Measuring Corporate Bond Market Dislocations *

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January 2021

Abstract

We measure dislocations in the market for corporate bonds in real time with the Corporate Bond Market Distress Index (CMDI), allowing for the aggregation of a broad set of measures of market functioning from primary and secondary bond markets into a single measure. The index quantifies dislocations from a preponderance-of-metrics perspective, ensuring that the measure of market distress is not driven by any one statistic. We document that the index correctly identifies periods of dislocations, is robust to alternative choices of the aggregation procedure, and provides differential predictive information for future real outcomes relative to common spread measures.

*The views expressed here are the authors' and are not necessarily the views of the Federal Reserve Bank of New York or the Federal Reserve System. Zachary Kuloszewski and Hunter Wieman provided excellent research assistance. The authors thank Josh Frost, Andreas Lehnert, Steve Sharpe, Daleep Singh, Clara Vega and Alex Zhou for discussions and comments on previous drafts of the paper. Emails: nina.boyarchenko@ny.frb.org; richard.crump@ny.frb.org; anna.kovner@ny.frb.org; or.shachar@ny.frb.org.

1 Introduction

With more than $6 trillion in outstanding corporate bonds, the corporate bond market is a significant source of funding for most large U.S. corporations. Despite the substantial academic literature on pricing and measures of secondary market liquidity, there is little consensus on how to identify periods of distress in the corporate bond market as a whole. In this paper, we use granular data on both primary market issuance and secondary market trading to construct a broad set of measures of corporate bond market conditions commonly used in the literature. Taking a preponderance-of-metrics approach, we propose a new measure of market functioning, the U.S. Corporate bond Market Distress Index (CMDI), to quantify joint dislocations in the primary and secondary corporate bond markets.

The CMDI identifies commonly-accepted periods of market dislocation such as those around the global financial crisis, peaking in late 2008/early 2009, with the next largest peak during the COVID-19-related market stress in March 2020. However, the index does not flag as dislocations all periods when economic fundamentals deteriorate and bond prices react accordingly. Thus, for example, although oil prices started to decline in the summer of 2014, the CMDI does not increase until fall of 2015, when these shocks led to credit losses in oil companies and translated into the liquidation of the Third Avenue bond mutual fund and associated corporate bond market distress. Although at times the CMDI gives similar signals to frequently used measures of financial market stress, such as financial conditions indexes, and measures of market risk aversion, such as the VIX, the information provided by the CMDI is distinct and captures conditions specific to the corporate bond markets.

A natural question to ask is whether such a broad measure of corporate credit market conditions contains predictive information for future real outcomes over and above that of corporate credit spreads.[1] We document that the CMDI is an economically and statistically significant predictor of cumulative one-year-ahead economic activity as measured by a va-

[1] See e.g. Gilchrist and Zakrajšek (2012); López-Salido et al. (2017); Krishnamurthy and Muir (2017) for studies of the predictive power of credit spreads for future economic outcomes.

riety of indicators, even after controlling for standard predictors, such as the term spread. We further show that, in predictive regressions where we include both the CMDI and measures of credit spreads, the CMDI remains economically and statistically significant, which is generally not the case for credit spreads. This may reflect the fact that the measure's incorporation of primary market measures adds a dimension of access to credit, or this may reflect the fact that deteriorations in the price of credit that are accompanied by deteriorations in liquidity are particularly negative signals. While our sample is limited due to the relatively recent introduction of data collection on individual corporate bond transactions, these results suggest that there is information in the level and type of activity in both the primary and secondary corporate credit markets, beyond the pricing of credit, that is important for predicting future economic outcomes.

A key feature of the CMDI is that it combines both primary market and secondary market measures to offer a full picture of corporate bond markets. We calculate the index weekly beginning in 2005, using data that would be available in real time. Primary markets measures come from Mergent and include issuance data on volume and pricing as well as issuer characteristics. For secondary markets, we exploit the rich secondary market trading data available for corporate bonds through the Trade Reporting and Compliance Engine (TRACE) and include measures that reflect both the central tendencies and other aspects of distributions of volume, liquidity, non-traded bonds, spreads and default-adjusted spreads. Another strength of the CMDI is that it 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).

One contribution of the paper is to apply index methods to create a comprehensive measure of market functioning. We adapt the methodology of the Composite Indicator of Systemic Stress (CISS, Hollo et al., 2012), but apply it to the systematic distress of a market rather than of the economy. The basic intuition is to use insights from portfolio theory to optimally combine measures of different facets of dislocation into a single index. More specifically, we standardize each metric using its empirical cumulative distribution function, allowing us to combine variables with different units without assuming a particular parametric transformation. We group metrics into sub-categories by the type of information they capture and, for each sub-category, construct the category-specific sub-index as the equal weighted average of the standardized constituent series. In this way, we do not overweight sub-categories for which we have more measures, as would be the case in an index computed as an equal-weighted average or the first principal component of all measures. Finally, we combine the sub-indices using time-varying correlation weights, corresponding to an optimal portfolio allocation interpretation of the index. We find significant variation in both the sign and magnitude of the correlations between sub-components, suggesting that a time-varying approach is particularly valuable. Although each individual sub-index is noisy, the combined index is not.

Several 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. Finally, the index incorporates a large number of different metrics, ensuring that the dislocations captured by the index are multi-faceted, rather than reflecting fluctuations in only some measures. Indeed, constructing "leave one out" indices, we document that both the level and the dynamics of the CMDI are robust to the exclusion of any one sub-category of metrics, including spread sub-indices.

In addition to providing an index of broad market functioning, we construct the index separately for investment-grade and high-yield bonds. In general, the two rating-specific

CMDIs move together, suggesting the market CMDI is unlikely to miss any individual part of the credit spectrum. We find that there is limited bifurcation in credit market conditions, with generally either both credit rating categories in distress, or the high-yield market in distress and conditions for investment-grade bonds little changed. To the extent that the indices move differently for different ratings, across multiple real activity indicators, we find the investment-grade index to be a better predictor of future activity. This suggests that the predictive content of the CMDI is more likely to be related to conditions faced by more productive or less levered firms, rather than speculative activity in risky bonds.

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.,[2] 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"). Pasquariello (2014) measures aggregate, time-varying intensity of arbitrage parity violations across assets and constructs a monthly market dislocation index (MDI), showing that financial market dislocations are a priced risk factor. While MDI captures episodes in which financial markets on aggregate cease to price assets correctly on a relative basis, CMDI attempts to tackle the challenges of constructing an asset-specific index. Constructing an asset-specific index, even if narrower than an aggregate approach, allows us to identify which market is dislocated rather than whether two markets are dislocated relative to each other. As we discussed above, the methodology for the construction of our index is adapted from the construction of the CISS which, after the original Hollo et al. (2012) paper, has been extended to measure systemic financial distress for a number of countries including the U.S.

In addition to these and other economy-wide measures of market distress, the literature

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

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' distress – capturing functioning in of debt capital markets. While our focus in this paper is the corporate bond market, the methodology can be applied to measure dislocations in other markets and is particularly advantageous when both primary and secondary market functioning is of interest. 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, making robust measures of market dislocations particularly salient.

In the construction of the index, we rely on previous studies of corporate bonds that have analyzed the determinants of either the levels or the changes of corporate yield spreads, identifying credit risk and trading activity as key drivers (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). We expand on this literature by extracting information from all these factors at once, showing that these factors combined can be used to identify dislocations in the functioning of the corporate bond market as a whole.

Moreover, unlike previous studies that consider patterns in individual secondary corporate bond market measures or aggregate market measures like the VIX, we also take into account conditions in the primary corporate bond market, given that the two markets are interlinked (Boyarchenko et al., 2020). We observe that during periods of broad market distress, conditions across both the primary and secondary markets deteriorate, amplifying the individual contribution of each market to the CMDI. During normal times, however, the secondary-primary market amplification spiral does not arise.

The rest of the paper is organized as follows. We summarize the data used in the paper and the properties of the raw market conditions indicators in Section 2. Section 3 describes the construction of the CMDI, and documents how the index evolves over time. We investigate robustness of the index with respect to alternative choices for each step of the index construction in Section 3.3, and the differential information in the CMDI relative to common measures of financial stress in Section 4. We investigate the predictive information in the CMDI for future real outcomes in Section 5. Section 6 considers whether periods of distress occur simultaneously across credit rating categories. We discuss possible extensions to the index in Section 7. Section 8 concludes. Technical details can be found in the Appendix.

2 Data

2.1 Secondary market measures

We use corporate bond transactions data from a regulatory version of TRACE, which contain price, uncapped trade size, and buyer and seller identities as well as other trade terms. 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). 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. We also address multiple reporting of interdealer trades, as well as trades that were executed through a non-exempt Alternative Trading System (ATS). Additional details on cleaning of TRACE data are available in Appendix A.1.

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-trading date level measures of liquidity and secondary market spreads.

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.2.

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 1a 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 1b plots the time series of these four metrics. Figure 1b 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 1c 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 but reflect 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). 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 1d 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 quoted duration-matched and default-adjusted spreads.[3] The difference between these quoted average spread series and their traded counterparts – the quoted-traded spread – thus captures the relative conditions for non-traded bonds. Figure 1e shows that the quoted-traded spread increases during periods of market stress, such as the 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.

2.2 Primary market measures

We obtain information about the functioning of the primary market of U.S. corporate bonds 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. As with the secondary market metrics, we start with the granular data on issuance at the bond level. We construct two sets of weekly metrics of primary market functioning, with details available in Appendix A.3.

Measures of primary market issuance We construct four metrics of primary market issuance: year-over-year growth rate of dollar amount issued, year-over-year growth rate in

[3] 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.

the number of bonds issued, and issuance relative to maturing within the next year, in both dollar and number of bonds terms. Considering issuance on a year-over-year growth rate basis 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 1f shows that while these four metrics mostly co-move together, with the rate of issuance declining during periods of distress, the information they provide is not identical. Intuitively, while the growth rate of dollar amount issued captures the volume of debt issued in the market, the growth rate in the number of bonds issued proxies for the number of issuers able to access the corporate bond market.

Measures of primary-secondary spread Finally, we construct metrics of the spread between prices of bonds traded in the secondary market and the prices of bonds issued in the primary market. As with the secondary market pricing, we construct two measures: duration-matched and default-adjusted spreads.[4] Figure 1g shows that, while the primary-secondary spread is positive and relatively small during "normal" periods, the spread 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. The primary-secondary duration-matched spread is more volatile than the primary-secondary default-adjusted spread.

[4] As with the secondary market default-adjusted spread indices, 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.

2.3 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 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 1,945 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.

3 Corporate Bond Market Distress Index

3.1 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 dislocations. 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 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 discussed in Hollo et al. (2012), the transformation (1) can be applied to the full sample of each variable, creating an “in-sample” transformation, or on an expanding sample, producing a pseudo-real-time estimate of the index. 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 plotted in Figure 2. Figure 2 shows that, across sub-categories, we can see both strong co-movement between the individual metrics, as is the case for the different measures of secondary market liquidity, and more mild co-movement, as is the case for the different measures of secondary market volume.

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 3 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 3 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 corporate bond market distress index is to combine the sub-indices using time-varying correlation weights, corresponding to an "optimal" portfolio allocation interpretation of the index. 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.[5] 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).

Figure 4 plots the estimated time-varying correlation matrix across the 7 sub-indices. A couple of 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 4 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 is almost never 1 and, moreover, dips below 0.5 during both the 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 eight sub-indices $s_t = [s_{1t}, \ldots, s_{7t}]'$. In the special case

[5]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.

when all the sub-indices are perfectly correlated, so that $\mathcal{R}_t$ is the 7×7 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 $\text{CMDI}_t = \left(\sum_{i=1}^{7} s_{it}\right)/7$.

3.2 Results

We begin by examining the time series of the CMDI, plotted in Figure 5 for both the full sample (Figure 5a) and zoomed-in for 2020 (Figure 5b). Starting with the full 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 distribution on the right axis, which offers a more intuitive context, as well as highlighting the historically extreme levels of dislocation reached in 2020.

Turning next to the more recent period, plotted in Figure 5b, 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 rises above the historical 90th percentile – estimated based on data prior to January 2020 – the week ending on March 21 for the first time since the financial crisis. The announcement of Federal Reserve interventions on March 22 halts any further increases in the level of the CMDI, but the index remains above this historical benchmark until the week ending on April 11, which coincides 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 trigger an immediate acceleration in 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. (2020).

How do conditions in primary and secondary markets enter into the overall index? In Figure 6, we decompose the square of the CMDI into contributions from the two primary-market-related sub-indices (primary market issuance growth, primary-secondary spread), the five secondary-market-related sub-indices (secondary market volume, secondary market liquidity, duration-matched spreads, default-adjusted spreads, traded-quoted spreads), and the interactions between the two. 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 to changing economic conditions. 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 4, the sign of the contribution from the interaction terms fluctuates over time, and is positive during periods of broad market distress (financial crisis, European debt crisis, 2015 – 2016 manufacturing recession, end of 2018 market turmoil, 2020 recession). 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.

Examining the contributions from these three components since the beginning of the year, we see that the secondary market conditions deteriorated dramatically in March. Since this coincided with a mild deterioration in primary market conditions, the contribution from the interaction terms also increases. Notice that the relatively mild deterioration in the primary market is consistent with Federal Reserve's interventions in the broad market forestalling a credit crunch for corporate issuers. Since the March 22 facilities announcement, all three components have retraced, with the interactions terms contributing negatively at the end of the sample. Driven by the record issuance since April 2020, the conditions in the primary market are approaching those prior to the COVID shock (February 2020); likewise, conditions in the secondary market have improved substantially.

3.3 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.[6] Figure 7 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 7 demonstrates that the CMDI provides a timely measure of

[6] 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.

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 8 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 8 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:

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

one assuming a perfect correlation matrix:[7]

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

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

Figure 9 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.

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

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. That being said, Figure 9b shows that market conditions deteriorated in late February/early March across all four versions of the index and have improved materially since.

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 10 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.

4 CMDI and common measures of financial stress

As we see in Figure 5, 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. 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.

Measures of broad market risk-aversion We begin by comparing the time series evolution of the CMDI to two commonly used proxies for market participants' overall risk-aversion: VIX and Treasury curve fitting errors (Treasury market "noise") for both the nominal and the real Treasury curves.[8] Figure 11a shows that, while the CMDI is relatively highly correlated (74% correlation in levels) with the VIX, the CMDI does provide distinct information. For example, while the CMDI increases already in the summer of 2007, the sharp increases in the VIX during the financial crisis only materialize in the fall of 2008. On the other hand, the VIX rises noticeably at the beginning of the European debt crisis in spring of 2010 when Greece requested initial assistance,[9] whereas the CMDI only signals a deterioration in bond market conditions starting in the second half of 2011, when additional peripheral European countries began to experience marked sovereign distress. Similarly, the VIX spiked up at month end January 2018, reportedly caused by an unwinding of "short volatility" trades. While this represented equity market stress, the CMDI remained flat during the same period, highlighting that the CMDI measures corporate bond market distress in particular, rather than stress of related markets.

Turning to Figure 11b, we see that the CMDI has a much weaker relationship with measures of Treasury market frictions. While all three measures rise dramatically in the later stages of the financial crisis and during the March 2020 broad market turmoil, there is little co-movement between the CMDI and the nominal and real Treasury curve fitting errors otherwise. Thus, the CMDI provides distinct information about the overall condition of the corporate bond market rather than commonly used proxies of market participants' attitudes towards risk.

[8] See Appendix A.4 for details on the construction of the Treasury curve fitting errors. We obtain these data from the Federal Reserve Board of Governors. Hu et al. (2013) show that Treasury noise predicts fixed income hedge fund arbitrage returns.

[9] On April 23, 2010, the Greek government requested an initial loan of €45 billion from the European Union and International Monetary Fund, triggering an increase in global uncertainty.

Measures of corporate borrowing conditions Potentially more closely related to the CMDI are measures which reflect frictions in corporate borrowing markets more broadly. Figure 11c plots the CMDI together with the ETF-NAV basis[10] for exchange traded funds (ETFs) that specialize in investment-grade bonds, as well as the ETF-NAV basis for ETFs that specialize in high-yield bonds. A couple of features are readily apparent. The ETF-NAV basis is fairly volatile, fluctuating around 0, with periods of stress manifesting as increased amplitude of fluctuations around 0, rather than a prolonged period of deviation to one side of parity. Moreover, the ETF-NAV basis exhibits this increased volatility during some periods of corporate bond market stress but not others, suggesting that the information value of signals from this measure is limited. Both of these features translate into the ETF-NAV basis having almost no co-movement with the CMDI.

Figure 11d plots the CMDI together with the market-wide bankruptcy rate. While the bankruptcy rate is, as expected, generally close to zero with intermittent spikes during periods of distress, the major increases tend to follow periods of heightened corporate bond market stress as measured by the CMDI. For example, we see an increase in the bankruptcy rate in the fall of 2007, foreshadowed by the rise of the CMDI in August 2007. Similarly, the increase in CMDI in late 2018 is then followed by a small uptick in the bankruptcy rate in early 2019. In general, the increases in the bankruptcy rate somewhat lag increases in the CMDI as bond market distress does not immediately translate into borrower inability to make scheduled interest or principal payments.

Finally, considering the relationship between corporate bond markets and commercial and industrial (C&I) loan market for similarly-sized borrowers, Figure 11e plots the CMDI against the net tightening of lending standards for C&I loans made to medium and large firms as reported in the Senior Loan Officer Opinion Survey (SLOOS). Broadly speaking, the low frequency movements in the CMDI are mirrored in the SLOOS series, suggesting that periods of bond market distress are also periods when the C&I loan market is also

[10] See Appendix A.4 for details on the construction of the ETF-NAV basis series.

constrained. This is consistent with theories of intermediary asset pricing, with bank holding companies (BHCs) acting as the marginal intermediary in both bond and loan markets (see e.g. Adrian et al., 2017a,b, for evidence on the role of BHCs in corporate bond market liquidity). That said, the precise timing of deterioration in corporate borrowing conditions is somewhat asynchronous across the two markets. The asynchronicity suggests that, while the SLOOS series provides a useful summary of conditions in the corporate loan market, it is not a substitute for the CMDI, both in terms of the periods of stress captured by each metric, as well as in terms of the timeliness and observation frequency of the metric.[11]

Broad indicators of financial conditions Moving to measures of financial conditions more generally, Figure 11f compares corporate bond market conditions to the Chicago Fed National Financial Conditions Index (NFCI)[12] and ECB's Composite Indicator of Systemic Stress (CISS)[13] for the U.S. In general, consistent with both NFCI and CISS capturing aggregate financial conditions, the three series broadly co-move, with CISS exhibiting the most and NFCI exhibiting the least high frequency variation. Similar to the VIX, both the CISS and the NFCI increase around the start of the European debt crisis in April 2010 and at month end January 2018. Furthermore, the CMDI shows a deterioration in corporate bond markets in summer of 2007, before either CISS or NFCI.

Dealer constraints Recent literature (see e.g. Adrian et al., 2017a, and the literature within) has emphasized the role that dealer constraints play in determining bond liquidity.

[11] Notice that the SLOOS series is only available at a quarterly frequency, with the survey timed so that results are available for the January/February, April/May, August, and October/November meetings of the Federal Open Market Committee. Note that in prior periods of increased economic uncertainty or stress, such as 1998 and 2001, additional surveys had been conducted.

[12] 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).

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

Figure 11g plots the CMDI together with average dealer value-at-risk (VaR) per unit of dealer equity.[14] While dealer VaR has broadly the same time series behavior as the CMDI, there are important differences in the post-crisis sample, with the dealer VaR exhibiting a secular decline starting in 2009 up until the start of the pandemic. In contrast, as we have discussed above, the CMDI increases during the European debt crisis, the 2015 – 2016 manufacturing recession, and during the market distress episode at the end of 2018.

Alternative bond market conditions indices We conclude by comparing the CMDI to corporate bond market conditions indices constructed via alternative methodologies. In particular, we use principal components analysis to construct three indices: the first principal component of the four liquidity measures (as in Adrian et al., 2017a; Dick-Nielsen et al., 2012), the first principal component of the 16 secondary market measures, and the first principal component of all the 22 individual measures that underlie the CMDI. Figure 11h shows that the CMDI is substantially less volatile than these alternative indices, once again highlighting the importance of the time-varying correlation weights in producing a well-behaved index out of a medium-sized panel of individual indicators.

Overall, Figure 11 demonstrates that, although at times the CMDI gives similar signals as commonly used measures of financial market stress, the information provided by the CMDI is distinct and captures conditions specific to the corporate bond market. Moreover, the construction of the CMDI offers a distinct advantage over the principal component approach used in prior literature for coalescing information from multiple metrics in this market, honing the signal from the underlying (somewhat noisy) indicators. Finally, Table 1 summarizes the correlation in levels between the CMDI and the alternative measures, both for the full sample and the sample excluding the financial crisis (August 1, 2007 – December 31, 2009) and 2020 (January 1, 2020 – November 28, 2020). Correlations of the CMDI with the VIX, NFCI, CISS and, not surprisingly, the secondary market metrics' and all metrics' principal components remain relatively large and positive even if we exclude periods of broad

[14] See the Appendix for details on the construction of the aggregate VaR time series.

market and economic distress.

5 Bond market distress and real outcomes

Recent literature (see e.g. Gilchrist and Zakrajšek, 2012; López-Salido et al., 2017; Krishnamurthy and Muir, 2017) has stressed the predictive content of credit spreads for future real activity. We now investigate the natural question of 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:

$$\Delta y_{t,t+H} = \alpha + \varphi \Delta y_{t-H,t} + \beta_{\text{FF}} \text{Real eff. FFR}_t + \beta_{\text{Slope}} 10\text{y}/1\text{y TSY slope}_t + \gamma' \text{CS}_t + \epsilon_{t+H}, \tag{5}$$

where Real eff. FFR_t is the real effective federal funds rate,[15] 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. For monthly variables (log industrial production and unemployment rate), $\Delta y_{t,t+H}$ is the 12 month change ($H = 12$); for quarterly variables (log real business fixed investment, log real GDP, log Compustat capital expenditures, log Compustat sales),[16] $\Delta y_{t,t+H}$ is the 4 quarter change ($H = 4$). 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 (5)). Column (1) of Table 2 reports

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

[16] In unreported tables, we find similar results for payroll growth as for changes in the unemployment rate and similar results for profitability (EBITDA) growth as for sales growth.

the estimated coefficient when credit market conditions are measured using the market-level CMDI. In this and the rest of the regression specifications in Table 2, we include additional lags of our variables of interest; as shown in Olea and Plagborg-Møller (2020), 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.[17]

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 2.3 percentage point (p.p.) decrease in annual industrial production growth, a 48 bps increase in the unemployment rate over a 12 month period, a 2.7 p.p. decrease in annual real business fixed investment growth, a 67 bps decrease in annual real GDP growth, a 5.2 p.p. decrease in capital expenditures by publicly-listed firms and a 3 p.p. decrease in sales of publicly-listed firms.

Turning to column (2), we see that these results are robust to controlling for the commonly-used "G-Z" spread (Gilchrist and Zakrajšek, 2012) measure of average duration-adjusted credit spreads. For all our measures of real outcomes, the CMDI remains statistically (at at least the 5% significance level) and economically significant. The G-Z spread, instead, is either not statistically significant in most specifications or, in the case of sales growth, is statistically significant but with the wrong sign. The only exception is the unemployment rate, where both the CMDI and the G-Z spread are statistically significant.

Overall, the results in Column (1) and Column (2) 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 reliability of the CMDI as a predictor across a variety of real outcome variables provides reassurance about the robustness of these

[17]We include 3 additional lags in the monthly regressions and one additional lag in quarterly regressions. Results are robust to alternative lag choices.

results.

6 Market conditions at the credit rating level

The results of the previous two sections suggest that the CMDI is a good summary measure of the overall conditions in corporate credit markets. A natural question to ask is whether conditions for different credit ratings evolve together. To answer this, we now apply the same index construction methodology separately to investment-grade (those rated BBB- and above) and high-yield bonds (those rated BB+ or below but CCC/C and above).[18] While investment-grade bonds represent the investable universe of bonds for long-horizon investors, such as insurance companies, high-yield bonds are more risky and attract more specialized investors. Investment-grade bonds represent roughly 2/3 of the total amount outstanding and roughly 3/4 of the total volume traded in U.S. corporate bonds.

6.1 Credit-rating-level CMDI

Figure 12 plots the time series of credit-rating-level CMDI for both the full history (Figure 12a) and zoomed-in to the evolution over 2020 (Figure 12b). Figure 12a shows that, in general, the rating-level CMDIs move together, suggesting the market CMDI is not unrepresentative of any individual part of the credit spectrum. In particular, although there are periods when the dislocation is particularly pronounced for high-yield bonds, there does not appear to be a corresponding off-setting improvement in investment-grade bonds, and vice versa. That is, there is limited bifurcation in credit market conditions, with either all credit rating categories in distress or some rating categories in distress but no situations where conditions simultaneously improve in a different part of the market.

Examining the individual indices more closely, we see that the initial market distress in summer of 2007 was concentrated in the high-yield part of the market, perhaps reflecting

[18] Recall that the sample for the market-level measures also includes unrated bonds. Since the coverage on unrated bonds is not stable over time, we do not construct a separate "unrated" index.

spillovers from the subprime mortgage market. As the crisis evolved, conditions deteriorated for the remaining credit rating categories, with the peak of market distress in late 2008/early 2009 manifesting across the entire credit spectrum. Moreover, at the height of the crisis, conditions for investment-grade bonds deteriorated even more than for high-yield bonds, consistent with the relatively high concentration of financial institutions in the A rating category.

The COVID-19-related market distress in March 2020 likewise translates into an increase in CMDI levels for all credit ratings. Figure 12b shows that the improvement in market conditions following the Federal Reserve facilities announcement on March 22 was more readily apparent for investment-grade bonds, which were eligible for direct purchases by the facilities, with the investment-grade CMDI returning to close to pre-pandemic levels by mid-summer. Conditions in the high-yield part of the market took much longer to normalize and, as of the time of writing, still remain somewhat more distressed than at the beginning of 2020.

Outside of these periods of broad economic distress, episodes of tightening credit market conditions are usually either confined to the high-yield part of the market or manifest across credit rating categories. For example, consistent with sharp declines in oil prices in 2015 – 2016, dislocations were first observed in the market for high-yield bonds in early 2015 before propagating to investment-grade bonds in the later half of 2016.[19] Similarly, perhaps reflecting the relatively high net leverage of such companies, the market disruption at the end of 2018 was focused in the BBB+/BBB credit rating category, that is, the tail end of the investment-grade spectrum.

Finally, comparing the overall market CMDI to these two individual series, both the baseline CMDI and coincident increases in the two credit-rating indices provide the same signals of periods of distress in the overall corporate bond market. Coupled with the robustness evidence in Section 3.3, this further reinforces the conclusion that the CMDI is a stable

[19]Many oil companies were either already high-yield going into this episode or were downgraded to high-yield subsequent to oil price declines.

index of market conditions even in real time.

6.2 Credit-rating level credit market conditions and real outcomes

Measuring market conditions separately in the investment grade and high yield parts of the market allows us to investigate further the results in Section 5. In Columns (3) – (6) of Table 2, we estimate the predictive regression using either the IG CMDI only, the HY CMDI only, and the two credit-rating-category indices jointly as measures of conditions in the corporate bond market. Considering conditions in these two parts of the bond market separately allows us to address the issue that the investor base for investment-grade corporate bonds is substantially different from that of high-yield bonds.[20] Moreover, industries in secular decline, such as the oil & gas industry, are more likely to be in the high-yield part of the corporate bond market; by measuring their market conditions separately, we thus allow a differential predictive role for conditions of more stable industries.

Comparing the individual performance of the IG CMDI and the HY CMDI (columns (3) and (4)), we see that, while both measures are individually significant, the specifications with the IG CMDI consistently have substantially higher adjusted R^2, which is consistent with the intuition that conditions in the high-yield market can evolve separately from the business cycle. Indeed, including both metrics in the regression in column (5) of Table 2, only the IG CMDI remains economically and statistically significant.[21] That is, the predictive content in the market-level index in column (1) primarily arises from conditions in the investment-grade part of the corporate bond market. Finally, as with the market-level index, including the G-Z spread in column (6) does not affect the significance of the IG CMDI as a predictor, while the G-Z spread is either not statistically significant or, as is the case for sales growth, statistically significant but with the wrong sign.

The results in columns (5) and (6) of Table 2 highlight the importance of conditions in

[20]For example, insurance companies are a major investor in investment-grade but not high-yield bonds. See Getmansky Sherman et al. (2018) and related literature.

[21]The only exception is real GDP growth, where the HY CMDI remains marginally statistically significant at the 10% level, but with the wrong sign.

the less risky, investment-grade part of corporate bond markets for future real outcomes. From a policy perspective, this perhaps underscores the key role that the corporate credit facilities – which almost exclusively focused on supporting access to credit for investment-grade firms – played in supporting the real economy in 2020 (see Boyarchenko et al., 2020, for details on the effects of the facilities on the corporate credit market). Moreover, the greater predictive power of the IG CMDI suggests that the significance for predicting real outcomes is more likely to be related to conditions for productive or less levered firms, through either direct funding costs or risk premia more generally, than to speculative activity in the risky, high-yield part of the market.

Finally, our results contrast with those in Greenwood and Hanson (2013), who find that issuance by lower-quality firms predicts corporate bond market returns, over and above the information contained in market-wide credit growth. In contrast, we find that, for real outcomes in the last 15 years, it is the conditions in the investment-grade market that contain important predictive information. This differential predictive ability across real and financial outcomes could be consistent with asynchronicity between business and credit cycles.

7 Potential additional metrics

Our corporate bond market distress index incorporates information from a large set of metrics of primary and secondary market functioning. In this section, we discuss some additional metrics that could be incorporated into the index to capture other facets of corporate market distress. While all of the measures discussed below have some drawbacks, we view metrics related to stressed customer flows as being more promising than metrics of cross-market dislocations.

7.1 Alternative transactions-based measures

Transactions data in both the secondary and the primary markets can be used to construct additional measures of market conditions beyond those considered in this paper. One such measure is the credit term-structure slope, that is, the difference between the secondary market spread on longer maturity (5 year) and shorter maturity (3 year) corporate bonds. Structural models of default, such as Merton (1974), suggest that, while the credit term-structure should be upward sloping for higher quality issuers, as the probability of default increases with horizons, for lower-quality issuers the term-structure is hump-shaped or even downward sloping, as such issuers either default in the near term or survive in the long run.[22] Inversion of the term-structure at the market level – so that the spread on longer maturity bonds is lower than the spread on shorter maturity bonds – thus signals that bond market participants perceive the market as a whole to be dominated by lower quality issuers. We do not include the credit term-structure slope in our metrics of secondary market conditions as the maturity of bond issuance has declined over time, making the coverage of trades in the same maturity bonds over time patchy. This leads the term-structure slope to be extremely volatile empirically. In addition, from a theoretical perspective, it is unclear whether it is just the sign of the slope – a binary indicator for term-structure inversion – or the magnitude of the slope that should be used as an indicator.

TRACE transactions data can also be used to measure the frequency of the absence of trading in the market. Common measures include the frequency of days on which the price of a bond doesn't change ("zero return days" Lesmond et al., 1999) or days on which the bond does not trade ("zero trade days") as a fraction of total trade days in a trading week. At the market-level, zero trade days has a secular trend in our sample, as more bonds are traded over time. Similarly, while the zero return days metric has been shown to be informative at the individual bond-level, at the market level it fluctuates between 2 and 3 zero return days per week. Given the infrequent trading of many corporate bonds, tracking the non-

[22]See Bedendo et al. (2007) for a summary of the literature on the credit term-structure.

traded universe is important, so instead we use information from quoted spreads to capture conditions for non-traded bonds, as described above.

In the primary market, a potential metric would be the fraction of new issuance below a particular threshold, with issuers potentially shortening the maturity structure of their bond offering during periods of stress, as argued in He and Milbradt (2016). As noted above, however, there is a secular downward trend in the maturity of corporate bond issuance over our sample period, which dominates any local decreases in offering maturity during credit cycle downturns.

7.2 Measures of stressed customer flows

Institutional investors play a key role in the corporate bond market, with insurance company and mutual fund holdings representing the majority of U.S. non-financial corporate bonds outstanding. Consistent with their significant corporate bond holdings, Ellul et al. (2011) show that fire sales by insurance companies of downgraded bonds lead to secondary market illiquidity for bonds sold by the insurance companies which, during periods of broad downgrades, may translate into overall secondary market illiquidity. This suggests that one potential indicator of corporate bond market distress is the net sales by insurance companies and, in particular, by life insurance companies that tend to be more active participants in the market. For example, Chodorow-Reich et al. (2020) argue that depletion of life insurance companies' equity during the crisis lead to a withdrawal of the "insulation" that insurers normally provide to the corporate bond market, making the bond market particularly susceptible to fire sales. While measures based on insurance companies' transactions are theoretically appealing, the key source of that data is NAIC filings Schedule D, which are usually observed with a substantial lag.

Investor outflows from bond mutual funds can also affect market dynamics, especially in times of stress. For example, Manconi et al. (2012) find that bond mutual funds faced with customer outflows during the financial crisis responded by exiting from positions in their more liquid holdings first, leading to a spillover of illiquidity between different parts of the corporate credit space. These dynamics can be further exacerbated by the fact that the fund flow-to-performance sensitivity of bond funds is particularly high during periods of market illiquidity (see e.g. Goldstein et al., 2017). While bond mutual fund data arrives more promptly than the insurance company filings, a substantial number of mutual funds only file monthly reports, again potentially compromising the timeliness of mutual fund outflows as a component of a market distress index. Thus, the relative advantages of mutual fund data for monitoring credit market conditions documented in Ben-Rephael et al. (2020) may not be feasible in real time.

7.3 Measures of cross-market dislocation

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 ETF-NAV basis measures the relative deviation of the ETF price from the price of the replicating basket of corporate bonds, with a positive basis indicating that the ETF is valued more than the corporate bond portfolio it holds. As we observe in Figure 11c, the relationship between the CMDI and the ETF-NAV basis at the credit rating category level is tenuous. This is further exacerbated by the fact that the corporate bond ETF market is relatively novel, with a large number of corporate bond ETFs only launched in the post-crisis period, which complicates historical comparisons.

Similarly, the CDS-bond basis measures the 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 positive CDS-bond basis indicating that buying protection against corporate default in the CDS market is relatively "cheap". There are two primary concerns with using the CDS-bond basis as a measure of corporate bond market distress. First, since both bonds and CDS trade over-the-counter, a larger magnitude CDS-bond basis may signal dislocations in either the CDS or the bond market or both. For example, Choi et al. (2019) show that an unwinding of CDS-bond basis trades in the aftermath of Lehman bankruptcy spilled over into greater corporate bond market illiquidity. Second, while the CDS-bond basis was generally positive prior to the financial crisis, it switched signs during the financial crisis and has remained mostly negative ever since. Thus, to incorporate the CDS-bond basis into the corporate bond market dislocation index one would need to take a stand on whether the sign of the basis carries additional information or if the magnitude of the deviation is the only relevant metric. From a theoretical perspective, the answer to this question is unclear. On the one hand, since a CDS contract provides exposure to (almost) the same risks as the matched corporate bond itself, the CDS-bond basis should be close to zero and thus any deviation away from parity indicates market distress. On the other hand, the "limits to arbitrage" to closing a negative CDS-bond basis are smaller than those to closing a positive basis.[23] Thus, the same magnitude deviation to the negative side may imply a bigger market dislocation than an equivalent magnitude positive-side deviation.

8 Conclusion

In March 2020, corporate bond markets across the world experienced severe distress related to the COVID-19 pandemic. The Federal Reserve reacted to these disruptions by introducing corporate debt purchase programs, aimed at stabilizing the flow of credit to the non-financial corporate sector, joining central banks in major advanced economies (including U.K., Euro-area, Japan) which were engaging in different types of corporate debt interventions. While interventions to ease corporate credit conditions can focus on the price of credit, interventions to ameliorate market functioning more broadly require a broader set of measures. In this paper, we introduced a unified measure of corporate bond market conditions, capturing price and activity metrics in both primary and secondary markets. As such, the CMDI broadens market distress measurement away from just identifying periods of high credit

[23]See Boyarchenko et al. (2018) for more information of the practical details of CDS-bond basis trades.

spreads or periods of increased illiquidity in secondary markets alone. Together with the real-time nature of the index, this makes the CMDI a valuable summary metric of market distress and functioning.

The index expands on existing measures of corporate credit conditions, taking a preponderance-of-metrics approach to identifying periods of market-wide distress. 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. Unlike the Treasury market, corporate bonds are issued by a diverse set of companies, making a broad index of market functioning particularly attractive.

The corporate bond market in the U.S. is a major source of funding for U.S. businesses, representing more than half of the total debt outstanding of non-financial corporations. Distress in the corporate bond market is thus likely to have meaningful consequences for economic outcomes more broadly. Indeed, 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 suggests that 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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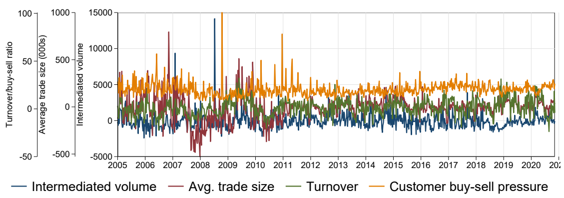
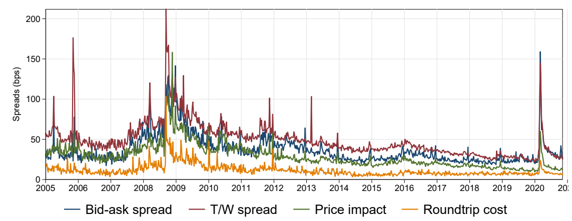
Figure 1. Time series of raw market conditions indicators. This figure plots the raw time series of measures of secondary and primary market functioning.

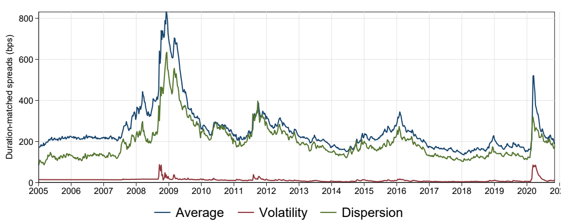
(a) Secondary market volume



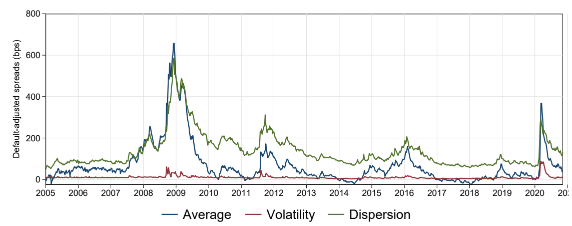
(b) Secondary market liquidity



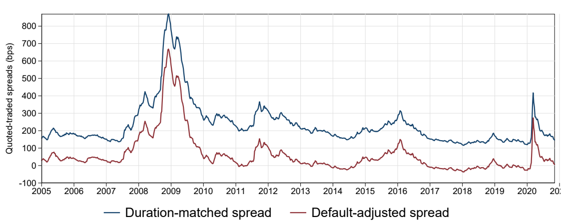
(c) Secondary market Z-spread



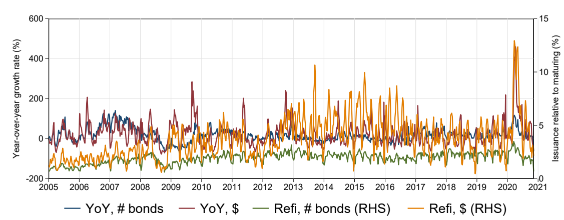
(d) Secondary market D-spread



(e) Traded-quoted spread



(f) Primary market volume



(g) Primary-secondary market spread

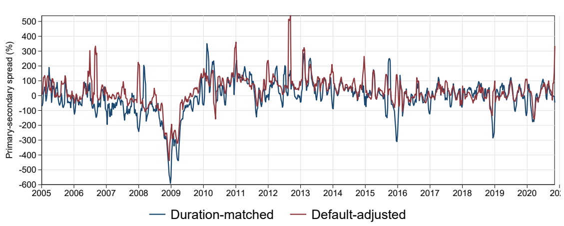
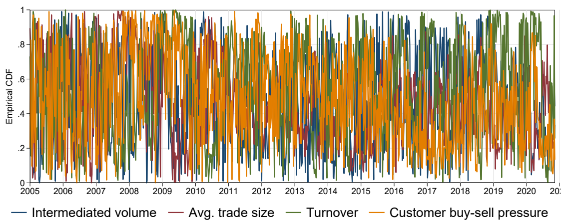
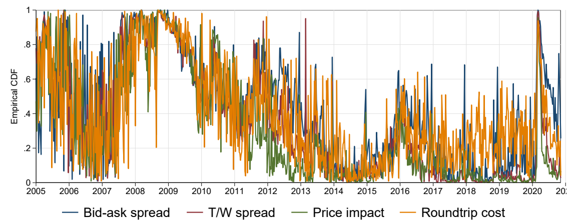


Figure 2. Time series of standardized market conditions indicators. This figure plots the standardized time series of measures of secondary and primary market functioning. Each individual metric is standardized relative to its own real-time empirical cumulative distribution function, with an initialization period of two years (January 2, 2005 – December 30, 2006).

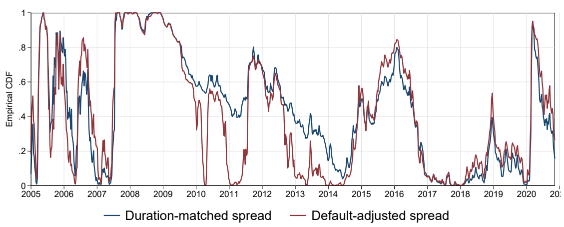
(a) Secondary market volume



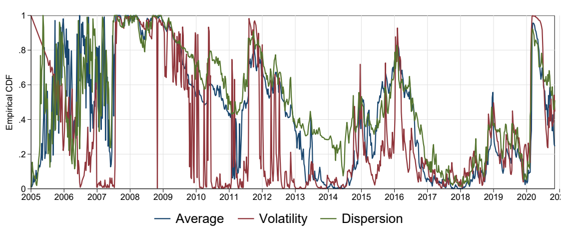
(b) Secondary market liquidity



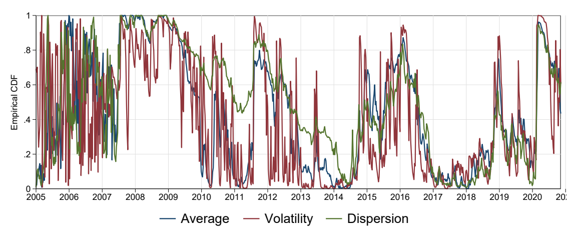
(c) Traded-quoted spread



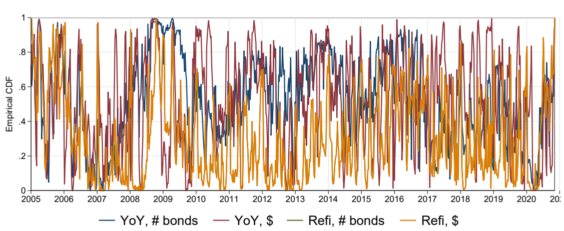
(d) Secondary market Z-spread



(e) Secondary market D-spread



(f) Primary market volume



(g) Primary-secondary market spread

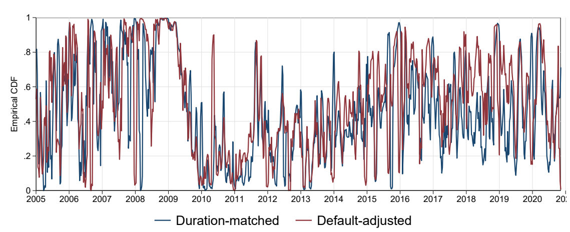
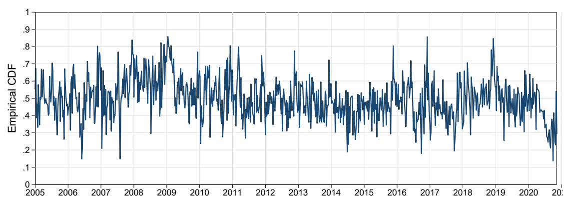
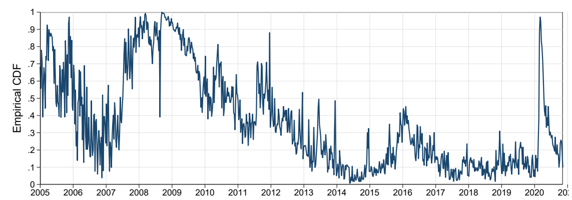


Figure 3. Category-level sub-indices. This figure plots the time series of category-level sub-indices of the corporate market dislocation index. Each sub-index is constructed as the equal-weighted average of the constituent individual measures.

(a) Secondary market volume



(b) Secondary market liquidity

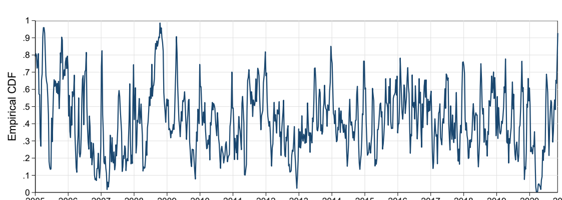


(c) Traded-quoted spread

(d) Secondary market Z-spread

(e) Secondary market D-spread

(f) Primary market volume



(g) Primary-secondary market spread

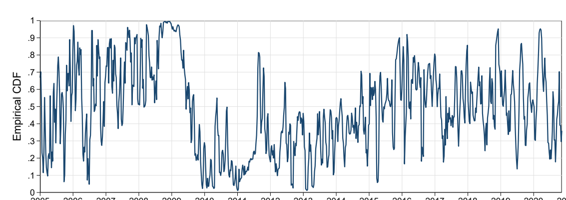
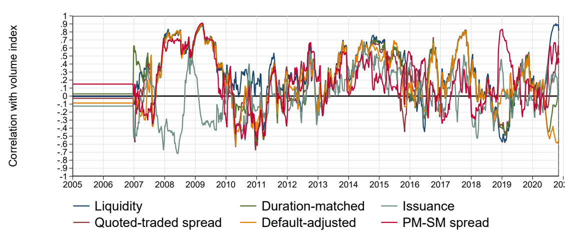
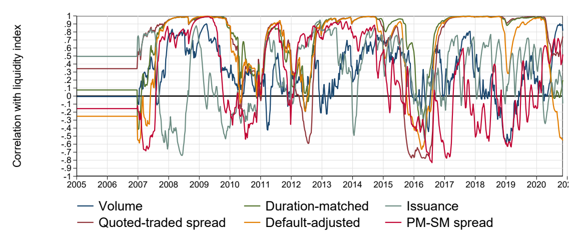


Figure 4. Time-varying correlations between market indicators. This figure plots the time series of estimated time-varying pairwise correlations between the category-level sub-indices. Time-varying variance-covariance matrix estimated using an exponentially-weighted moving average with smoothing parameter $\lambda = 0.9$.

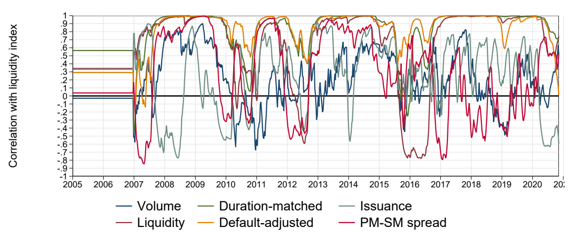
(a) Secondary market volume



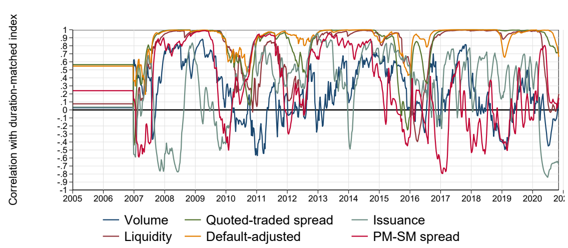
(b) Secondary market liquidity



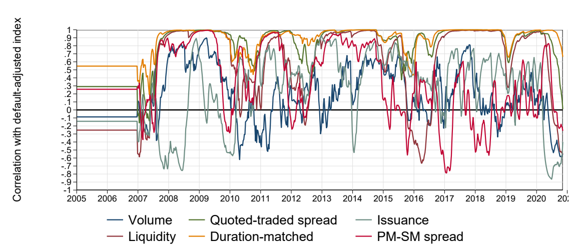
(c) Traded-quoted spread



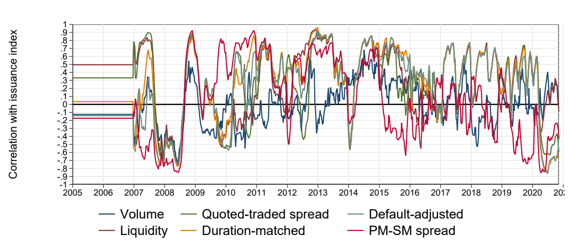
(d) Secondary market Z-spread



(e) Secondary market D-spread



(f) Primary market volume



(g) Primary-secondary market spread

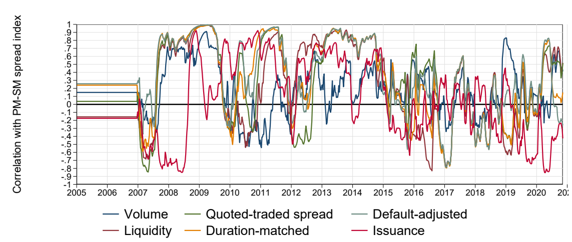
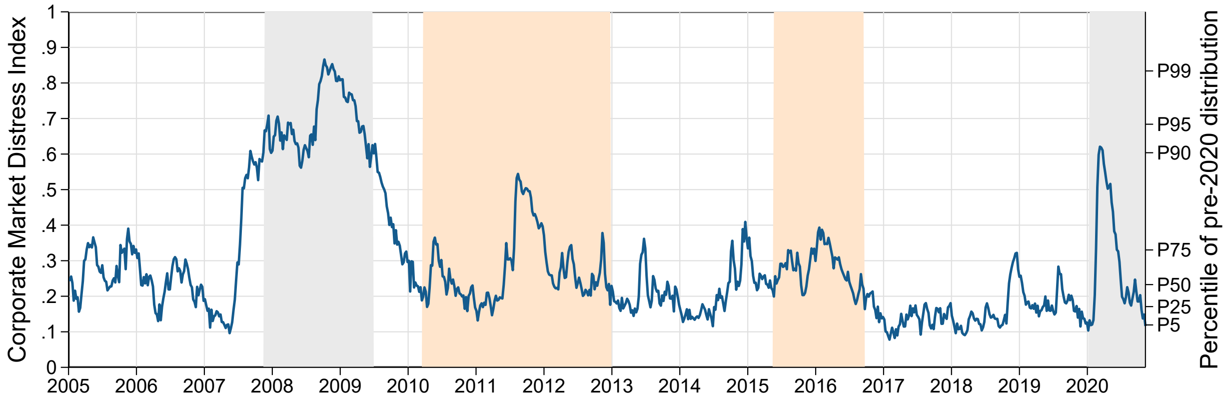


Figure 5. Corporate bond market distress index. This figure plots the full time series of the corporate market dislocation index (Figure 5a), as well as zoomed-in to the 2020 history (Figure 5b). In both panels, the dotted orange line is the pre-2020 75th percentile of the historical distribution and the dashed red line is the pre-2020 90th percentile of the historical distribution. Gray shaded areas in Figure 5a 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). Event lines in Figure 5b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date).

(a) Full sample



(b) 2020

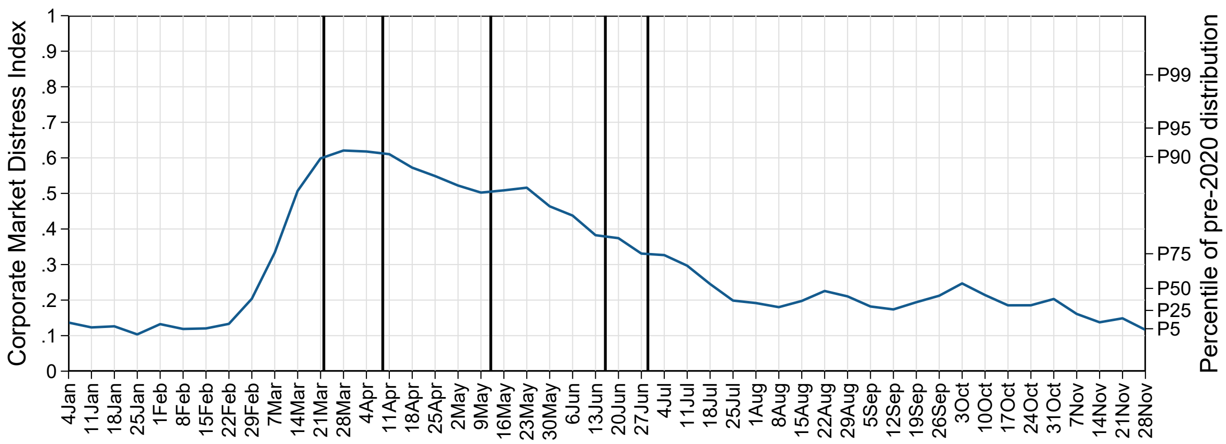
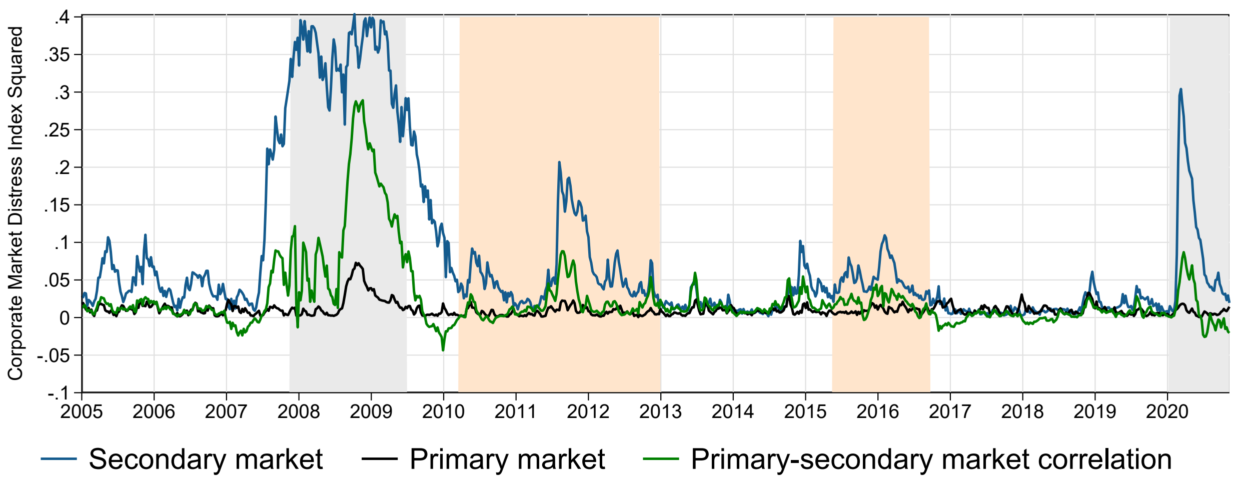


Figure 6. Contributions to CMDI. This figure plots the contribution of secondary market measures, primary market measures and correlation between the two to the aggregate (squared) index, for the full sample (Figure 6a) and zoomed-in to the 2020 history (Figure 6b). Primary market sub-indices are: issuance volume, primary-secondary spread, and issuance maturity choice. Secondary market sub-indices are: volume, liquidity, zero return/zero trade days, duration-matched spreads, default-adjusted spreads. Gray shaded areas in Figure 6a 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). Event lines in Figure 6b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date).

(a) Full sample



(b) 2020

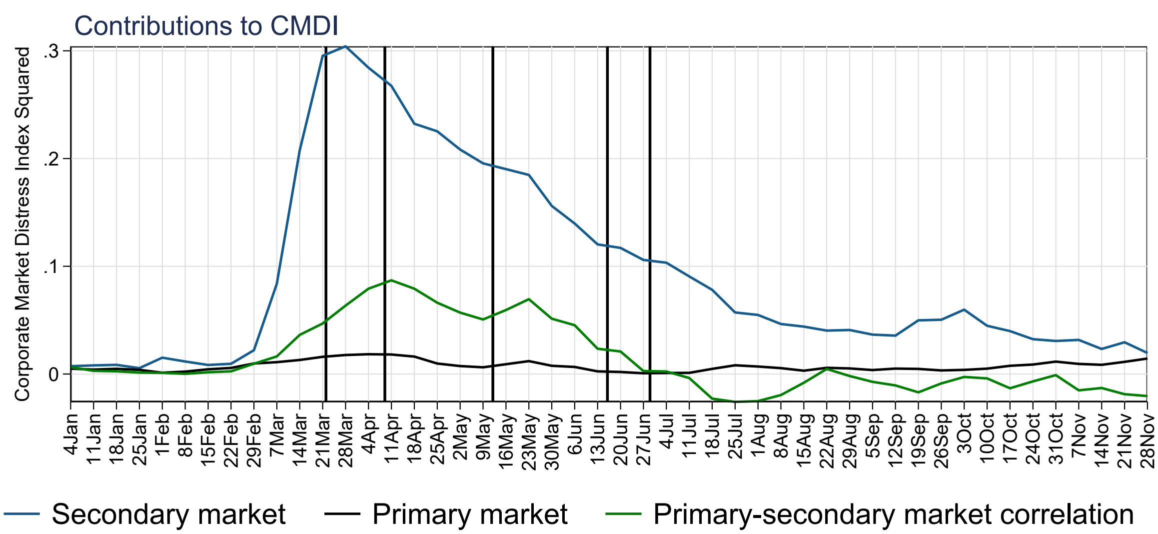


Figure 7. CMDI with full-sample ECDF. This figure compares the baseline CMDI to the infeasible index constructed using the full-sample ECDF standardization. Gray shaded areas correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016).

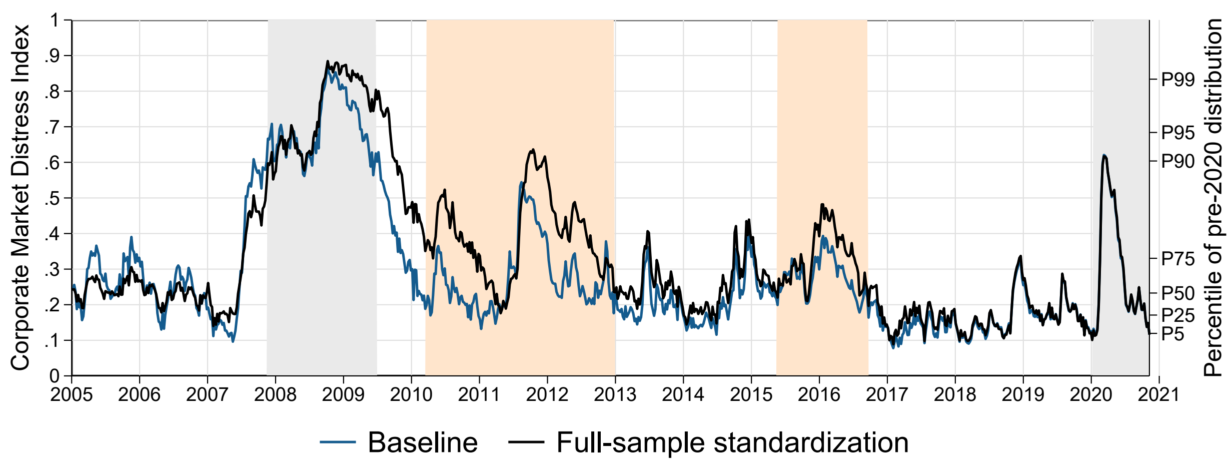
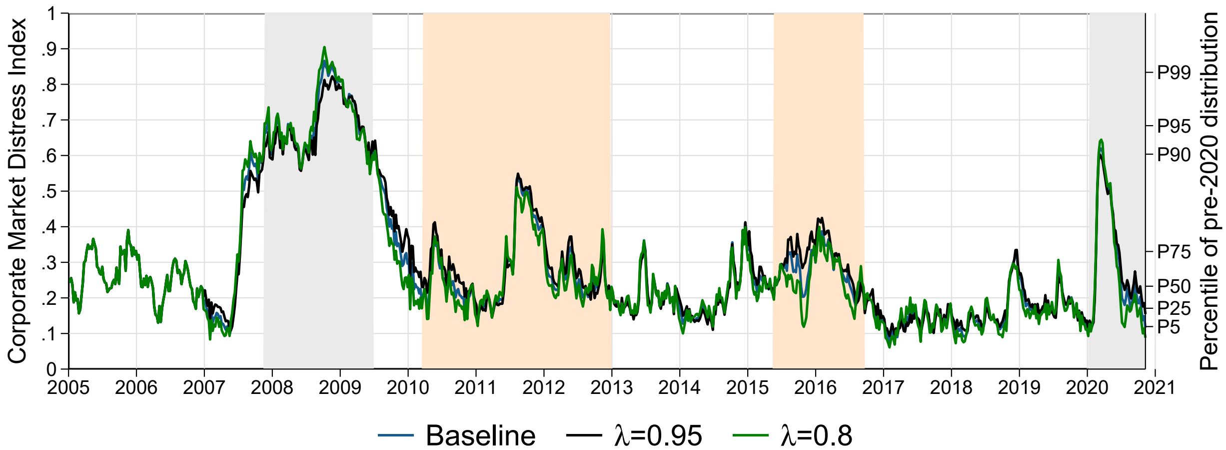


Figure 8. CMDI with alternative smoothing parameters. This figure plots the corporate market distress index constructed using different values of the exponentially-weighted moving average parameter λ, for the full sample (Figure 8a) and zoomed-in to the 2020 history (Figure 8b). Baseline index constructed using $\lambda = 0.9$. Gray shaded areas in Figure 8a 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). Event lines in Figure 8b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date).

(a) Full sample



(b) 2020

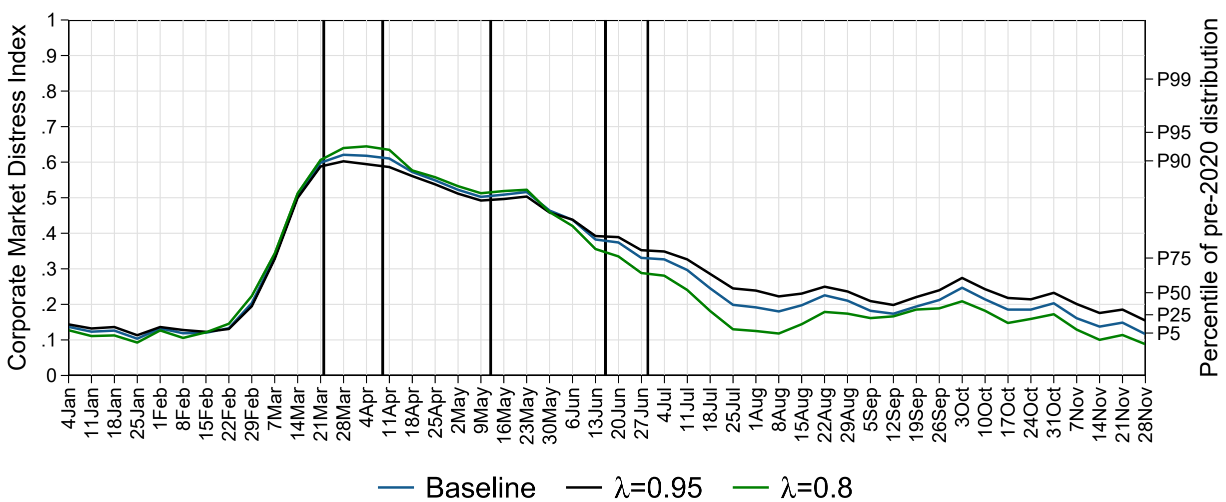
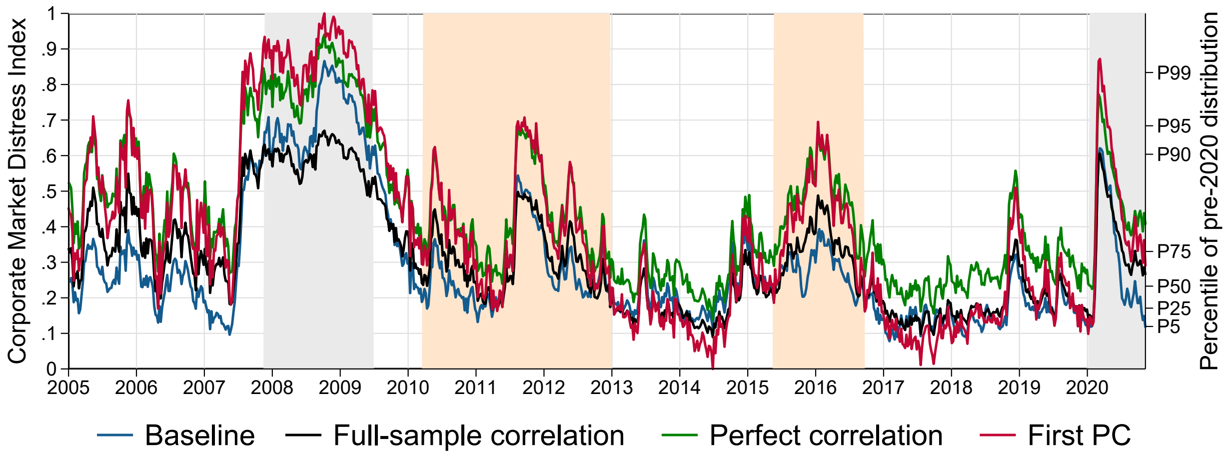


Figure 9. CMDI with alternative weights. This figure plots the corporate market distress index under different aggregation schemes across sub-indices, for the full sample (Figure 9a) and zoomed-in to the 2020 history (Figure 9b). "Full sample correlation" index uses the full-sample correlation matrix between the sub-indices to construct the weighted average. "Perfect correlation" index assumes perfect correlation between the sub-indices. Gray shaded areas in Figure 9a 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). Event lines in Figure 9b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date).

(a) Full sample



(b) 2020

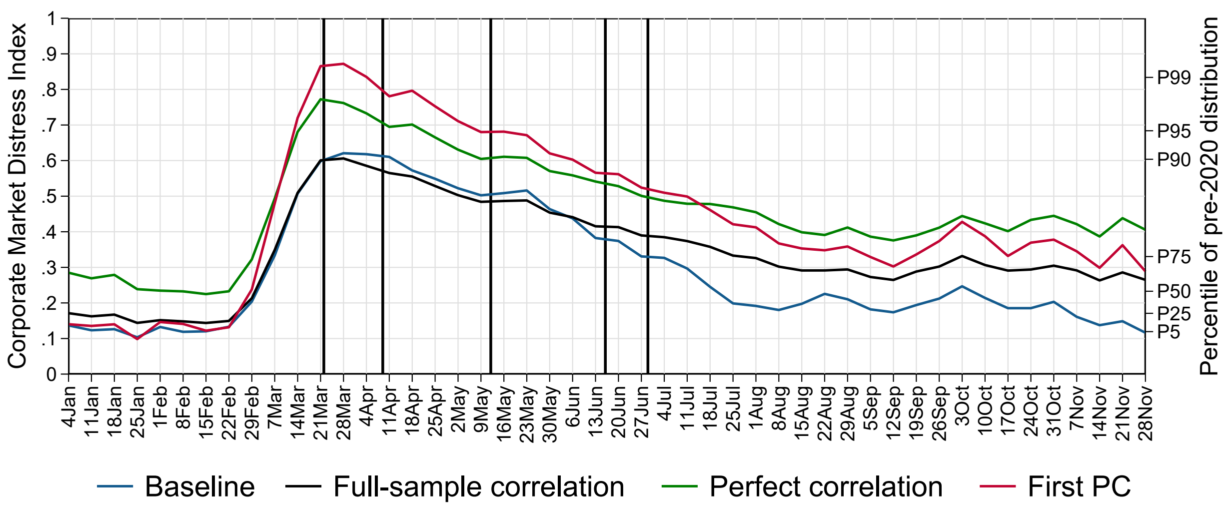
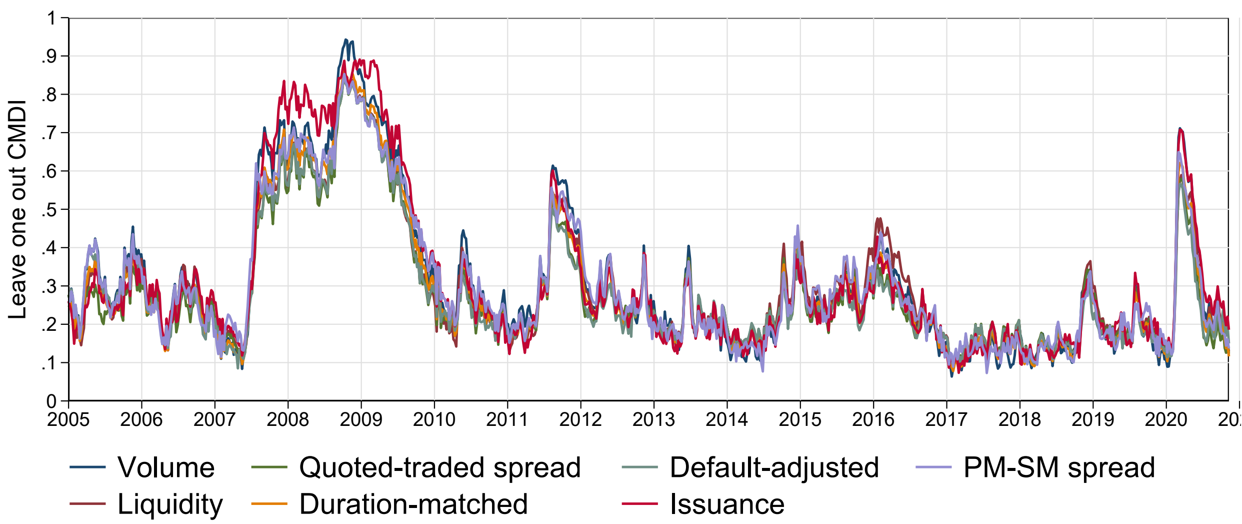


Figure 10. "Leave one out" indices. This figure plots the corporate market distress index when each individual sub-index is excluded, for the full sample (Figure 10a) and zoomed-in to the 2020 history (Figure 10b). Leave-out indices labelled with the *excluded* sub-index, so that e.g. "Volume" is the index that leaves out secondary market volume sub-index. Event lines in Figure 10b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date).

(a) Full sample



(b) 2020

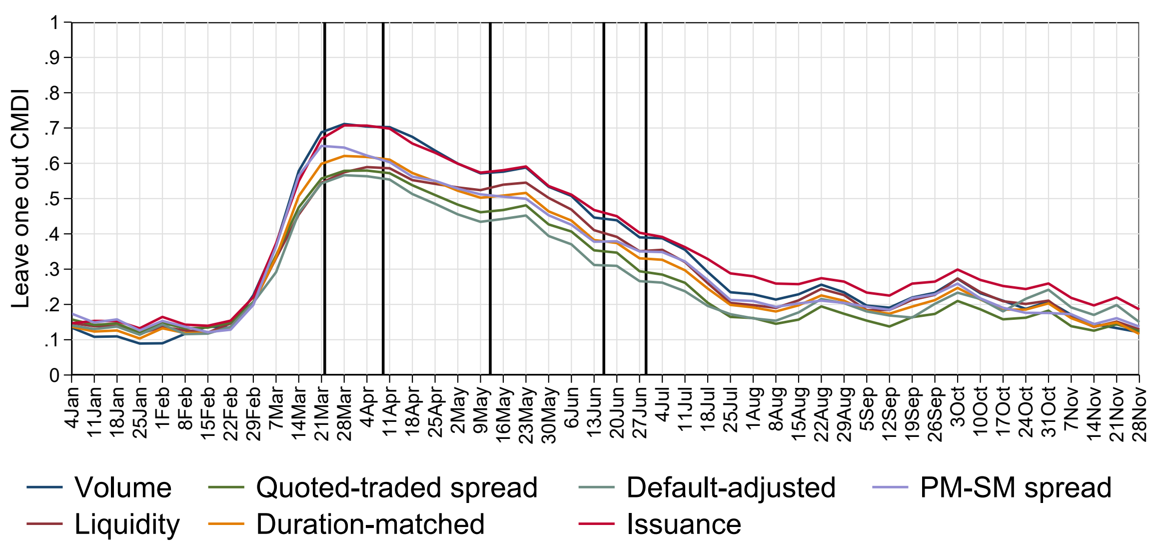
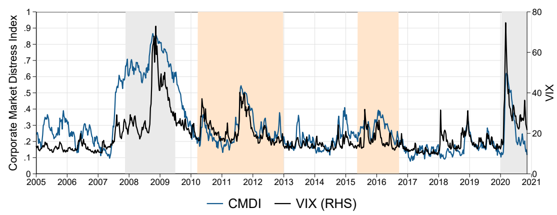
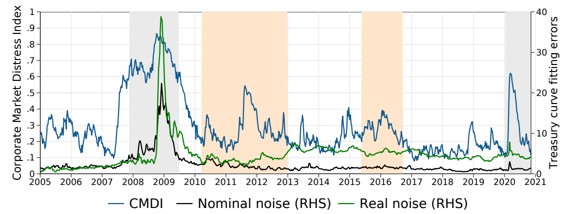


Figure 11. CMDI and common measures of financial distress. This figure plots the CMDI together with commonly used measures of distress. ETF-NAV basis computed as the assets under management weighted average across available bond ETFs at each date. "Noise" is the Hu et al. (2013) Treasury yield curve fitting error metric. NFCI is the Chicago Fed National Financial Index. CISS is the ECB's Composite Indicator of Systemic Stress. 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).

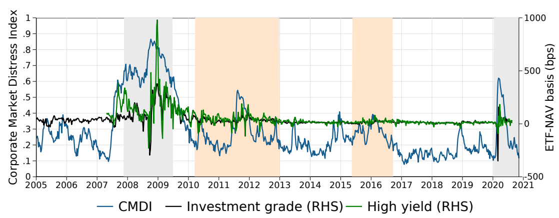
(a) VIX



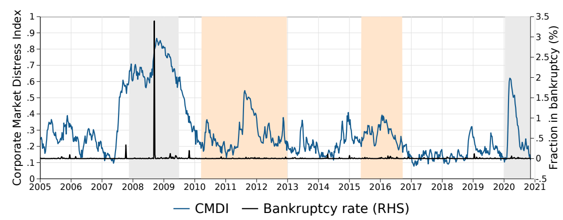
(b) Treasury curve fitting errors



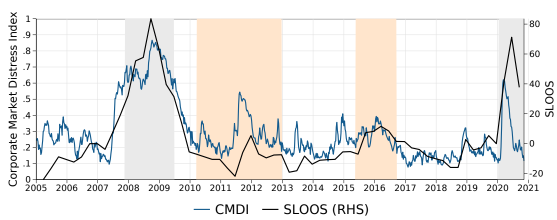
(c) ETF-NAV basis



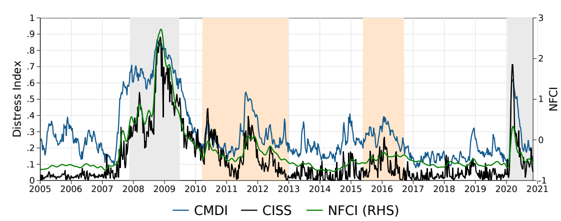
(d) Bankruptcy rate



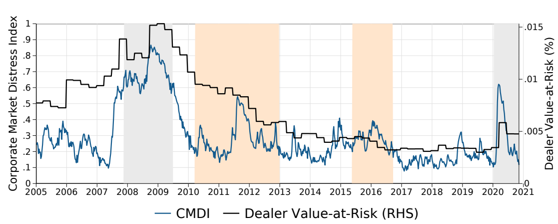
(e) Tightening standards for C&I loans



(f) Broad distress indices



(g) Unit dealer VaR



(h) Principle components of indicators

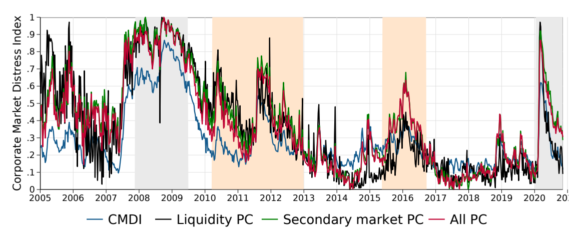


Figure 12. Credit-rating-level indices. This figure plots the corporate market distress index at the credit rating level, for the full sample (Figure 12a) and zoomed-in to the 2020 history (Figure 12b). Gray shaded areas in Figure 12a correspond to NBER recessions; peach shaded areas correspond to the European debt crisis (Q2 2010 – Q4 2012) and the 2015 – 2016 manufacturing recession (Q3 2015 – Q3 2016). Event lines in Figure 12b at: March 22 (initial CCF announcement); April 9 (first term sheet update); May 12 (commencement of ETF purchases); June 16 (commencement of cash bond purchases); June 29 (PMCCF go-live date). For credit rating categories definitions, see the Appendix.

(a) Full sample

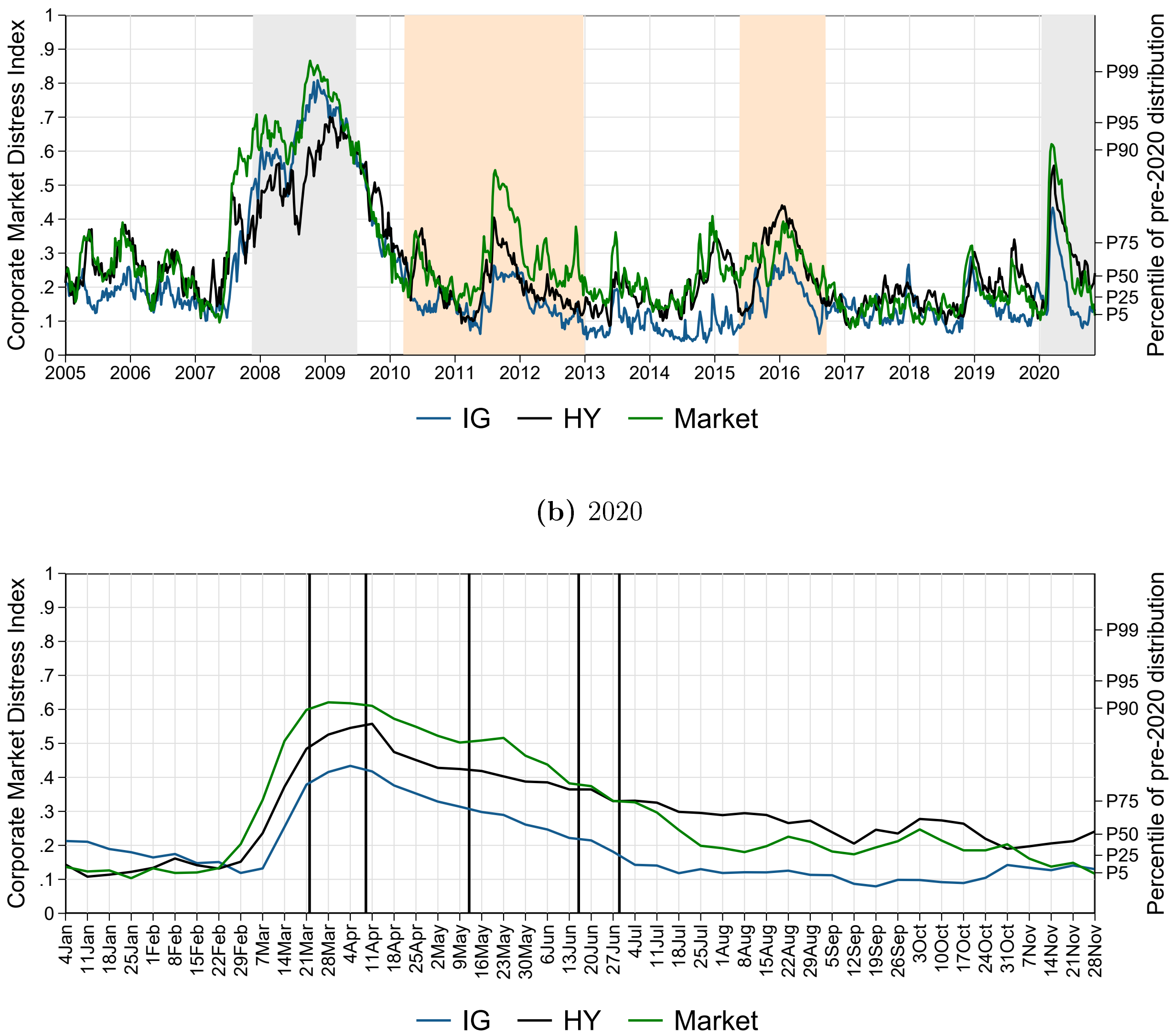


Table 1: CMDI correlation with common measures of financial stress. This table reports correlation (in levels) of CMDI and common measures of financial stress. "Crisis" defined as the period from August 1, 2007 to December 31, 2009, inclusive. ETF-NAV basis computed as the assets under management weighted average across available bond ETFs at each date. NFCI is the Chicago Fed National Financial Index. CISS is the ECB's Composite Indicator of Systemic Stress.

	Full-sample correlation	Excld. Crisis and 2020
VIX	74%	58%
Nominal Treasury fitting error	76%	34%
Real Treasury fitting error	43%	-19%
IG ETF-NAV basis	53%	20%
HY ETF-NAV basis	61%	22%
Fraction in bankruptcy	12%	8%
C&I loans credit standards	77%	19%
CISS	85%	53%
NFCI	89%	60%
Unit VaR	72%	29%
Liquidity 1st PC	81%	54%
Secondary market indicators 1st PC	89%	78%
All indicators 1st PC	91%	81%

Table 2: CMDI and real activity. This table reports the estimated coefficients from the predictive regression of one-year ahead industrial production(Table 2a), unemployment (Table 2b), real business fixed investment (Table 2c), real GDP (Table 2d), capital expenditures (Table 2e) and sales (Table 2f) 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 (Olea and Plagborg-Møller, 2020) 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)	(4)	(5)	(6)
Market CMDI	-23.34	-21.26				
	(5.95)***	(6.37)***				
IG CMDI			-36.97		-35.33	-29.72
			(9.22)***		(10.11)***	(10.89)***
HY CMDI				-27.59	-3.75	-3.69
				(9.48)***	(8.34)	(8.21)
G-Z spread		-1.08				-1.48
		(1.20)				(1.45)
Adj. R-sqr.	0.46	0.59	0.44	0.24	0.43	0.47
N. of obs	167	167	167	167	167	167

(b) Unemployment rate

	(1)	(2)	(3)	(4)	(5)	(6)
Market CMDI	4.97	3.37				
	(1.23)***	(1.40)**				
IG CMDI			6.55		6.73	5.85
			(1.26)***		(1.41)***	(1.35)***
HY CMDI				5.97	-0.49	-0.09
				(1.98)***	(1.30)	(1.24)
G-Z spread		0.60				0.27
		(0.24)**				(0.18)
Adj. R-sqr.	0.67	0.72	0.78	0.50	0.79	0.82
N. of obs	167	167	167	167	167	167

(c) Investment

	(1)	(2)	(3)	(4)	(5)	(6)
Market CMDI	-27.92	-25.98				
	(6.77)***	(10.01)**				
IG CMDI			-53.13		-53.28	-56.49
			(8.32)***		(10.60)***	(10.03)***
HY CMDI				-40.53	0.01	-5.74
				(11.34)***	(11.69)	(12.59)
G-Z spread		-0.38				1.00
		(1.40)				(1.53)
Adj. R-sqr.	0.54	0.63	0.61	0.38	0.60	0.63
N. of obs	55	55	55	55	55	55

(d) Real GDP

	(1)	(2)	(3)	(4)	(5)	(6)
Market CMDI	-7.09	-6.22				
	(1.64)***	(2.48)**				
IG CMDI			-14.63		-17.09	-17.16
			(2.34)***		(2.71)***	(3.83)***
HY CMDI				-6.84	4.23	3.95
				(3.06)**	(2.30)*	(2.38)
G-Z spread		0.03				0.05
		(0.41)				(0.47)
Adj. R-sqr.	0.59	0.64	0.60	0.27	0.61	0.59
N. of obs	55	55	55	55	55	55

(e) CAPEX

	(1)	(2)	(3)	(4)	(5)	(6)
Market CMDI	-53.48	-41.29				
	(14.43)***	(20.20)**				
IG CMDI			-104.43		-99.52	-91.55
			(13.87)***		(19.18)***	(23.07)***
HY CMDI				-69.50	-7.43	-7.98
				(19.32)***	(23.84)	(27.22)
G-Z spread		-2.30				-1.19
		(2.24)				(2.84)
Adj. R-sqr.	0.40	0.44	0.48	0.27	0.46	0.44
N. of obs	55	55	55	55	55	55

(f) Sales

	(1)	(2)	(3)	(4)	(5)	(6)
Market CMDI	-32.66	-55.50				
	(14.61)**	(15.64)***				
IG CMDI			-69.91		-71.25	-101.18
			(18.61)***		(21.54)***	(25.04)***
HY CMDI				-28.08	-0.64	-2.09
				(19.86)	(23.08)	(21.89)
G-Z spread		7.02				5.45
		(2.41)***				(2.62)**
Adj. R-sqr.	0.13	0.43	0.25	0.04	0.24	0.27
N. of obs	55	55	55	55	55	55

A Technical appendix

A.1 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 needs 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.2 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 de-trend intermediated volume relative to the average intermediated volume over the previous year (52 weeks), plotted in red in Figure A.1a.

- *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 de-trend average trade size relative to the average trade size over the previous year (52 weeks) and remove month-end and start-of-the-quarter seasonality from the de-trended weekly time series, plotted in red in Figure A.1b.

- *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 de-trend turnover relative to the average turnover over the previous year (52 weeks) and remove month-end and start-of-the-quarter seasonality from the de-trended weekly time series.

  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

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

  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 Treasuryimplied yield $y^f_{b,t}$ on bond b on trade date t as

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

where T is the time-to-maturity of the bond, C_b is the coupon on the bond, and $Z_t(s)$ 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

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

where $\mathrm{EDF}_{b,t}$ is the one year expected default probability for bond b on day t estimated by Moody's KMV,[24] 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.[25] 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

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

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

expected duration-matched spreads and bond characteristics.[26] 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:

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

  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-traded spread*: we compute equal-weighted average duration-matched spreads and default-adjusted spreads for bonds with quotes in the ICE-BAML database. The duration-matched quoted-traded spread is then the difference between the average duration-matched spread based on quotes and the average duration-matched spread based on trades in TRACE. Similarly, the default-adjusted quoted-traded spread is the difference between the average default-adjusted spread based on quotes and the average default-adjusted spread based on trades in TRACE.

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

A.3 Primary market metrics definitions

Primary market volumes We construct four measures of primary market issuances: year-over-year changes in dollar amount issued, year-over-year changes in the number of bonds issued, dollar amount issued relative to amount outstanding scheduled to mature within a year, and number of bonds issued relative to number of bonds scheduled to mature within a year. While the dollar amount issued captures the volume of bonds issued, the number of bonds proxies for ease of access to market. Comparing changes in both relative to the same amounts issued in the same period in the prior year corrects for both the general time trend in corporate bond issuance, as well as for seasonalities in bond issuance. Similarly, comparing both amount outstanding and number of bonds issued to the corresponding maturing amounts captures the ability to satisfy near-term issuance needs.[27] Figures A.1d – A.1g show 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 considering year-over-year changes in four week moving averages of dollar amount issued and number of bonds issued, respectively, plotted in red in Figures A.1d and A.1e, and four week moving averages of dollar amount issued and number of bonds issued relative to four week moving averages of dollar amount and number of bonds maturing, plotted in red in Figures A.1f and A.1g.

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.[28] We use offering-amount-weighted averaging to construct the time series of market-level primary duration-matched and default-adjusted spreads, averaging across all fixed coupon bonds that satisfy the sample inclusion criteria outlined in Section 2.3. To isolate the information in primary market spreads that is distinct from the information in the secondary market, we compute primary-secondary market duration-matched and default-adjusted spreads. Figures A.1h and A.1i show that, since primary market issuance occurs infrequently, the raw primary-secondary market spreads series are fairly volatile. We smooth both series by applying a four week moving average, plotted in red in each panel.

A.4 Common measures of financial stress

Treasury curve fitting errors We use nominal and real Treasury curve fitting errors provided by the Federal Reserve Board of Governors. Treasury curve fitting errors are constructed as the average absolute fitting errors (in basis points) from the Nelson–Siegel–Svensson fit of the Treasury (Gurkaynak et al., 2007) and TIPS curves (Gurkaynak et al., 2010).

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

[28] 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.2 reports the estimated coefficients for the primary market duration-matched spreads regression for the full sample January 1, 2005 – November 28, 2020.

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 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.

Bankruptcy rate We construct the weekly bankruptcy rate as the number of bonds that default on either principal or interest payments in a given week as a percent of the number of bonds with non-zero amount outstanding as of the previous week. Data on defaults and bonds outstanding from Mergent FISD.

Dealer Value-at-Risk We follow Adrian and Shin (2013) to construct the average 99% unit dealer Value-at-Risk (VaR) as follows. We start with the total VaR disclosed by 11 major commercial and investment banks,[29] obtained from Bloomberg.[30] For those firms that report VaRs at the 95% confidence level, we scale the VaR to the 99% using the Gaussian assumption. We then compute the dealer-level unit VaR as the ratio between the (potentially imputed) 99% VaR and total assets of the dealer. Finally, we average across dealers using lagged assets as weights.

A.5 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

[29]Bank of America, Citibank, JPMorgan, Bear Stearns, Goldman Sachs, Lehman Brothers, Merrill Lynch, Morgan Stanley, Credit Suisse, Deutschebank, and UBS.

[30]The Bloomberg code is ARDR_TOTAL_VALUE_AT_RISK.

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

A.6 Real outcomes for publicly-listed firms

We use balance sheet data from COMPUSTAT. From the universe of firms that have observations in the quarterly dataset, we remove financial firms (SIC code between 6000 and 6999, inclusive), "miscellaneous" firms (SIC codes 9900 and above), unclassified firms (missing SIC code), and observations with missing total assets or negative total assets. We compute four-quarter-ahead log growth rates of quarterly capital expenditures and sales at the firm-quarter level, and average to the aggregate level using lagged assets as weights. Figure A.4 plots the resulting aggregate time series, together with the market-level CMDI realizations.

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 bond-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.

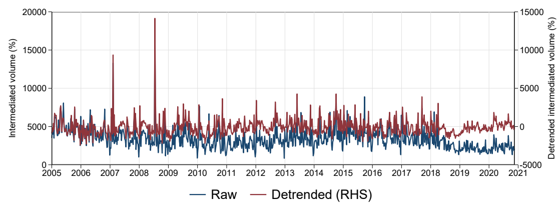
	AAA,AA	A+,A,A-	BBB+, BBB	BBB-	BB+, BB, BB-	B+ and Lower	All
Constant	-5.81***	-5.47***	-5.17***	-4.32***	-4.03***	-3.82***	-4.99***
	(0.11)	(0.07)	(0.08)	(0.10)	(0.13)	(0.10)	(0.05)
Log duration	0.31***	0.44***	0.43***	0.52***	0.36***	0.13***	0.40***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Log coupon	0.92***	0.69***	0.73***	0.56***	0.58***	0.63***	0.71***
	(0.03)	(0.01)	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)
Log amount outstanding	-0.06***	-0.07***	-0.08***	-0.13***	-0.09***	-0.06***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)
Log age	-0.10***	-0.06***	-0.07***	-0.03***	-0.03***	-0.01*	-0.05***
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Callable	-0.10***	-0.12***	-0.10***	0.06**	-0.16***	-0.13***	-0.12***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)	(0.01)
$\text{EDF}_{1y}\times$ Firm EDF dummy	0.02***	0.14***	0.09***	0.08***	0.07***	0.04***	0.05***
	(0.00)	(0.01)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)
$\text{EDF}_{1y}\times$ Bond EDF dummy	-0.16***	-0.10***	0.12***	0.11***	0.08***	0.05***	0.06***
	(0.04)	(0.02)	(0.02)	(0.02)	(0.01)	(0.00)	(0.00)
N. obs.	656,166	3,389,793	3,660,248	1,158,148	1,407,280	1,477,813	11,749,448
N. clusters	4,268	22,204	26,567	10,835	15,765	23,612	95,643
Adj. R^2	0.42	0.38	0.39	0.40	0.20	0.20	0.55

Table A.2: 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 bond-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.

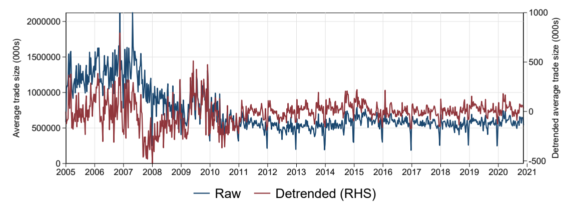
	AAA,AA	A+,A,A-	BBB+, BBB	BBB-	BB+, BB, BB-	B+ and Lower	All
Log duration	-0.19**	-0.12	0.03	-0.05	-0.26***	-0.62***	-0.27***
	(0.08)	(0.09)	(0.02)	(0.03)	(0.04)	(0.03)	(0.02)
Log coupon	0.38***	0.43***	0.52***	0.69***	0.79***	0.88***	0.63***
	(0.07)	(0.07)	(0.03)	(0.05)	(0.04)	(0.03)	(0.02)
Log offering amount	0.07***	0.09***	0.03***	0.01	0.08***	0.05***	0.07***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Callable	-0.09*	-0.10***	0.17***	0.29***	0.24***	0.54***	0.14***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.02)
$EDF_{1y}\times$ Firm EDF dummy	0.02	-0.01*	-0.02***	0.09***	-0.01***	-0.01***	-0.01***
	(0.02)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)
$EDF_{1y}\times$ Bond EDF dummy	0.07***	0.05***	0.08***	0.05*	0.02***	0.04***	0.05***
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.01)	(0.01)
N. obs.	4,350	11,125	8,481	3,851	2,753	7,627	38,189
N. clusters	1,551	4,989	4,555	2,034	2,051	5,820	20,394
Adj. R^2	0.11	0.10	0.19	0.25	0.43	0.51	0.41

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.

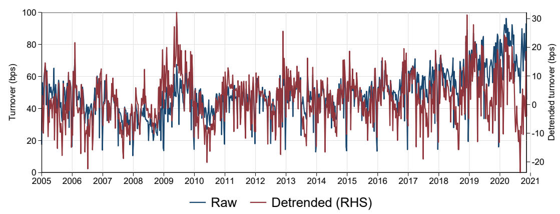
(a) Intermediated volume



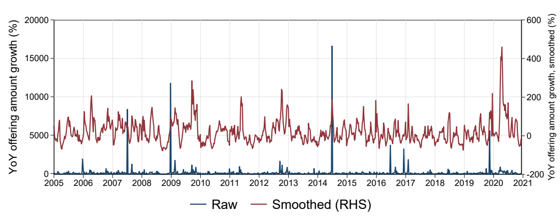
(b) Average trade size



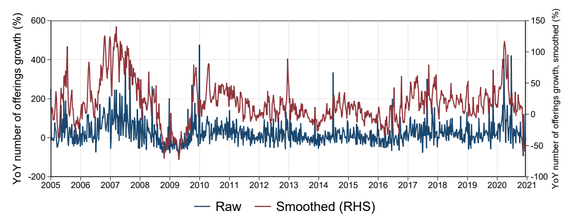
(c) Secondary market turnover



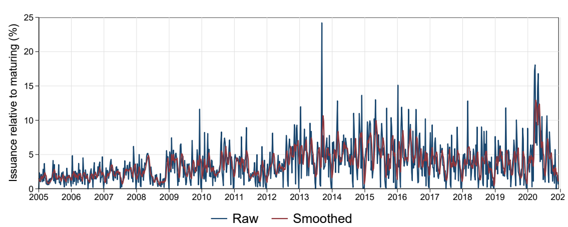
(d) YoY offering amount growth



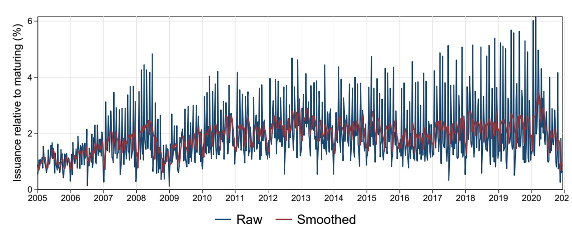
(e) YoY number of issues growth



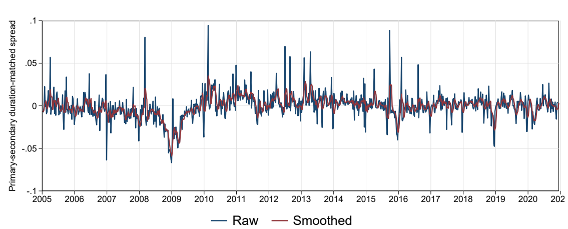
(f) Offering amount relative to maturing



(g) Offering bonds relative to maturing



(h) PM-SM duration-matched spread



(i) PM-SM default-adjusted spread

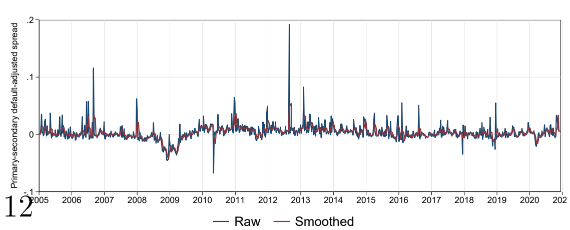
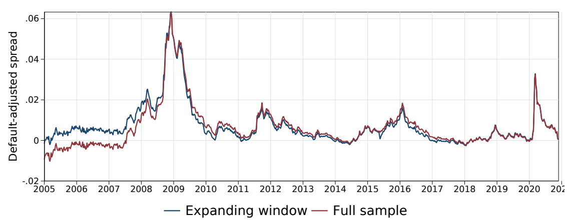
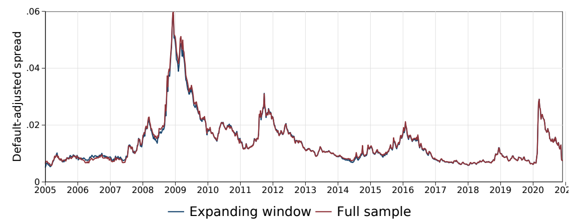


Figure A.2. Full-sample and expanding sample spread estimates. This figure plots full-sample and the expanding-sample default-adjusted spread, as well as the full-sample and the expanding-sample GARCH model estimates. The expanding sample initialized with the first two years of data (January 2, 2005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

(a) Default-adjusted spread level

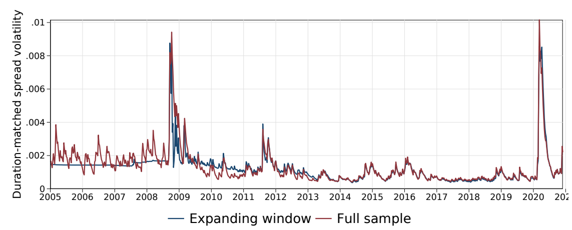


(b) Default-adjusted spread dispersion

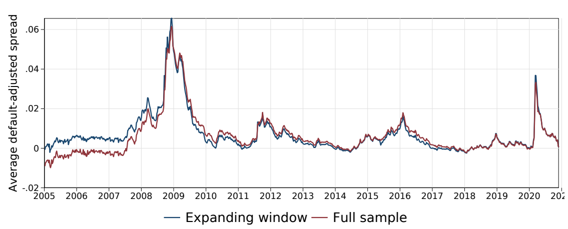


(c) Duration-matched, mean

(d) Duration-matched, volatility



(e) Default-adjusted, mean



(f) Default-adjusted, volatility

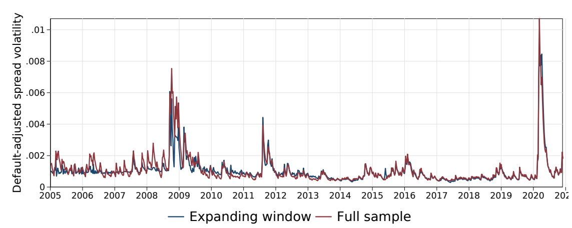
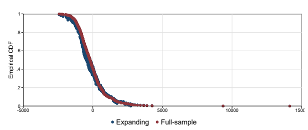
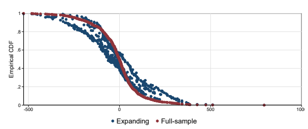


Figure A.3. Full-sample and expanding sample ECDF estimates. This figure plots full-sample and the expanding-sample empirical cumulative distribution functions (ECDFs) of measures of secondary and primary market functioning. The expanding sample ECDF initialized with the first two years of data (January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

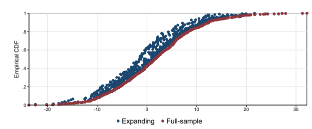
(a) Intermediated volume



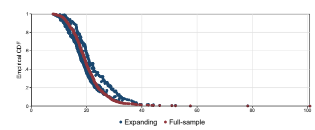
(b) Avg. trade size



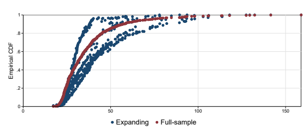
(c) Turnover



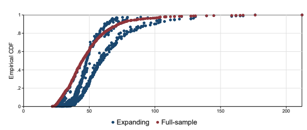
(d) Customer buy-sell pressure



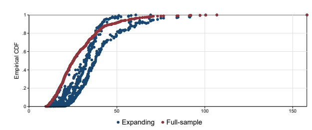
(e) Bid-ask spread



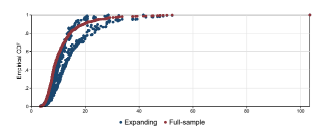
(f) T/W spread



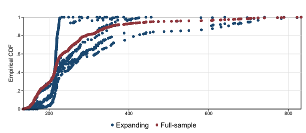
(g) Price impact



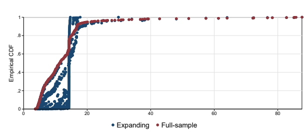
(h) Round-trip cost



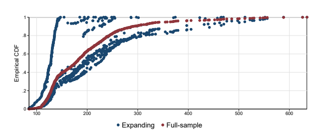
(i) Avg. Z-spread



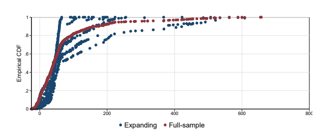
(j) Vol. Z-spread



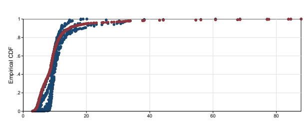
(k) Disp. Z-spread



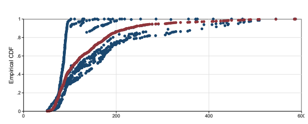
(l) Avg. D-spread



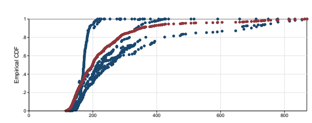
(m) Vol. D-spread



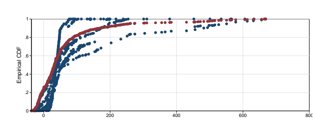
(n) Disp. D-spread



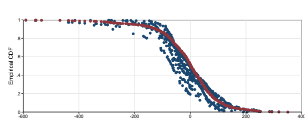
(o) Trd-quoted Z-spread



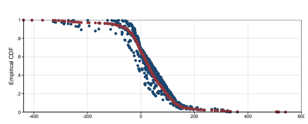
(p) Trd-quoted D-spread



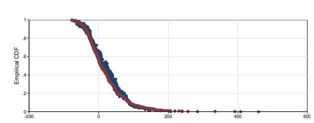
(q) PM-SM Z spread



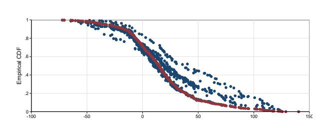
(r) PM-SM D spread



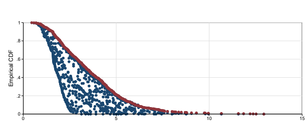
(s) Offering amount growth



(t) Offering number growth



(u) Iss. rel. to maturing amount



(v) Iss. rel. to maturing number

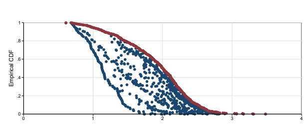


Figure A.4. COMPUSTAT growth series. This figure plots the time series of aggregate cumulative four-quarter-ahead log CAPEX and sales growth, computed as the lagged-assets-weighted average of firm-level growth rates. Sample includes non-financial firms only.