even relative to a perfect foresight index.

Alternative exponential smoothing parameters Turning next to the choice of the smoothing parameter λ, Figure A.5 plots the baseline CMDI, which corresponds to $\lambda = 0.9$, together with the index constructed using two alternative choices: $\lambda = 0.95$, roughly corresponding to observations more than 18 months in the past receiving essentially no weight in the index, and $\lambda = 0.8$, roughly corresponding to observations more than six months in the past receiving essentially no weight in the index. Figure A.5 shows that, although the index constructed with $\lambda = 0.8$ is somewhat more volatile than the two alternatives with a higher choice of λ, the three versions of the index move closely together and identify similar periods of both market distress and market functioning.

Alternative weighting schemes Recall that the last step in the construction of the CMDI is the choice of how to weight across the 7 individual sub-indices. We now explore three alternative weighting schemes: one using the full-sample (constant) correlation matrix as the weighting matrix:

$$\text{CMDI}_t^{FS} = \frac{\sqrt{s_t' \mathcal{R}^{FS} s_t}}{7},$$

[22] Note, however, that we still keep the real-time series for duration-matched and default-adjusted spread means and volatilities. Similarly, we still use a time-varying correlation matrix to combine the sub-indices in constructing the perfect foresight index.

one assuming a perfect correlation matrix:[23]

$$\text{CMDI}_t^{EW} = \frac{\sum_{i=1}^{7} s_{it}}{7},$$

and one constructed as the first principal component of the 7 individual sub-indices.

Figure A.6 plots these three alternatives together with our baseline index. While all four indices have broadly consistent patterns over time, the equal-weighted index and the first PC of individual sub-indices exhibit more variation outside of periods of market stress, suggesting that they would too frequently classify the corporate bond market as in distress. The index based on the full-sample constant correlation matrix is more akin to the baseline index constructed using time-varying correlations. However, the full-sample correlation index does not recognize the further deterioration of market conditions in the wake of the Lehman bankruptcy, nor the nadir of corporate bond market distress in 2006 and first half of 2007. Thus, the time-varying correlation between the 7 sub-indices plays a meaningful role in diagnosing both positive and negative market conditions.

An alternative way of examining the role of the weighting scheme in the construction of the overall index is to study how the index changes if we assign a weight of zero to a particular sub-index; that is, to study so-called "leave one out" indices. Figure A.7 shows the result of this exercise. Overall, the dynamics of the index are essentially unchanged regardless of which sub-index is omitted, and match closely with the dynamics of the CMDI. Moreover, the absolute levels of the leave one out indices are similar, with the exception of when we omit either the primary market issuance or the secondary market volume indices during the financial crisis. In that episode, the level of the index that omits either the primary market issuance or the secondary market volume indices is higher than that of the full index. Overall, the results of this exercise suggest that the construction of the CMDI is not sensitive to the inclusion of any one measure but rather, as desired, captures overall market conditions.

D CMDI and common measures of financial stress

D.1 Bond market distress and contemporaneous market conditions

As we see in Figure 4, the CMDI increases during periods that have colloquially been identified as periods of stress in the corporate bond market, with the peak of the CMDI occurring during the financial crisis and the next largest peak during the COVID-19-related market stress in March 2020. In order to understand the value of the measure, we now compare and contrast the information about corporate bond market functioning provided by the CMDI with that provided by common measures of financial stress used by market participants and in the prior literature. We consider the following types of indicators:

1. **Measures of broad market risk-aversion**: we follow the literature and use VIX as a proxy for aggregate risk in the economy.

[23] Recall that this is equivalent to an equal-weighted average on the 7 individual sub-indices.

2. **Broad indicators of financial conditions**: we use two common indicators of broad financial conditions in the U.S.: the Chicago Fed National Financial Conditions Index (NFCI)[24] and the ECB's Composite Indicator of Systemic Stress (CISS).[25]

3. **Measures of corporate borrowing conditions**: The corporate bond market is closely linked to two derivatives markets: corporate bond ETFs and credit default swaps (CDS). The relationship of the corporate bond market with each of these derivatives markets is usually summarized using the ETF-NAV basis and the CDS-bond basis, respectively. In particular, the absolute ETF-NAV basis measures the absolute relative deviation of the ETF price from the price of the replicating basket of corporate bonds, with a large basis indicating greater divergence between the value of the ETF and the value of the corporate bond portfolio it holds.[26] Similarly, the absolute CDS-bond basis measures the absolute relative deviation of a CDS-market-implied bond yield for a particular firm to the yield on a matched-maturity bond of the same firm, with a larger CDS-bond basis indicating that buying protection against corporate default in the CDS market is relatively mispriced.

To investigate the relationship between the CMDI and these measures of market conditions, we estimate the following regression:

$$\text{CMDI}_t = \alpha + \varphi \text{CMDI}_{t-1} + \vec{\beta}' \mathcal{M}_t + \epsilon_t, \tag{8}$$

where $\mathcal{M}_t$ is the (vector of) market condition metrics.[27] Table A.4 reports the estimated coefficients from the above regression. Across all specifications, including the market conditions variables adds little explanatory power for movements in the CMDI beyond that explained by lags of the CMDI itself. Beyond explanatory power, the statistical significance of the estimated $\vec{\beta}$ coefficients on these measures is concentrated in a few variables, namely the VIX, NFCI, CISS, bid-ask spreads and duration-matched spreads. In column (11), which includes all the measures, only the VIX has a statistically-significant relationship with the CMDI. Thus, while the CMDI is correlated with commonly-used measures of market conditions, it contains differential information, which we investigate in the next sections.

D.2 Bond market distress and future market conditions

We now examine whether market distress today predicts future realizations of commonly-used proxies for corporate credit market conditions. Similarly to the analysis in the previous

[24] The NFCI is computed by the Federal Reserve Bank of Chicago, available at `https://www.chicagofed.org/publications/nfci/index`. The NFCI provides a weekly estimate of U.S. financial conditions in money markets, debt and equity markets, and the traditional and shadow banking systems. The index is a weighted average of 105 measures of financial activity, each expressed relative to their sample averages and scaled by their sample standard deviations. The list of indicators is provided at `https://www.chicagofed.org/~/media/publications/nfci/nfci-indicators-list-pdf.pdf`. The methodology for the NFCI is described in Brave and Butters (2011) and is based on the quasi maximum likelihood estimators for large dynamic factor models developed by Doz et al. (2012).

[25] CISS data available at `https://sdw.ecb.europa.eu/browse.do?node=9689686`.

[26] See Appendix A.5 for details on the construction of the ETF-NAV basis series.

[27] We include 13 additional lags in these weekly regressions. Results are robust to alternative lag choices.

subsection, we focus here on high frequency measures of aggregate risk (VIX), measures that suggest dislocations between markets (CDS-bond basis, ETF-NAV basis), and measures of secondary market pricing and liquidity (duration-matched spreads, bid-ask spreads). A predictive relationship between the CMDI and future realizations of such commonly-used metrics would indicate that the index provides relevant and timely information, identifying imminent distress that may not be consistently captured by any one metric.

Formally, we estimate the following predictive regression for h period ahead metric:

$$X_{i,t+h} = \alpha_i + \sum_j \varphi_{ij} X_{j,t} + \epsilon_{i,t+h}, \tag{9}$$

where $X_{i,t}$ is a single measure of market stress (including the CMDI). Table A.5 reports the estimated coefficients from regression (9) 6 months ahead, across the VIX, NFCI, CISS, duration-matched spreads, bid-ask spreads, IG and HY CDS-bond basis, IG and HY ETF-NAV basis, and the CMDI.

Three features are notable. First, the CMDI is a significant predictor of other measures of market stress (as can be seen from the coefficients in the first row of the table). Thus, for example, from the first column of Table A.5, we can observe that a 0.1 increase in the CMDI predicts a 1.9 increase in the VIX in 6 months' time.

Second, while the CMDI is consistently statistically significant, the other predictors may become significant for some variables. Indeed, including the CMDI often drives out the significance of even the lagged values of the predicted series (e.g. when predicting future VIX realizations, the current level of the VIX is not significant once we control for the CMDI).

Third, future realizations of the CMDI (last column) are not consistently predicted by the other market distress measures. The only indicator that remains statistically significant at the 6 month horizon is the NFCI. However, it is important to emphasize that, in contrast to the CMDI, the NFCI is not a real-time indicator as the index is substantially revised as lower frequency indicators are released. This reinforces the conclusion that the CMDI has strong predictive ability as it performs comparably to an alternative which features look-ahead bias.

Overall, the results in Table A.5 show that CMDI predicts future realizations of commonly-used measures of market stress, even when controlling for contemporaneous realizations of those measures, but not vice versa. In other words, the CMDI Granger-causes future market conditions, highlighting the benefits of using the CMDI to measure corporate bond market distress. We conjecture that the index provides more timely and precise signals of market functioning exactly because it is an aggregate index constructed from a "preponderance of metrics" approach. While any individual measure is noisy, signaling both false positives (e.g. credit spreads increasing when credit risk rises) and false negatives (primary market volume remaining flat during the 2015–2016 manufacturing recession), the index coalesces information from multiple sources. Thus, false positives are discounted when deteriorations are idiosyncratic to a single measure; likewise, false negatives are "corrected" when other metrics indicate distress.

Table A.1: Estimated relationship between secondary market duration-matched spreads and characteristics. This table reports the estimated coefficients from the regression of secondary market log duration-matched spreads on firm-level 1 year expected default frequency (EDF) and bond issuer characteristics. Standard errors clustered at the issuer-quarter level reported in parentheses below the point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	AAA/AA	A	BBB+/BBB	BBB-	BB	B	CCC/C	UR	Market
Constant	-7.03	-6.80	-6.38	-6.07	-5.27	-4.92	-3.99	-5.63	-6.17
	(0.03)***	(0.02)***	(0.03)***	(0.05)***	(0.06)***	(0.07)***	(0.09)***	(0.18)***	(0.01)***
Log EDF	0.01	0.02	0.02	0.03	0.06	0.06	0.07	0.07	0.03
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.01)***	(0.00)***
Log duration	0.52	0.65	0.68	0.70	0.59	0.43	0.12	0.07	0.62
	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.05)	(0.00)***
Log coupon	0.74	0.62	0.59	0.55	0.46	0.58	0.51	1.22	0.61
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.04)***	(0.08)***	(0.01)***
Log amt out	-0.01	-0.06	-0.08	-0.07	-0.06	-0.03	0.02	-0.05	-0.06
	(0.01)	(0.00)***	(0.00)***	(0.01)***	(0.01)***	(0.00)***	(0.01)***	(0.02)**	(0.00)***
Log age	-0.05	-0.03	-0.03	-0.01	-0.03	-0.01	0.08	-0.02	-0.02
	(0.01)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)**	(0.01)***	(0.02)	(0.00)***
Callable	-0.03	-0.07	-0.11	-0.07	-0.13	-0.15	0.03	0.01	-0.06
	(0.02)	(0.02)***	(0.02)***	(0.03)**	(0.02)***	(0.03)***	(0.03)	(0.10)	(0.01)***
Adj. R-sqr.	0.47	0.48	0.48	0.43	0.29	0.20	0.16	0.55	0.65
N. of obs	374246	2101385	2604213	1070546	1156313	970430	326172	17335	8620642
N. of clustes	2178	15814	22186	10812	14677	17812	7233	1278	83273

Table A.2: Estimated relationship between quoted duration-matched spreads and characteristics. This table reports the estimated coefficients from the regression of quoted log duration-matched spreads on firm-level 1 year expected default frequency (EDF) and bond issuer characteristics. Standard errors clustered at the issuer-quarter level reported in parentheses below the point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	AAA/AA	A	BBB+/BBB	BBB-	BB	B	CCC/C	UR	Market
Constant	-7.34	-7.13	-6.54	-6.24	-5.39	-5.17	-4.34	-6.24	-6.39
	(0.03)***	(0.02)***	(0.02)***	(0.04)***	(0.04)***	(0.05)***	(0.09)***	(0.21)***	(0.01)***
Log EDF	0.03	0.03	0.03	0.03	0.04	0.05	0.04	0.03	0.03
	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.01)***	(0.00)***
Log duration	0.80	0.76	0.71	0.70	0.48	0.29	0.07	0.06	0.65
	(0.02)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.05)	(0.00)***
Log coupon	0.55	0.57	0.56	0.54	0.54	0.77	0.72	0.83	0.59
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.03)***	(0.10)***	(0.00)***
Log amt out	0.01	-0.04	-0.02	0.02	0.02	0.02	0.05	-0.03	-0.01
	(0.01)	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.00)***	(0.01)***	(0.02)*	(0.00)***
Log age	0.03	0.02	-0.00	0.02	0.01	0.01	0.10	0.03	0.02
	(0.01)***	(0.00)***	(0.00)	(0.00)***	(0.00)***	(0.00)***	(0.01)***	(0.03)	(0.00)***
Callable	0.05	0.16	0.10	0.15	0.16	0.08	0.11	0.87	0.16
	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.02)***	(0.02)***	(0.03)***	(0.08)***	(0.01)***
Adj. R-sqr.	0.42	0.42	0.40	0.33	0.19	0.17	0.16	0.48	0.64
N. of obs	935281	5800224	6101581	2405776	2487706	2156202	794654	60637	20742061
N. of clustes	3517	20197	25629	12632	18097	21696	8599	997	101440

Table A.3: Estimated relationship between primary market duration-matched spreads and characteristics. This table reports the estimated coefficients from the regression of primary market log duration-matched spreads on firm-level 1 year expected default frequency (EDF) and bond issuer characteristics. Standard errors clustered at the issuer-quarter level reported in parentheses below the point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

	AAA/AA	A	BBB+/BBB	BBB-	BB	B	CCC/C	UR	Market
Constant	-6.03	-6.05	-5.73	-5.29	-5.17	-4.93	-4.13	-5.28	-5.31
	(0.16)***	(0.04)***	(0.05)***	(0.08)***	(0.14)***	(0.32)***	(0.32)***	(0.14)***	(0.04)***
Log EDF	-0.03	-0.00	-0.00	-0.01	0.00	-0.00	-0.01	-0.15	-0.04
	(0.01)**	(0.00)	(0.00)	(0.01)*	(0.01)	(0.00)	(0.01)	(0.02)***	(0.00)***
Log duration	-0.04	0.30	0.29	0.04	-0.08	-0.23	-0.44	-0.50	-0.15
	(0.09)	(0.03)***	(0.03)***	(0.04)	(0.07)	(0.10)**	(0.10)***	(0.06)***	(0.03)***
Log coupon	0.77	0.53	0.56	0.63	0.87	0.99	0.88	1.24	0.79
	(0.06)***	(0.02)***	(0.02)***	(0.03)***	(0.04)***	(0.06)***	(0.08)***	(0.05)***	(0.02)***
Log offering amt	0.06	0.08	0.07	0.10	0.14	0.21	0.06	0.04	0.09
	(0.01)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***	(0.02)***	(0.01)***	(0.01)***
Callable	0.31	0.32	0.25	0.36	0.38	0.42	0.13	0.29	0.40
	(0.05)***	(0.03)***	(0.04)***	(0.05)***	(0.04)***	(0.09)***	(0.08)	(0.07)***	(0.02)***
Adj. R-sqr.	0.36	0.32	0.32	0.29	0.58	0.73	0.61	0.70	0.59
N. of obs	2815	9285	6334	2301	2618	1874	351	4249	29860
N. of clustes	1174	4639	3874	1566	1593	1663	339	1156	15382

Table A.4: Relationship between CMDI and contemporaneous market conditions. This table reports the estimated coefficients from the regression of CMDI on a constant, one week lag of the dependent variable, and contemporaneous VIX, nominal and real Treasury noise, NFCI, CISS, duration-matched spreads, bid-ask spreads, IG and HY absolute CDS bond-basis, IG and HY ETF-NAV basis. NFCI is the Chicago Fed National Financial Index. CISS is the ECB's Composite Indicator of Systemic Stress. VIX divided by 100 in the regressions. Lag-augmented (Montiel Olea and Plagborg-Møller, 2021) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

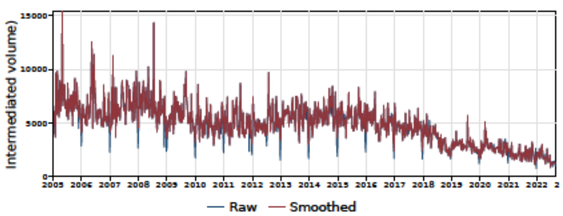
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Lagged CMDI	0.91	0.85	0.83	0.88	0.88	0.87	0.90	0.90	0.91	0.94	0.84
	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.04)***	(0.05)***	(0.05)***
VIX		0.25									0.21
		(0.05)***									(0.06)***
NFCI			0.47								0.44
			(0.19)**								(0.30)
CISS				0.08							-0.04
				(0.03)***							(0.03)
Duration-matched					0.02						0.01
					(0.01)***						(0.01)
Bid-ask						0.08					0.01
						(0.02)***					(0.02)
IG CDS-bond							1.83				-0.48
							(1.67)				(2.80)
HY CDS-bond								1.46			0.42
								(0.67)**			(0.95)
IG ETF-NAV									-0.64		-1.17
									(0.90)		(1.15)
HY ETF-NAV										0.36	0.88
										(0.29)	(0.58)
Adj. R-sqr.	0.97	0.98	0.98	0.98	0.97	0.97	0.97	0.97	0.97	0.98	0.98
N. of obs	768	768	768	768	767	768	768	768	768	650	650

Table A.5: CMDI and future market conditions. This table reports the estimated coefficients from the predictive regression of 6 months ahead VIX, NFCI, CISS, duration-matched spreads, bid-ask spreads, IG and HY absolute CDS bond-basis, IG and HY ETF-NAV basis, on a constant, lags of all market conditions variables, and corporate bond market conditions metrics. VIX divided by 100 in the regressions. Lag-augmented (Montiel Olea and Plagborg-Møller, 2021) standard errors reported in parentheses below point estimates. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

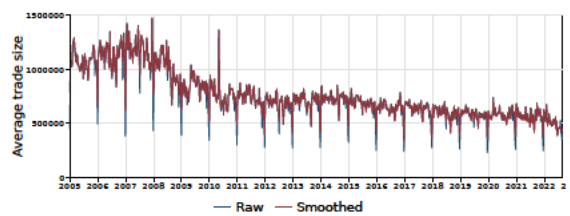
	VIX	NFCI	CISS	Duration-matched	Bid-ask	IG CDS-bond	HY CDS-bond	IG ETF-NAV	HY ETF-NAV	CMDI
CMDI	0.19	1.60	0.28	3.24	0.49	0.01	0.02	0.01	0.04	0.63
	(0.10)*	(0.48)***	(0.14)**	(1.20)***	(0.17)***	(0.00)**	(0.01)**	(0.01)**	(0.01)***	(0.19)***
VIX	0.03	0.31	-0.06	2.05	0.23	0.01	0.02	-0.00	0.01	0.11
	(0.14)	(0.61)	(0.17)	(1.42)	(0.20)	(0.01)	(0.01)	(0.01)	(0.01)	(0.22)
NFCI	2.08	12.04	1.88	18.58	1.43	0.10	0.16	0.13	0.04	3.86
	(0.75)***	(3.64)***	(0.94)**	(8.50)**	(1.22)	(0.04)***	(0.08)**	(0.04)***	(0.10)	(1.33)***
CISS	0.01	-0.17	0.03	-0.32	-0.06	-0.00	-0.00	-0.00	-0.01	-0.11
	(0.08)	(0.36)	(0.10)	(0.77)	(0.13)	(0.00)	(0.01)	(0.00)	(0.01)	(0.12)
Duration-matched	-0.00	-0.03	-0.01	0.22	0.03	0.00	0.00	0.00	0.00	0.02
	(0.02)	(0.10)	(0.03)	(0.23)	(0.04)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)
Bid-ask	-0.02	0.05	-0.01	0.09	0.09	-0.00	0.00	0.01	0.00	-0.03
	(0.08)	(0.32)	(0.09)	(0.73)	(0.10)	(0.00)	(0.01)	(0.00)**	(0.01)	(0.12)
IG CDS-bond	14.51	24.63	-2.08	56.84	-0.89	0.59	1.17	-0.23	-1.72	-2.34
	(8.41)*	(39.84)	(9.77)	(85.41)	(13.28)	(0.38)	(0.89)	(0.37)	(1.09)	(11.78)
HY CDS-bond	-4.64	-24.96	-1.72	-31.22	-4.02	-0.05	-0.03	-0.07	-0.10	-4.62
	(2.47)*	(11.55)**	(2.81)	(26.92)	(3.68)	(0.11)	(0.26)	(0.12)	(0.30)	(3.85)
IG ETF-NAV	2.39	-2.24	8.28	27.34	-0.39	-0.04	-0.09	0.03	0.02	3.63
	(2.76)	(12.99)	(3.31)**	(26.86)	(4.01)	(0.11)	(0.27)	(0.12)	(0.23)	(4.07)
HY ETF-NAV	-3.17	-18.74	-2.25	-34.67	-4.09	-0.10	-0.21	-0.21	-0.32	-2.92
	(1.09)***	(5.69)***	(1.53)	(13.21)***	(1.77)**	(0.05)*	(0.13)	(0.06)***	(0.13)**	(1.84)
Adj. R-sqr.	0.59	0.86	0.78	0.72	0.69	0.78	0.76	0.77	0.63	0.71
N. of obs	625	625	625	625	625	625	625	625	625	625

Figure A.1. Raw and smoothed time series. This figure plots the raw and smoothed time series of measures of secondary and primary market functioning. Turnover smoothed to remove end-of-month and beginning-of-quarter seasonality. Intermediated volume and average trade size detrended relative to a lagged one year (52 week) moving average. Primary market metrics (offering amount growth, number of issues growth, amount outstanding issued relative to maturing amount, number of bonds issued relative to maturing bonds) smoothed by applying a four week moving average to both the numerator and denominator. Primary-secondary spreads smoothed by applying a four week moving average.

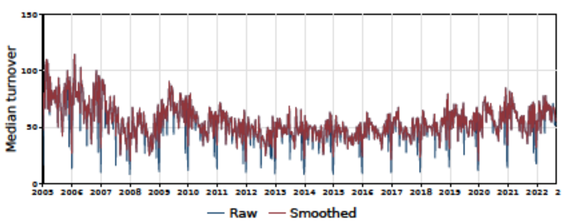
(a) Intermediated volume



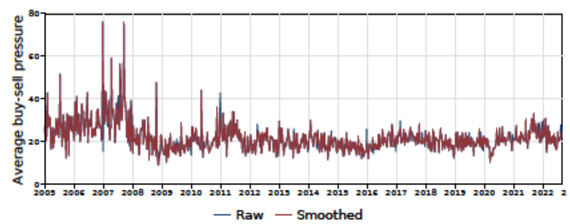
(b) Average trade size



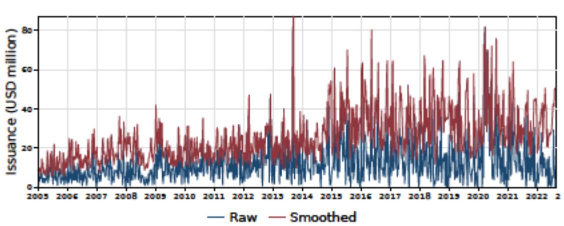
(c) Secondary market turnover



(d) Customer buy-sell pressure ratio



(e) Primary market volume



(f) Offering spread

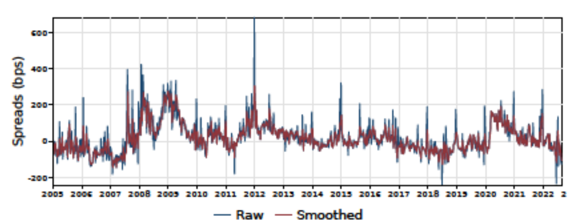
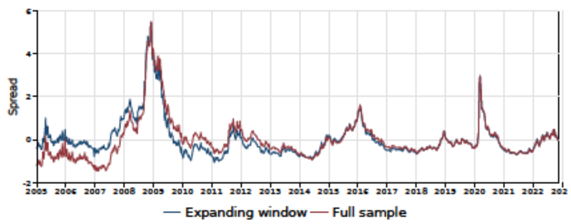
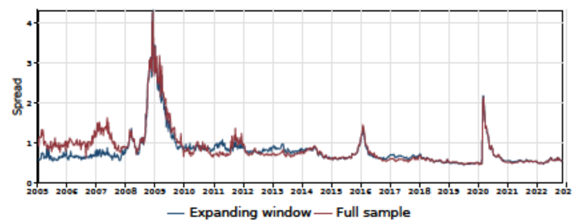


Figure A.2. Full-sample and expanding sample spread estimates. This figure plots full-sample and the expanding-sample default-adjusted spread, as well as the full-sample and the expanding-sample GARCH model estimates. The expanding sample initialized with the first two years of data (January 2, 2005 – December 30, 2006).

(a) Default-adjusted spread level

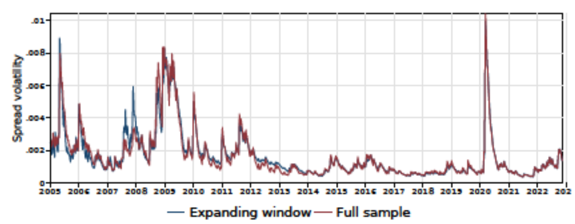


(b) Default-adjusted spread dispersion

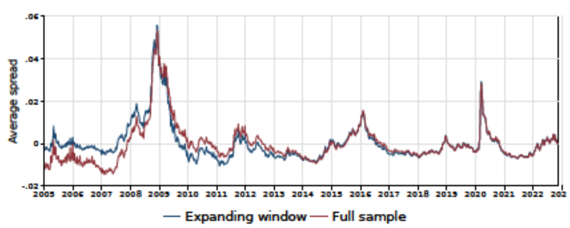


(c) Duration-matched, mean

(d) Duration-matched, volatility



(e) Default-adjusted, mean



(f) Default-adjusted, volatility

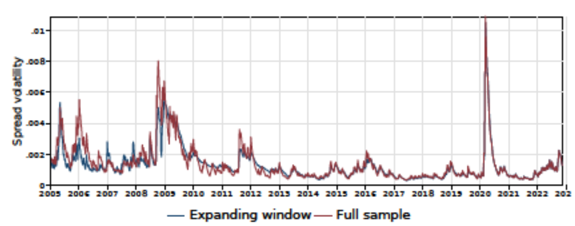


Figure A.3. Full-sample and expanding sample ECDF estimates. This figure plots full-sample and the expanding-sample empirical cumulative distribution functions (ECDFs) of measures of secondary and primary market functioning. The expanding sample ECDF initialized with the first two years of data (January 2, 2005 – December 30, 2006).

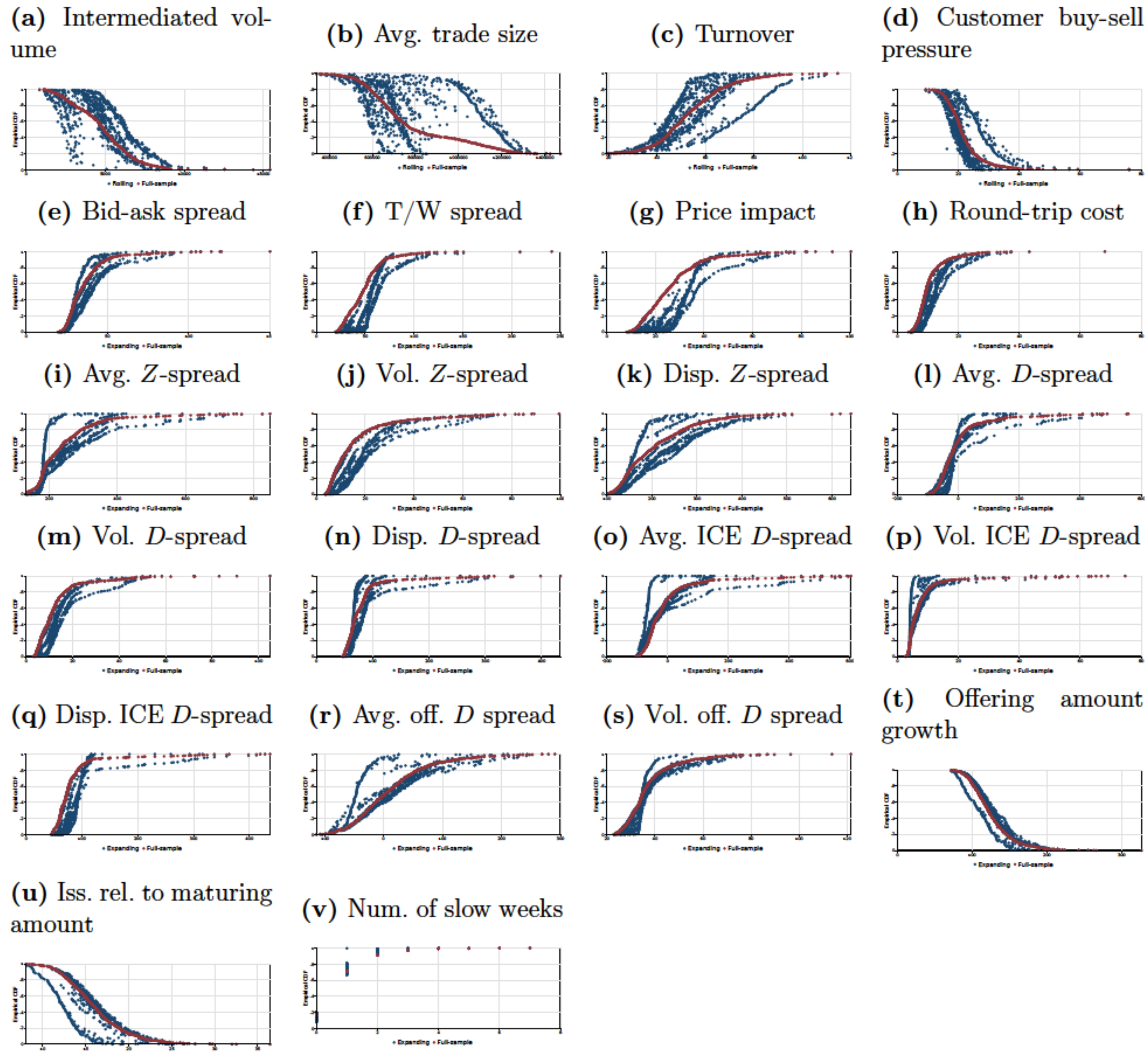


Figure A.4. CMDI with full-sample ECDF. This figure compares the baseline CMDI to the infeasible index constructed using the full-sample ECDF standardization. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). For reference, the right y-axis presents selected percentiles of the pre-2020 CMDI distribution.

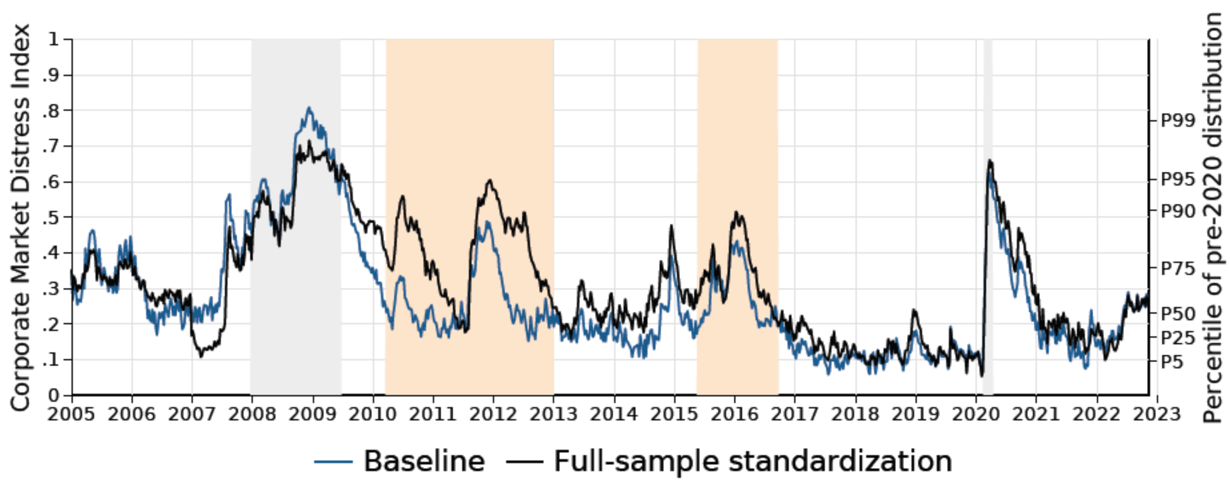


Figure A.5. CMDI with alternative smoothing parameters. This figure plots the corporate market distress index constructed using different values of the exponentially-weighted moving average parameter λ. Baseline index constructed using $\lambda = 0.9$. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). For reference, the right y-axis presents selected percentiles of the pre-2020 CMDI distribution.

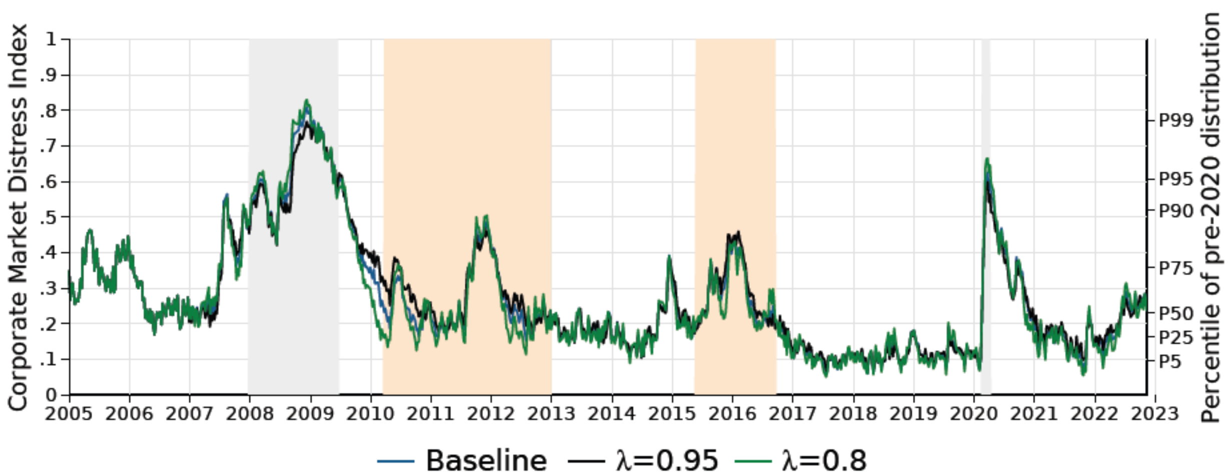


Figure A.6. CMDI with alternative weights. This figure plots the corporate market distress index under different aggregation schemes across sub-indices. "Full sample correlation" index uses the full-sample correlation matrix between the sub-indices to construct the weighted average. "Perfect correlation" index assumes perfect correlation between the sub-indices. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). For reference, the right y-axis presents selected percentiles of the pre-2020 CMDI distribution.

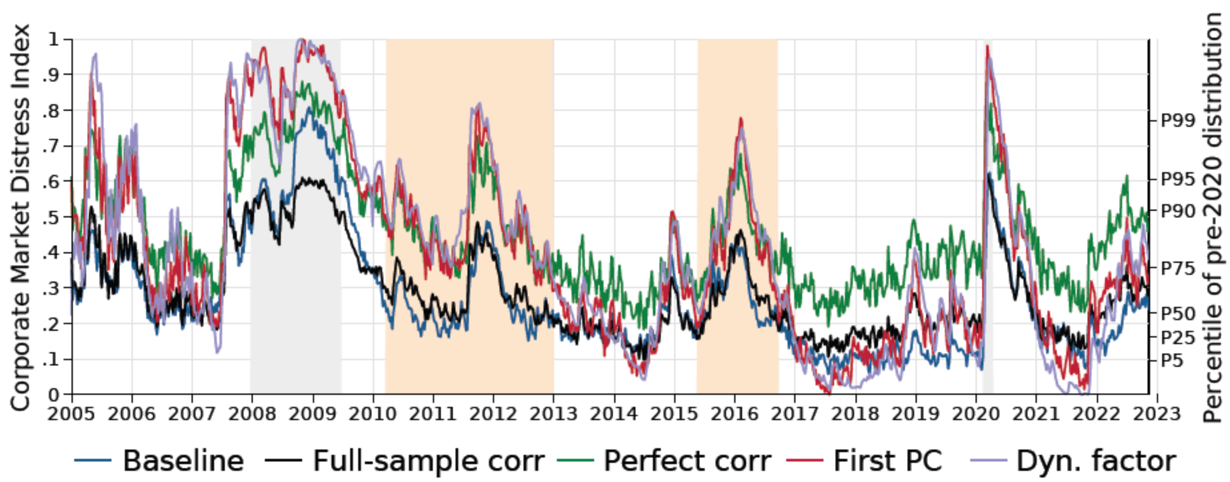


Figure A.7. "Leave one out" indices. This figure plots the corporate market distress index when each individual sub-index is excluded. Leave-out indices labelled with the *excluded* sub-index, so that e.g. "Volume" is the index that leaves out secondary market volume sub-index.