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The Term Structure of the Excess Bond Premium: Measures and Implications

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Summary:

In this article, we construct daily aggregate as well as short-, medium-, and long-term "excess bond premium" (EBP) measures using a widely available corporate bond database (known as "TRACE"). The novel EBP measures we construct provide an important gauge of strains in the financial sector at different horizons. We find that the short-term EBP measure increased more dramatically at the peaks of the COVID-19 pandemic and the 2007–09 global financial crisis, but the pattern was reversed around the interest rate liftoff at the end of 2015.

Key findings:

1. The authors find that the short-term EBP measure increased more dramatically at the peaks of the COVID-19 pandemic and the 2007–09 global financial crisis.
2. The pattern was reversed around the interest rate liftoff at the end of 2015.

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Key words: excess bond premium, term structure, TRACE, COVID-19

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The Term Structure of the Excess Bond Premium: Measures and Implications

Summary: In this article, we construct daily aggregate as well as short-, medium-, and long-term "excess bond premium" (EBP) measures using a widely available corporate bond database (known as "TRACE"). The novel EBP measures we construct provide an important gauge of strains in the financial sector at different horizons. We find that the short-term EBP measure increased more dramatically at the peaks of the COVID-19 pandemic and the 2007–09 global financial crisis, but the pattern was reversed around the interest rate liftoff at the end of 2015.

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Comments to the authors are welcome at bin.wei@atl.frb.org.

1 Introduction

In an influential paper, Gilchrist and Zakrajšek (2012) propose a novel measure of the so-called "excess bond premium" (EBP) and show that their EBP measure has considerable predictive power for economic activity. According to Gilchrist and Zakrajšek (2012), the EBP measure reflects the effective risk-bearing capacity of the financial sector: An increase in the EBP—reflecting the reduced risk-bearing capacity of the financial sector—is associated with a contraction in credit supply and declines in consumption, investment, and output. In subsequent studies, various authors document further evidence for the EBP's important roles in predicting recessions (Favara et al., 2016) or driving sovereign bond spreads (Gilchrist et al., 2021).

In this article, we construct a *daily* aggregate EBP measure using data provided by the Trade Reporting and Compliance Engine (TRACE) between July 1, 2002, and September 30, 2020. Our daily aggregate EBP measure is an important gauge of strains in the financial sector during times when strains occur speedily. Moreover, the TRACE database contains bond-level transactions data and is free to all academic subscribers of the Wharton Research Data Services (WRDS).

An illustration of the advantages of our daily aggregate EBP measure can be found in Gilchrist et al. (2020), who document the destabilizing impact of the COVID-19 shock on the corporate bond market and assess the efficacy of the Federal Reserve's crisis policies. The onset of the COVID-19 pandemic caused financial market turmoil in a matter of days or weeks. For example, the average credit spread of corporate bonds widened more than 200 basis points within 10 days to 5.33% on March 23, 2020. In addition, the swift actions taken by the Fed had an almost immediate effect of restoring investors' confidence. As shown in Gilchrist et al. (2020), the announcement of the Fed's corporate bond facilities on March 23, 2020, as well as the announcement of the expansion of the facilities on April 9, 2020—the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF)—both significantly improved the functioning of the corporate bond market within the first 10 days following the announcements. The existing monthly or quarterly EBP measures would have been too coarse to capture the rapidly emerging turmoil and quick reaction by the Federal Reserve. We believe that our daily EBP measure will be useful for 4 analyzing other rapidly emerging events. We plan to update our daily EBP measure from time to time and make it available for download from this website.

A second contribution of this paper is that we construct new daily EBP measures for short-, medium-, and long-term time horizons, besides the above aggregate measure. Specifically, we divide our corporate bond sample into three groups: the first group for bonds with time to maturity less than or equal to two years, the second group for bonds with time to maturity greater than two years but less than or equal to five years, and the third group for the rest of bonds with time to maturity greater than five years. We then construct separate EBP measures for each of these three groups, which we refer to as the short-, medium-, and long-term EBP measures, respectively. In most of the sample period, the three EBP measures are very similar across these groups of bonds. However, we find that—similar to the 2007–09 global financial crisis (GFC)—the short-term EBP measure increased more dramatically than the medium-term or long-term EBP measures in mid-March 2020 at the height of the pandemic. Reminiscent of the inverted credit curve of corporate bond spreads documented in Gilchrist et al. (2020), the larger movement in the short-term EBP measure reflects a “dash for cash” by investors for fear of COVID-induced uncertainties in the near future. Interestingly, we find that the pattern is reversed in a different episode. In the end of 2015 and early 2016 around the time of liftoff by the Federal Reserve (which is to say the first increase in the federal funds rate target from nearly zero on December 14, 2015), we find that it is the long-term EBP that had the largest increase, whereas the short-term EBP changed little. The larger movement in the medium-term or long-term EBP measures in the liftoff episode is attributable to the larger interest rate risk for longer-term bonds as a result of liftoff.

In the rest of the article, we provide detailed information about how we construct the TRACE-based EBP measures in Section 2. We further discuss implications based on the EBP measures we constructed in Section 3, particularly implications about the COVID-19 pandemic. We conclude in Section 4.

2 Constructing the TRACE-based EBP Measures

In this section, we provide a brief sketch of the process for constructing our TRACE-based EBP measures. To this end, we first discuss various databases used in the construction, and then we describe the construction process. We discuss the implications of our EBP measures in the next section. We relegate the details about how we construct the TRACE-based EBP measures to Appendices 4-4 at the end of this article.

Data

The main database used in our analysis is the enhanced TRACE database from Wharton Research Data Services (known as WRDS). TRACE stands for “Trade Reporting and Compliance Engine,” which is the Financial Industry Regulatory Authority’s (FINRA) over-the-counter corporate bond market real-time price dissemination service. All broker-dealers who are FINRA member firms have an obligation to report transactions in TRACE-eligible securities, including corporate bonds. As such, the TRACE database contains information about individual corporate bond transactions in the secondary market, namely, the date and time of individual corporate bond transactions, transaction prices and volumes, the direction of a transaction (buy or sell), as well as information about whether a transaction is “dealer-to-customer” or “dealer-to-dealer.”

The available EBP measures are constructed using primarily the proprietary Merrill Lynch (ML) database.[1] The ML database is a proprietary data source of daily bond prices that starts in 1997 for all individual corporate bonds in the Merrill Lynch U.S. Corporate Master index and its High-Yield Master II index. By construction, it focuses on the most liquid corporate bonds in the

[1] To be more precise, the ML database covers the period starting January 2, 1997. The earlier bond pricing data come from Lehman Brothers for the period between January 1973 and March 1998.

secondary market.[2]

Compared to the proprietary ML database, which includes only the most liquid corporate bonds, the TRACE database is more readily available from WRDS and covers the entire universe of existing corporate bonds. In addition, the transactions data from TRACE can be used to construct intraday EBP measures at an even higher frequency. However, the TRACE database only covers the period since July 2002, when TRACE was introduced. In contrast, the ML database contains bond pricing information that starts in 1997.

To construct our EBP measure, we combine the TRACE data with the Mergent's Fixed Income Securities Database to obtain bond characteristics, with Compustat to retrieve issuers' income and balance sheet data, and with CRSP to get data on equity valuations. See Appendix 4 for more details about our data sources and our final sample of corporate bonds.

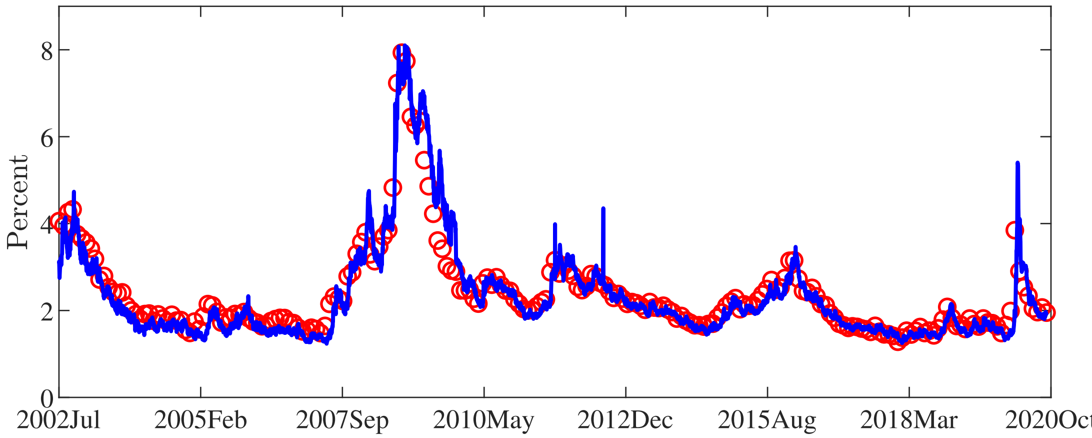
Methods

There are three major steps in constructing the EBP. At the first step, we construct the so-called "GZ spread" for each bond on each day by following Gilchrist and Zakrajšek (2012), which is the difference between the bond's yield-to-maturity implied by its daily price and the yield-to-maturity of a synthetic risk-free security that mimics exactly the cash flows of the corresponding corporate bond. We use the last transaction price recorded between 9 a.m. and 4:00 p.m. on a given business day to calculate GZ spreads. The yield of the synthetic risk-free security is calculated from its hypothetical price, which is equal to the present value of the promised cash flows, discounted by the term structure of zero-coupon US Treasury yields, as estimated on that day by Gürkaynak, Sack and Wright (2007).

Figure 1 plots the average GZ spread based on the TRACE database (solid blue line) along with that based on the ML database (red circles) from Favara et al. (2016). Despite the different data sources, the average GZ spread we constructed is very similar to that constructed in the latter paper.

[2] For inclusion in the ML database, a corporate bond must satisfy the following criteria: at least two years until maturity, a fixed coupon schedule, and a minimum amount outstanding ($150 million and $100 million for investment-grade, and non-investment-grade issuers, respectively).

Figure 1: Credit Spreads



Note: The solid blue line shows the time-series of the cross-sectional average of GZ spreads between July 1, 2002 and September 30, 2020 based on the TRACE database. The red circles represent the average GZ spread constructed primarily based on the ML database from Favara et al. (2016).
Source: Authors' calculation using TRACE data.

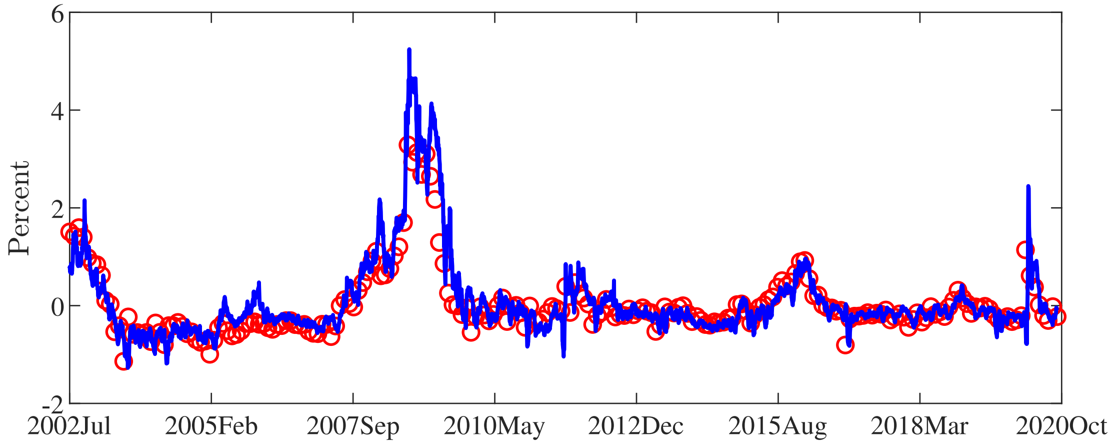
The key in constructing the EBP in Gilchrist and Zakrajšek (2012) is to decompose each bond's GZ spread into two components: one component is the expected default component, and the other component is the residual (related to the risk premium, etc.). At the second major step, we need to construct a firm's default risk measure, which is needed in the above decomposition. For each publicly listed firm in our sample, we measure its default risk by the standard "distance-to-default" (DD) framework developed in the seminal work of Merton (1974) (see Appendix 4 for details).

At the third and last step, we run the following bond-level regression to decompose a bond's (log) credit spread into the expected default and the residual components.

$$\ln S_{i,j,t} = \alpha_0 + \alpha_1 DD_{i,t} + \lambda' \mathbf{Z}_{i,j,t} + \nu_{i,j,t}, \tag{1}$$

where $S_{i,j,t}$ denotes the GZ spread for bond j issued by firm i in day t, $DD_{i,t}$ denotes the distance-to-default default risk measure, and $\mathbf{Z}_{i,j,t}$ denote explanatory variables. The estimated residual $\hat{\nu}_{i,j,t}$, the (log) credit spread "pricing error," reflects a portion of the credit spread that is not attributable to issuer's default risk and which we interpret as an estimate of the credit risk premium. When averaged across issuers, the resulting average residual credit spread—the so-called EBP—captures fluctuations in the average price of bearing US corporate credit risk, above and beyond the compensation that investors in the corporate bond market require for expected defaults.

Figure 2: The Excess Bond Premium (EBP)



Note: The solid blue line shows the time-series of our EBP measure between July 1, 2002 and September 30, 2020, which is the cross-sectional average of the residual credit spreads estimated from the regression (1). The red circles represent the monthly EBP measure primarily based on the ML database from Favara et al. (2016).
Source: Authors' calculation using TRACE data.

In Figure 2, we plot our daily EBP measure based on the TRACE database (solid blue line) as well as the measure based on the ML database (red dots) from Favara et al. (2016). From the figure, we can see that the two measures are close to each other. Also, the EBP has considerable time variations with large spikes during crisis periods. For example, the EBP jumped to almost 5 percent in late October and early November 2008 at the peak of the GFC. It then took more than half a year for the EBP to decrease to the pre-GFC level. Recently, the onset of the COVID-19 shock drove up the EBP again, but—this time in a matter of a few days—the EBP increased from nearly zero in early March to about 2.5 percent on March 20, 2020. The Fed's swift interventions helped restore investors' confidence and drove down the EBP to nearly zero in early June.

As discussed earlier, our daily EBP measure is useful for analyzing rapidly emerging events, compared to the measures at monthly or lower frequency. As another advantage, it provides a more accurate gauge of strains in the financial sector, especially during crisis periods. For example, as shown in Figure 2, the monthly EBP measure peaks at around 3.3 percent at the height of the GFC in October, 2008, which, however, understates the severity of the turmoil during that time. In contrast, our daily measure takes it maximal value of 5.2 percent on October 10, 2008, hence providing more precise information on the magnitude and timing of the turmoil in the financial markets. Similarly, in the recent COVID-19 episode, the monthly EBP measures spikes again to 1.1 percent in March, 2020, while our daily measure peaks at around 2.4 percent on March 20, 2020.

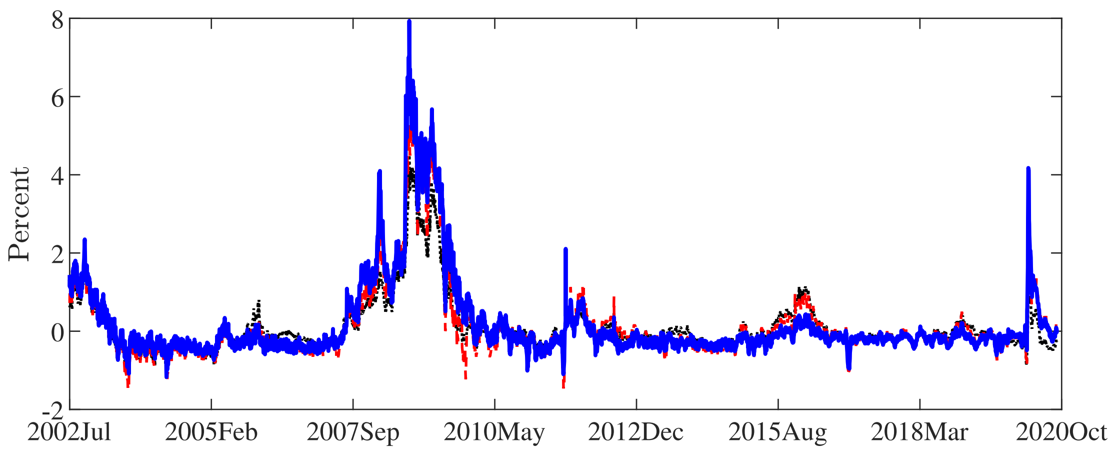
The Term Structure of the EBP

After constructing the aggregate EBP measure in the previous subsection, we construct three new EBP measures for different time horizons. Specifically, we divide our corporate bond sample into three groups: the first group for bonds with time to maturity less than or equal to two years, the second group for bonds with time to maturity greater than two years but less than or equal to five years, and the third group for the rest of bonds with time to maturity greater than five years.

We then repeat the regression (1) and construct a separate EBP measure for each of these three groups. See Appendix 4 for estimation results. We refer to the new EBP measures as the short-, medium-, and long-term EBP measures, respectively.

Figure 3 plots the short-, medium-, and long-term EBP measures between July 1, 2002, and September 30, 2020. As shown in the figure, these three EBP measures are very similar in most of the sample period. The short-term EBP measure tends to be slightly smaller than the other two measures. For example, it is smaller than the long-term EBP measure for about 60 percent of the time, possibly because, all else equal, short-term corporate bonds are more liquid than long-term ones. (Note that these measures can diverge significantly in a few episodes. We will provide more discussion along this line in the next section.)

Figure 3: The Term Structure of the Excess Bond Premium



Note: This figure plots the short-, medium- and long-term EBP measures between July 1, 2002, and September 30, 2020, depicted by solid blue, dashed red, and dotted black lines, respectively.
Source: Authors' calculation using TRACE data.

3 Implications

Equipped by our daily EBP measures, we now examine its implications in a few recent episodes, particularly the pandemic. As we discuss below, our high-frequency EBP measures are well suited to analyzing the destabilizing impact of the COVID-19 shock, which occurred at astonishing speed.

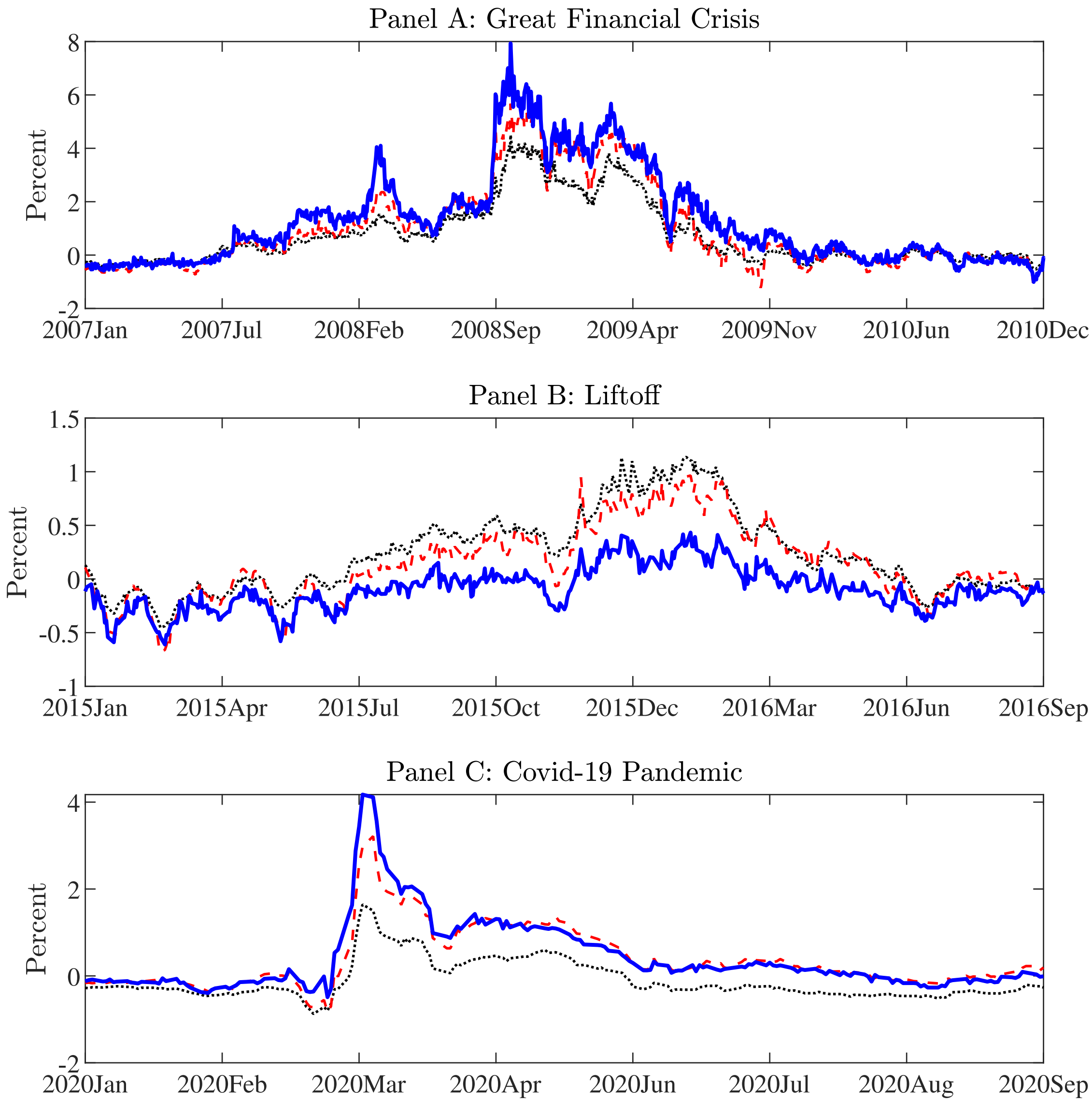
The onset of the COVID-19 shock caused substantial financial market turmoil in March 2020. The initial phase of investor de-risking in response to the COVID-19 pandemic in late February was characterized by a standard flight to safety into US Treasury securities. By mid-March, however, the market for US Treasuries—usually the most liquid in the world—became highly dysfunctional. Substantial sales of US Treasuries by leveraged nonbank investors and foreign holders, together with the limited capacity or unwillingness of dealers to intermediate these large flows, led to a severe deterioration in liquidity that quickly spilled to other markets. An important casualty of this bout of turmoil was the US money market mutual fund industry, which came under acute pressure, resulting in large redemptions from prime money market funds. Predictably, these strains had significant knock-on effects on other short-term funding markets as well as the corporate bond market. As shown in Figure 1, the average credit spread widened more than 200 basis points within 10 days to 5.33 percent on March 23, 2020.

Facing a dynamic eerily similar to that during the 2008–09 global financial crisis, the Fed reacted swiftly and on March 17 announced the establishment of the Commercial Paper Funding Facility (CPFF), whose mandate was to purchase highly rated, short-term unsecured and asset-backed paper from a wide set of eligible issuers. To further shore up the critical short-term funding markets, the Fed announced on March 18 the establishment of the Money Market Mutual Fund Liquidity Facility (MMLF), whose purpose was to make loans to eligible financial institutions to facilitate purchases of high-quality assets from eligible money market mutual funds, thereby enhancing overall market functioning and the provision of credit to the broader economy.

Although these (and other) actions stemmed redemptions and averted a wider market meltdown, liquidity in the US corporate bond market, which is limited in best of circumstances, continued to deteriorate and credit spreads surged further. In response to these escalating strains, the Fed announced on March 23 what is arguably its most sweeping and dramatic intervention in the economy to date: the creation of the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF). Despite a further narrowing of credit spreads over the remainder of that week, conditions in the corporate bond market remained strained. In response, the Fed moved further into uncharted territory and on April 9 announced updated terms for the two corporate bond-buying facilities. The most significant change in the updated terms was that eligible issuers now included companies recently downgraded from investment grade to "junk," the so-called fallen angels, an additional bold move intended to unfreeze the corporate credit markets. The announcement, which market participants characterized as "whatever it takes," had a significant effect and substantially improved the functioning of the corporate bond market.[3]

[3] The pandemic greatly affected functioning of various asset markets. Boyarchenko, Kovner and Shachar (2020), D'Amico, Kurakula and Lee (2020), Gilchrist et al. (2020), Haddad, Moreira and Muir (2021), O'Hara and Zhou (2021), and Nozawa and Qiu (2021) focus on the corporate bond market during the pandemic. The COVID-induced impact on the US Treasury market is analyzed in detail by Duffie (2020), Fleming and Ruela (2020), Schrimpf, Shin and Sushko (2020), He, Nagel and Song (2021), and Kruttli et al. (2021); Augustin et al. (2021) focus on non-US government bond markets, while Bahaj and Reis (2020) analyze COVID-induced strains in dollar funding markets; Gormsen and Koijen (2020) and Cox, Greenwald and Ludvigson (2020) study the impact of the COVID-19 shock on US equity markets; and Bi and Marsh (2020), Li and Lu (2020), and Wei and Yue (2020) examine disruptions in the US municipal bond market.

Figure 4: The Term Structure of the Excess Bond Premium: Three Episodes



Note: The solid blue line shows the time-series of our short-term EBP measure between July 1, 2002, and September 30, 2020, constructed from the subsample of corporate bonds with time to maturity less than or equal to two years, whereas the dashed red (dotted black) line shows the medium-term (long-term) EBP based on the subsample of corporate bonds with time to maturity greater than two years but less than or equal to five years (greater than five years). We plots these measures for three episodes: the 2007–09 global financial crisis (Panel A), the liftoff period in 2015–16 (Panel B), and the pandemic in 2020 (Panel C).
Source: Authors' calculation using TRACE data.

At the core of the COVID-induced market turmoil in mid-March is a "dash for cash" by investors (Haddad, Moreira and Muir, 2021); that is, amid "risk-off" sentiment, investors started liquidating risky assets to obtain cash by selling shorter-term, more liquid assets. As documented in Gilchrist et al. (2020), the curve of credit spreads across maturities inverted as a result. The authors further show that the Fed's interventions helped restore the normal credit curve. Importantly, they argue that the effects of SMCCF/PMCCF announcements on credit spreads are due primarily to a reduction in credit risk premia, or an improvement in credit market sentiment, rather than to a reduction in default risk.

The above findings suggest the importance of examining the term structure of the EBP across different horizons. Recall from figure 3, although the short-, medium-, and long-term EBP measures are very similar in most of the sample period, they do diverge in a few episodes. Figure 4 zeroes in on the dynamics of these EBP measures in three such episodes: the 2007–09 GFC (panel A), the liftoff period in 2015–16 (panel B), and the pandemic in 2020 (panel C).

Consider the pandemic in panel C first. The panel shows that the short-term EBP measure increased more dramatically than the medium-term or long-term EBP measures in mid-March 2020 at the height of the pandemic. This behavior is reminiscent of the inverted credit curve of corporate bond spreads documented in Gilchrist et al. (2020). A similar pattern is observed in the 2007–09 GFC (see Panel A). This pattern is consistent with a "dash for cash," as—facing unprecedented uncertainties induced by the COVID-19 shock—investors started selloffs of shorter-term and more liquid assets for cash. As a result, the dislocations were disproportionately larger for shorter-term securities, which is captured by the largest increase in our short-term EBP measure during this episode.

Interestingly, the pattern was reversed in the liftoff episode (see panel B). In the end of 2015 and early 2016 around the time of liftoff by the Federal Reserve (that is, the first increase in the federal funds rate target from nearly zero on December 14, 2015), we find that it was the long-term EBP that skyrocketed, whereas the short-term EBP changed little. The larger movement in the medium-term or long-term EBP measures is attributable to the larger interest rate risk for longer-term bonds as a result of liftoff.

4 Conclusions

In this article, we construct a variety of EBP measures based on the publicly available TRACE database. We uncover some interesting dynamics among the short-, medium-, and long-term EBP measures. By making these measures available for free download, we hope to facilitate future research that uses these measures.

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Appendix

In the appendices below, we provide detailed information about data sources and about how we construct our TRACE-based EBP measures.

Data

The main databases for our analysis are TRACE, Mergent's Fixed Income Securities Database (FISD), Compustat, and CRSP. We run the TRACE data through filters developed by Dick-Nielsen (2014). We then combine the resulting security-level transactions data with the information from the FISD database to obtain bond characteristics, such as bond type, coupon frequency and payout dates, seniority, date and amount of issuance, maturity date, and credit ratings. We restrict our TRACE sample to transactions involving senior unsecured bonds with fixed coupon schedules that were issued by US companies. From this sample, we drop all transactions involving bonds with a remaining maturity of less that six months or more than 30 years or with a par value less than $1 million. To ensure that our results are not driven by a small number of extreme observations, we eliminated all observations with credit spreads below 5 basis points and greater than 3,500 basis points.

Last, we match the sample of corporate bonds with their issuer's quarterly income and balance sheet data from Compustat and daily data on equity valuations from CRSP, yielding a matched sample of 2,597 firms.

Table A-1: Summary Statistics of Corporate Bond Characteristics

Characteristics	Mean	SD	Min	P25	Median	P75	Max
Maturity at issue (years)	11.1	8.4	1	5	10	10	100
Time to maturity (years)	8.4	7.8	0.5	3.1	5.7	9.4	30.0
Duration (years)	5.9	4.1	0.5	2.9	4.9	7.5	22.5
Coupon rate (pct.)	5.14	2.07	0.0	4.0	5.0	7.0	15.0
Credit spread (pct.)	2.23	2.82	0.05	0.77	1.38	2.61	35.0
Number of bonds per firm/day	3.54	4.97	1	1	2	4	161
Par value of issue ($mil.)	731	689	1	300	500	1000	15,000
Credit rating (S&P)	–	–	D	BBB-	BBB+	A	AAA

Note: Sample period: daily data from June 1, 2002, to September 30, 2020. Obs.=10,324,560. Number of bonds=22,628. Number of firms=2,597. We report summary statistics such as mean, standard deviation, minimum, 25-, 50-, and 75-percentiles, as well as maximum for various corporate bond characteristics.
Source: Authors' calculation using TRACE data.

Table A-1 contains summary statistics for the key characteristics of 22,628 bonds in our sample. Note that during the sample period of July 1, 2002, and September 30, 2020 (totally 6,667 days), there are 10,324,560 transactions observed for this sample of bonds. Therefore, a bond has 456 (=10324560/22628) transactions on average during the sample period, implying the average time span between consecutive trades is about two weeks (6667/456=14.6 days). The median firm in our sample has two senior unsecured bonds trading in a given month, and the median bond has a "BBB+" credit rating and about six years until maturity with a par value of

$500 million. The median credit spreads is 138 basis points. At the same time, there is a considerable amount of variation in credit spreads, with the interquartile range being almost 200 basis points. The large credit spread variations reveal the substantial amount of heterogeneity in the corporate bond market (for example, credit ratings). In the next subsection, we discuss our regression analysis, which estimates the EBP controlling for various bond/issuer characteristics.

Measuring Distance to Default

In this section, we provide details about measuring distance to default following Merton (1974). Specifically, the daily firm-specific distance-to-default over the one-year horizon is given by

$$\text{DD} = \frac{\ln(V/D) + \left(\mu_V - 0.5\sigma_V^2\right)}{\sigma_V}, \tag{B-1}$$

where V is the market value of the firm's assets, D is the face value of its debt—the so-called default point—and μ_V and σ_V denote the expected growth rate and the volatility of the firm's value, respectively. Following standard practice, we calibrate the default point D to the firm's current liabilities plus one-half of its long-term liabilities.

For each firm on each day, we infer V, μ_V, and σ_V using an iterative procedure proposed by Bharath and Shumway (2008). First, we initialize the procedure by letting $\sigma_V = \sigma_E \left[D/(E+D)\right]$, where E denotes the market value of the firm's equity and σ_E denotes the volatility of its equity. We estimate σ_E from historical daily stock returns using a 250-day moving window. Using this initial value of σ_V, we infer the market value of the firm for every day of the 250-day moving window based on the following equation for the value of the firm's equity implied by the Merton model:

$$E = V\Phi(\delta_1) - e^{-r\tau}D\Phi(\delta_2), \tag{B-2}$$

where r denotes the instantaneous risk-free interest rate (measured by the one-year US Treasury yield), $\Phi(\cdot)$ is the cumulative standard normal distribution function, and

$$\delta_1 = \frac{\ln(V/D) + \left(r + 0.5\sigma_V^2\right)}{\sigma_V} \quad \text{and} \quad \delta_2 = \delta_1 - \sigma_V.$$

Second, we calculate the implied daily log-return on assets (that is, $\Delta \ln V$) and use the resulting series to generate new estimates of σ_V and μ_V. We then iterate on σ_V until convergence.

Credit Spread Decomposition

In this appendix, we provide more details about credit spread decomposition based on the regression (1), the third major step in constructing the EBP measures.

We estimate equation (1) by OLS using daily TRACE data from June 2002 to September 2020. The explanatory variables, denoted by $\mathbf{Z}_{i,j,t}$, include the following bond-specific characteristics as controls: the bond's duration ($\text{DUR}_{i,j,t}$), the par amount ($\text{PAR}_{i,j}$), the bond's (fixed) coupon rate ($\text{COUP}_{i,j}$), the age of the issue ($\text{AGE}_{i,j,t}$), a 0/1-indicator variable $\text{Call}_{i,j}$ that equals one if the bond is callable, as well as their interactions. We also include credit rating and industry fixed effects, the Treasury yield curve factors (such as level, slope, and curvature), and the interest rate volatility.[4] The standard errors are clustered in the firm and time dimensions and are thus robust to cross-sectional dependence and serial correlation (see, e.g., Cameron, Gelbach and Miller, 2011).

Table C-1: Decomposing Credit Spreads

Variables	Full Sample	Short-Term	Medium-Term	Long-Term
$-DD_{i,t}$	0.070***	0.079***	0.087***	0.055***
$\ln \text{DUR}_{i,j,t}$	0.268***	0.107***	0.314***	0.074**
$\ln \text{PAR}_{i,j}$	−0.059***	−0.104***	−0.063***	−0.019*
$\ln \text{COUP}_{i,j}$	0.444***	0.360***	0.451***	0.493***
$\ln \text{AGE}_{i,j,t}$	0.035***	0.004	0.001	0.073***
$\text{CALL}_{i,j}$	−0.674***	−0.505***	−0.453***	−0.751***
$-DD_{i,t} \times \text{CALL}_{i,j}$	−0.027***	−0.028***	−0.030***	−0.019***
$\ln \text{DUR}_{i,j,t} \times \text{CALL}_{i,j}$	0.024	0.010	0.055	0.054
$\ln \text{PAR}_{i,j} \times \text{CALL}_{i,j}$	−0.059***	−0.008	−0.027*	−0.051***
$\ln \text{COUP}_{i,j} \times \text{CALL}_{i,j}$	0.089*	−0.113**	−0.013	0.493***
$\ln \text{AGE}_{i,j,t} \times \text{CALL}_{i,j}$	−0.031***	0.048*	−0.006	0.073***
$LEV_t \times \text{CALL}_{i,j}$	−0.363***	−0.174***	−0.205***	−0.512***
$SLP_t \times \text{CALL}_{i,j}$	0.016***	0.162***	0.073***	−0.049***
$CRV_t \times \text{CALL}_{i,j}$	−0.015***	−0.035***	0.001	−0.025***
$VOL_t \times \text{CALL}_{i,j}$	0.610***	1.092***	0.853***	0.402***
Adjusted R^2	0.72	0.61	0.75	0.74
Bond Number	22,628	10,585	13,619	16,323
Firm Number	2,597	1,655	2,162	2,195
Obs.	10,324,560	1,422,703	3,201,081	5,700,776

Note: Sample period: daily data from June 1, 2002, to September 30, 2020. The dependent variable is $\ln S_{i,j,t}$, the log of the credit spread on bond *j* (issued by firm *i*) on day *t*. LEV_t, SLP_t, and CRV_t represent the level, slope, and curvature factors of the US Treasury term structure. VOL_t is the (annualized) realized monthly volatility of the daily 10-year Treasury yield. Asymptotic standard errors are clustered in both the firm (*i*) and time (*t*) dimensions, according to Cameron, Gelbach and Miller (2011). Significance levels: * $p < .10$; ** $p < .05$; and *** $p < .01$.
Source: Authors' calculation using TRACE data.

As discussed by Gilchrist and Zakrajšek (2012), this empirical approach removes equity investors' assessment of default risk of individual firms from the underlying credit spreads. Column "Full Sample" of Table C-1 reports the regression results. We use the coefficient estimates in Table C-1 to compute the marginal impact of variation in default risk. One finding is

[4] The level, slope, and curvature factors correspond, respectively, to the first three principal components of nominal Treasury yields at 3-month, 6-month, and 1-, 2-, 3-, 5-, 7-, 10-, 20-, and 30-year maturities.

that the distance-to-default is a highly significant predictor of the (log) credit spreads: A decrease of one standard deviation in the distance-to-default $DD_{i,t}$ leads to a widening of credit spreads of about 16 basis points for noncallable bonds and 10 basis points for callable bonds. Moreover, this market-based indicator of default risk, together with other observable bond characteristics, explains a considerable portion of the variation in the log credit spreads.

To construct the new short-, medium-, and long-term EBP measures, we repeat the regression (1) for each of three groups: the first group for bonds with time to maturity less than or equal to two years, the second group for bonds with time to maturity greater than two years but less than or equal to five years, and the third group for the rest of bonds with time to maturity greater than five years.

Columns “Short-Term,” “Medium-Term,” and “Long-Term” of Table C-1 report the regression results based on the three subsamples, respectively. Understandably, a bond’s duration and coupon rate are more important determinants of credit spreads for longer-term bonds than for shorter-term bonds. The results also suggest that the distance-to-default measure is a more important predictor of credit spreads for a medium horizon. Specifically, based on the coefficient estimates reported in the table’s “Medium-Term” column, we find a stronger marginal effect of default risk: at the medium horizon; a decrease of one standard deviation in the distance-to-default $DD_{i,t}$ leads to a widening of credit spreads of about 19 basis points for noncallable bonds and 12 basis points for callable bonds. The marginal effects are weaker at a short or long horizon. At the short (long) horizon, the same decrease in the distance-to-default widens credit spreads of about 16 (12) basis points for noncallable bonds and 10 (8) basis points for callable bonds.