Impact of the COVID-19 Pandemic on the U.S. Corporate Bond Market

Abstract

We analyze the price effects in the U.S. corporate bond market caused by the Covid-19 crisis. We consider the impact of protective measures on firms, focusing on their ability to implement social distancing measures. We find significant cross-sectional differences with highly affected firms showing a much stronger increase in yield spreads by 103 bp and document that this impact is only present in the crisis period. Controlling for these effects, we employ credit and liquidity risk factors to explain yield spread changes. Although, we find a highly significant impact of liquidity measures as discussed in the previous literature, our results show that credit and liquidity risk have effects of similar size, once we consider the rollover risk of firms.

JEL-Classification: G01, G12

Keywords: corporate bonds, covid-19, social distancing, rollover risk

1 Introduction

On March 11, 2020 the World Health Organization (WHO) declared the rapidly spreading SARS-CoV-2 virus a pandemic. Although it was not the first pandemic in the 21st century, the speed with which the virus was spreading together with case numbers and death tolls defined a global scale health crisis unseen for almost 100 years. Throughout the world, countries established border restrictions, closed non-essential businesses, encouraged companies to offer work from home (WFH), and required the general public to social distance. U.S. states and territories began introducing stay-at-home mandates. The U.S. Bureau of Labor Statistics recorded the largest over-month increase in the unemployment rate in its history. This led to uncertainty about future economic prospects and coinciding market reactions. Stock markets crashed, credit spreads and bond market illiquidity soared prompting government intervention. The magnitude of this pandemic-driven shock was so immense that it motivated distinctive intervention in the bond market by the Federal Reserve to purchase investment-grade U.S corporate bonds from the secondary market for the first time in its history. Bond markets calmed down comparatively quickly following these quantitative easing measures taken by the Fed. However, firms still struggled with the uncertainty induced by various social distancing measures.

In this paper, we analyze the impact of the Covid-19 crisis on U.S. corporate bond prices. We contribute to the existing literature by providing a detailed analysis of the main risk factors, while carefully considering the effects of protective measures in the pandemic on firms. In general, this crisis is comparable to other financial crises: We observe a quick and drastic increase of credit spreads and a severe deterioration of bond market liquidity. However, it became clear quickly that government policy in response to the pandemic will have a differential effect on firms depending on general social distancing measures and their ability to implement WFH. Thus, we employ the measure of Koren and Pető (2020) to consider social distancing exposure across industries and analyze the impact of this measure on credit spreads and transaction costs in the bond market. While taking into account the social distancing effects, we employ credit and liquidity risk variables to explain bond price reactions in our main analysis. We also cover the relation between credit and liquidity risk by analyzing the rollover channel. Previous research has shown that in crisis periods firms with significant refinancing needs are particularly affected, as the risk of higher costs for newly issued bonds due to illiquidity further increased the firms' credit risk (see Nagler (2020)). Overall, we document and quantify the importance of default, liquidity and rollover risk for bond yield spreads in the pandemic, providing new insights on the impact of the individual risk factors.

Recent literature primarily characterizes this crisis regarding the corporate bond market as a liquidity crisis. For example, Haddad et al. (2021) find evidence for large selling pressure in the most liquid bonds that was alleviated by the announcements of the Fed's intervention. Kargar et al. (2021) find that the surge in illiquidity was a result of pressure on dealers afraid of accumulation on their balance sheets so when the Fed announced its purchase programs, both bonds that were eligible and those that were ineligible saw improvements in liquidity. O'Hara and Zhou (2021) analyze the liquidity effects of the purchase programs that affected the corporate bond market, specifically the Primary Dealer Credit Facility (PDCF) and Secondary Market Corporate Credit Facility (SMCCF), and Gilchrist et al. (2020) also study the impact of the Fed's quantitative easing actions, both find the Fed's efforts vastly decreased illiquidity in the U.S. corporate bond market and that changing liquidity was the driver of credit spreads. In contrast to these results, Nozawa and Qiu (2021) find that the reduction in yield spreads induced by the corporate bond purchase programs was largely due to a decrease in default risk. They separate the credit effect into changes due to expected losses in default and in risk premiums, showing that both credit risk aspects contributed to the increase in credit spreads. Overall, the existing literature provides mixed evidence, although most papers argue for a higher importance of the liquidity shock.

We extend the literature on the nature of this crisis in the U.S. corporate bond market. In particular, we investigate how uncertainty about pandemic specific policies such as stay-at-home mandates or WFH affects traded credit spreads and consider the potential impact of the rollover channel. Our focus is on the period of intense market distress in March 2020, as well as on the weeks before and after. Leading up to the pandemic announcement of WHO on March 11, it became increasingly likely that there would be a strict response to curb the pandemic. However, it was unclear how companies would be affected by these measures. As a consequence, the financial markets in the U.S. crashed in response to these uncertainties in the following week. Figure 1 provides a detailed overview of the first months of the pandemic. This period presents the perfect quasi-natural experiment to analyze shocks to default and liquidity risk. In our main analysis, we therefore focus on bond-level yield spread changes between week nine (Feb. 24 to 28) showing no impact and week twelve (Mar. 16 to 20) representing the crash period.

We distinguish between firms that were most impacted by the social distancing measures and firms that were less affected or even potentially benefited. We use a social distancing measure based on Koren and Pető (2020) to capture this different impact. They provide an industry score between 0 and 100 based on the share of workers in certain occupations to measure reliance on human interaction, which makes distancing more costly. We argue that (mandatory) stay-at-home mandates, WFH and stern social distancing measures caused huge uncertainty in the economy. For example, it was ex-ante not clear how firms could handle large amounts of workers switching to remote work settings or being forced to maintain a considerable distance between each other. Companies differ in their capacity to absorb the negative effects of social distancing measures and thus, the impact on default risk varies across firms conditional along this dimension.

This setup gives us the unique opportunity to analyze different established risk channels in more detail. In addition to standard credit and liquidity risk factors, we also cover the rollover channel. Following, Nagler (2020) we estimate the notional amount of bonds outstanding that have to be refinanced within the next year at the beginning of the pandemic. We are interested in understanding whether the severe deterioration of liquidity in the bond market had a significant impact on the bond prices of firms with substantial short-term refinancing needs and whether such feedback loops to credit risk exist in this crisis as well, given the evidence from the global financial crisis in 2007/08. The U.S. corporate bond market offers a unique environment to study these effects, as all bond market transactions are available in the TRACE database, allowing a detailed view on market reactions.

We analyze bond transaction data from 520 U.S. firms with a total of 2,000 outstanding bonds, representing 52% of the total trading volume in March 2020. We cover the years 2019 to 2021 and focus in our main analysis on the weeks around mid-March 2020. First, we provide various descriptive statistics, documenting the dramatic impact of the Covid-19 pandemic. We find that average weekly bond yield spreads are around 1.1% at the beginning of the year and reach 4.35% in the week of March 18, 2020. In a similar manner, average transaction costs based on the price dispersion measure rise from 17 bp to a maximum of 230 bp in the week of March 18, 2020. Focusing on the difference between week nine and week twelve, we find an average increase of 296 bp in yield spreads and 193 bp in transaction costs. Both changes are highly statistically significant. The increase in yield spreads is lower compared to the financial crisis where yield spreads reached 10% (see Friewald et al. (2012)). However, in the financial crisis this increase in bond yields was stretched over a period of more than a year, whereas in the Covid-19 crisis the full impact was realized in less than a month. In contrast to this, the magnitude of the increase in transaction costs is of the same magnitude as in the financial crisis (see Schestag et al. (2016)), indicating a severe liquidity crisis.

We use the approach of Koren and Pető (2020) to separate highly and less affected firms by social distancing measures. We find that firms that are more affected by social distancing experience a stronger increase in yield spreads. On average, a bond of an affected firm increased by 103 bp more compared to an unaffected bond between weeks nine and twelve. We confirm this result in a regression analysis considering bond and firm controls. This documents an important cross-sectional difference in the exposure of firms to the Covid-19 crisis that has to be considered before employing standard risk factors. In an additional analysis, we find that a firm's ability to cope with social distancing is an important determinant of bond yield spreads during the crisis but not before the crisis and after the implementation of the Fed's quantitative easing programs. Thus, the social distancing measure is not a proxy for credit risk, in general. Based on weekly cross-sectional regressions, we show that the significance of the social distancing measure decreases sharply within several weeks after the Fed announced its quantitative easing measures on March 23. Thereafter, the significance slowly fades until the implementation of the Fed's measures in June 2020. Interestingly, we find no evidence that the social distancing measure affects the deterioration of bond liquidity across firms, indicating that the liquidity crisis impacted the whole market, even firms that were not directly affected by pandemic measures.

In our main analysis, we explore the impact of credit and liquidity factors based on multivariate regressions explaining bond yield changes between weeks nine and twelve, while controlling for the social distancing measure. As expected, standard credit risk measures, such as the credit rating and the liquidity measure, are important in explaining the cross-sectional difference in yield spread increases. A one standard deviation difference in the credit rating relates to a 61 bp increase in yield spreads and a one standard deviation higher price dispersion measure provides an effect of 84 bp. This documents that firms with low credit ratings and low liquidity show a significantly higher increase in yield spreads, with the liquidity risk showing a higher impact overall. Analyzing rollover risk, we find that firms with a one standard deviation higher refinancing need in the next year experience a significantly higher increase in yield spreads by 14 bp, increasing the overall credit risk effect by around 20%. Although the importance of the rollover risk is lower compared to the global financial crisis around the Lehman default, it is still an essential part of the overall credit risk.

When comparing the effects of credit, liquidity and rollover risk, we find, if the nature of the crisis is carefully considered by controlling for social distancing effects, then credit and rollover risk's combined economic significance in explaining the change in yield spread has the same economic significance as liquidity risk. This is confirmed by our weekly cross-sectional regressions, as well. Interestingly, our results show that the effect of rollover risk is more pronounced when we consider the social distancing measure. The effect would be smaller by around 27% without the adjustment. Overall, we provide evidence that analyses not considering the particular effects of social distancing and not including rollover measures run the risk of overestimating the effect of credit and liquidity risk.

We contribute to several strands of the literature. First, the literature on the effect of social distancing measures on financial markets. Pagano et al. (2021) show that social distancing measures and WHF affect stock markets and Cejnek et al. (2021) show that the futures market for stock dividends reacts to firms' exposure to the Covid-19 crisis. We show that social distancing measures also had an effect on bonds markets, as discussed as a potential factor in Halling et al. (2020). Second, we expand the literature on rollover risk. Choi et al. (2018) and Choi et al. (2021) show that firms indeed actively manage their debt maturities, i.e., control their rollover risk. Liu et al. (2021) measure the effect of the rollover channel in the market for credit default swaps during the pandemic while Friewald et al. (2021) document the rollover channel in stock markets before our sample period. Nagler (2020) discusses and quantifies the rollover channel in the U.S. corporate bond market during the financial crisis in 2007/08. Our results show that the rollover risk in crisis periods concerning bond markets is not limited to the particular case of the financial crisis. Third, we extend the literature on the bond market reaction to the recent pandemic crisis by providing further evidence on how the decrease in credit spreads in response to the Fed's intervention was driven by a decrease in risk via the credit, liquidity and rollover channel.

This paper is organized as follows: section 2 discusses the economic restrictions during the pandemic and presents the hypotheses, section 3 describes the data, section 4 introduces the credit, liquidity, rollover and social distancing variables, section 5 presents the models, results and robustness tests and section 6 concludes.

2 Covid-19 pandemic and corporate bond market

Following the increasing cases of the novel coronavirus in other parts of the world, the U.S. reports its first confirmed case on January 20, 2020. Only ten days after this report, the CDC identifies person-to-person transmission of the virus in the U.S. and WHO declares a Global Public Health Emergency. On February 11, 2020 WHO officially names the disease caused by the new coronavirus COVID-19. On March 11, 2020 WHO declares COVID-19 a pandemic and the U.S. announces travel restrictions to Europe will begin March 13. On March 13, the president of the United States declares COVID-19 a national emergency. On March 16, the president of the United States announces social distancing guidelines for all levels of society. On March 17, all 50 U.S. states have reported cases of COVID-19 and the Fed announces the Primary Dealer Credit Facility (PDCF) to be started on March 20. On March 19, the U.S. State Department issues a Global Level 4 Health Advisory informing U.S. citizens not to travel, the U.S. Department of Homeland Security issues guidance on classifying essential businesses, and the governor of California signs a stay-at-home order for everyone not working in essential infrastructure. On March 20, the governors of New York and Illinois order nonessential workplaces to close and ban all nonessential gatherings. In this same week the VIX hit its all-time high of 82.69 signaling increased economic and market uncertainty. As governors across the country began issuing executive orders with increased frequency, the unique features of this particular shock to financial markets became dependent on the ability for businesses to operate at a normal capacity as travel restrictions, non-essential business closures, WFH, and social distancing measures affect firms differently. On March 23, the Fed announces the Secondary Market Corporate Credit Facility (SMCCF) and the Primary Corporate Credit Facility (PMCCF). The SMCCF is the first credit facility in the Federal Reserve's history to purchase investment-grade U.S. corporate bonds from the secondary market. By March 26, 22 U.S. states have issued stay-at-home orders. On April 9, the Federal Reserve expands the SMCCF to include bonds with at least a BB-/Ba3 rating and fallen angels that were downgraded after March 22. On May 8, the U.S. Bureau of Labor

Statistics reports a 14.7 percent unemployment rate which is 10.3 percent greater than the previous month and the largest over-month increase in its history since it was established in 1948. By May 31, a total of 42 U.S. states and territories have had stay-at-home mandates. In stark comparison, while the great financial crisis in 2008 took years to observe its full effects, the impact of Covid-19 was realized within a matter of weeks.

Since the domino effect of policies to fight the spreading virus took place the week following the pandemic announcement and the week of the Department of Homeland Security's essential business guidance, we focus our analysis on the difference between before the impact and the peak of the crisis before the Federal Reserve announces its credit extension to businesses. The U.S. response to Covid-19 occurred on multiple levels of government from local, state, to federal. These responses flooded into fruition primarily in the first few weeks in March 2020. By the end of March, the Federal Reserve had made it clear that it was willing to support U.S. businesses in ways it had never done before. To focus on the effects to the corporate bond market as a result of the crisis, we therefore center our work on these weeks of uncertainty.

Given the nature of the crisis, it is necessary to measure and control for a firm's ability to cope with the policies ordered by the U.S. government. For example, airplanes were grounded and hence, airlines were basically out of business, whereas pharmaceuticals were expected to profit from the pandemic and were less affected by these measures since they were classified as essential businesses. The measure we use models a firm's exposure to these policies by evaluating the percent of occupations in a firm that rely on working with colleagues, interacting with customers, and operating machines. This measure gives information about firms during the weeks of uncertainty in the beginning of March that a credit rating and other accounting information would be unable to give in such a short time. Namely, it has information on how likely a firm will be affected by these social distancing measures.

As a result of the policies implemented by the U.S. government, the strong impact the pandemic had on the U.S. economy and Fed's decision to offer extensive help to corporate bond markets, it seems reasonable to inquire which firms and bonds were most affected and which variables preceded yield spread changes. In the corporate bond market, we would expect credit spreads to increase for bonds of firms that are heavily affected by social distancing measures. Some firms can implement social distancing measures easier than others and for the most affected firms, implementing such measures is a difficult and costly task. Further, we expect that social distancing ability is an additional determinant of credit spreads that works via the default risk channel during the pandemic shock. A firm's capacity to respond and adjust to new policy measures that limit their normal operations becomes increasingly relevant as the severity of the pandemic increases. Since credit ratings are sticky, information on companies' ability to adapt to a remote work environment becomes more relevant as uncertainty in financial markets grows. Therefore, this factor should act as additional information about a firms' default risk during the pandemic. Finally, we expect credit spreads to be higher for firms more exposed to rollover risk during the pandemic shock. Firms that need to refinance, i.e. rollover, their bonds will have to pay more and this ultimately increases their default risk. However, as the default risk of a firm rises investors are less willing to finance its debt and liquidity in the bonds of this firm falls. Firms that need to refinance more are relatively more exposed to rollover risk. Regardless of the materialization of the rollover risk exposure it should be reflected in bond prices.

3 Data

In this section, we discuss the data we use for our analysis. We explain how we get to our bond sample, define our sample period and clarify which data we use.

We filter our bond sample to plain vanilla bonds that can have either a put or call option. In such, we use bond characteristics from Mergent FISD and transaction data from TRACE to conduct the filtering process. Before filtering, there are 492,895 bonds that have been issued in the U.S. available in Mergent FISD, of these, 235,057 are corporate bonds. We remove all bonds with coupons that are non-fixed, zero-coupon, or those that are subject to change (96,647) and bonds that are missing a maturity or offering date (96,594). We also remove rule 144a bonds (81,544) and bonds that are exchangeable, convertible, or have enhancements (49,217). Further, we filter out all bonds that are asset-backed, defaulted, defeased (48,974), or mature before the beginning of 2019 (12,138). We only keep bonds with an issue size greater than 10 million USD (10,572) and a maturity that is less than 30 years (6,485). For all such bonds we remove trades that are non-institutional or occur on a weekend. Finally, we filter the remaining trades using the usual bond price transaction filters (see Dick-Nielsen (2009, 2014)) and apply a median and a price reversal filter (5,676). To aggregate prices at a weekly level we compute the volume-weighted price in each week. In our main analysis, we focus on weeks nine and twelve to capture the specific drivers of credit spreads during the onset of the crisis. Because of this, the bonds in our sample need to have traded at least once during weeks nine and twelve (3,419). Moreover, we restrict the sample to bonds for which we observe all relevant control variables in Mergent FISD and Compustat to make results on different models comparable (2,374).

We acquire the score we use to proxy a firms ability to social distance from Koren and Pető (2020) which is supplied at their github page. Specifically, we use an aggregate of the two sub-scores, the 'communication_interact_share' and the 'presence_interact_share' to classify firms according to their social distancing ability. After applying the filters above, we only keep bonds that have a score measuring their social distancing ability (2,000).

Finally, from the Federal Reserve we obtain the parameters for the Svensson model to estimate the U.S. Treasury yield curve. We use this for the calculation of a duration-matched risk-free rate to calculate the yield spread for each bond at each traded date.

3.1 Descriptive Statistics

In this section, we provide descriptive statistics of our sample on the bond and firm level. Table 1 presents descriptives on the bond level, panel A displays all bonds while panels B and

C detail the sample split into investment and speculative grade bonds respectively. In total our sample consists of 2,000 bonds, with around 1,700 of them rated BBB or better. The median bond has an issue size of 700 million USD and investment grade bonds are on average larger by about 200 million USD than speculative grade bonds. Speculative grade bonds are traded more often than investment grade bonds (13 vs. 9 trades per week), but standard measures of liquidity show that there are substantial transaction costs. Also the average yield spread is higher by more than four percentage points for speculative grade bonds. We compute the summary statistics for yield spreads, price dispersion, Amihud and Roll measure over the year 2019 to avoid possible distortions due to the crisis. Coupons are higher by about 2 percentage points and the duration is slightly lower for speculative grade bonds. Panel A of Table 2 presents descriptive statistics for bonds that are affected by social distancing measures and panel B for bonds that are not affected by social distancing measures. Not affected bonds have a slightly larger issue size and are traded a bit more frequently. However, along all other dimensions the two sub-samples do not differ substantially.

Table 3 shows descriptive statistics on the firm level, panel A reports statistics for all firms and panels B and C for firms affected by social distancing and for firms not affected by social distancing measures respectively. The total number of firms represented in the sample is 520 and the average firm has about 6 bonds outstanding and 6% of outstanding bond volume maturing between March 2020 and March 2021. Firms affected by social distancing measures are slightly smaller than not affected firms and have higher leverage, but do not differ substantially in number of outstanding bonds, refinancing intensity and debt dispersion. Also, volatility was a bit larger for affected than for not affected firms in February 2020.

4 Methodology

4.1 Social distancing ability

In this paper we use the term *social distancing ability* to describe a firm's ability to cope with stern social distancing measures, (mandatory) stay-at-home mandates, work from home and all other pandemic related policies that are supposed to slow down the spread of the SARS-CoV-2 virus by physical means. Koren and Pető (2020) model different aspects of a firm's cost of social distancing by measuring industries' reliance on communication and machine dependent jobs. They use job description data from O*NET and sort the tasks listed in these descriptions by activities that require close proximity to other workers and customers (communication dependent), and to machines (physical proximity). In addition they use Current Employment Statistics (CES) from the U.S. Bureau of Labor Statistics to find the employment share of all 809 occupations for 3-digit NAICS industries. Next, they sum up all occupations that are heavily affected by social distancing for each industry weighted by the percent of workers that make up each occupation in that industry. Ultimately, they obtain two scores each ranging from 0 to 100 for each industry that explains what fraction of workers in each industry will be affected by social distancing policies with respect to communication or physical presence.

We want to aggregate these two scores and condense them into one variable. The social distancing ability is best captured by an indicator variable. We measure above a firm level median and account for a firm as being affected or not affected when either the communication or the physical presence score is above its firm-level median value. We do this because a firm may be affected by social distancing measures even when scoring high on only one of these dimensions. Combining both scores into a single variable might result in a wrong identification. For example, employees of a car manufacturer do not rely on close proximity to their customers and thus score low in the communication dimension. However, the firm has a very high score in the presence dimension as it can only operate when workers are present and control the machinery. Condensing these two orthogonal dimensions into one leads to a loss of information and more importantly might lead to firms that are highly affected in one dimension be classified as not affected. Therefore, for the main analysis, we use a dummy variable $s_{d,i}$ that is set to one if a firm is likely affected by social distancing measures. We make use of two sub-scores from Koren and Pető (2020). $s_{comm,i}$, 'communication_interact_share', measures the relative amount of "workers in teamwork-intensive or customer-facing occupations who cannot work from home" and $s_{pres,i}$, 'presence_interact_share', measures the relative amount of "workers in occupations requiring physical presence who cannot work from home".[1] A firm is likely affected if $s_{comm,i}$ or $s_{pres,i}$ are above their respective firm-level median. In the robustness section we provide results when we use the two scores separately and interacted. The social distancing measure is based on the subindustry level. Table 4 presents summary statistics on the distribution of the scores on the industry level. The industries mining, retail trade and transportation are almost entirely affected whereas the construction industry is hardly affected at all. The services industry has the most balanced sample in the sense that around 47% of firms are affected. Moreover, the table also displays the overall statistics on the scores. The span of s_{pres} has its maximum at 66, that of s_{comm} reaches up to 90. The respective firm-level medians are 11 and 16.

4.2 Bond risk

We measure the riskiness of a bond along three dimensions, default risk, liquidity risk and rollover risk and collect these in the bond risk-profile vector X^{risk}.

To measure a bond's default risk we use its credit rating. We use credit ratings from S&P, Moody's and Fitch and map all to the S&P scale. If not stated otherwise, we use the credit rating mapped to integers, where AAA=1, AA+=2, AA=3, and so on, i.e. a higher number means higher default risk. If we observe multiple ratings for a bond, we use the ceiling of the median of all ratings at that point in time.

[1] https://github.com/ceumicrodata/social-distancing/

We measure bond market liquidity with the price dispersion measure introduced by Jankowitsch et al. (2011). For every bond in each week t we compute

$$\text{Price Dispersion}_t = \sqrt{\frac{\sum_{i \in I} v_i (p_i - \bar{p})^2}{\sum_{i \in I} v_i}}, \tag{1}$$

where I is the set of all trades in week t, p_i and v_i are the price and volume of trade i and $\bar{p}$ is the volume weighted price of the bond in week t.

A high price dispersion means that trades occur at prices other than the market valuation price. Hence, higher price dispersion implies that the bond is less liquid and thus, carries higher liquidity risk.

To measure a firm's rollover risk we compute the ratio of the amount outstanding in bonds that mature within the next year over the total amount outstanding, the so-called refinancing intensity. We compute the refinancing intensity for each week t as

$$\text{Refinancing intensity}_t = \frac{x_{t,1}}{\sum_s x_{t,s}}, \tag{2}$$

where $x_{t,1}$ is the amount outstanding of all bonds of a firm maturing within the next year and $x_{t,s}$ is the bond amount maturing between the next $s-1$ and s years. This or similar measures are used frequently, e.g., Friewald et al. (2021), Nagler (2020) or Liu et al. (2021).

According to Nagler (2020) it is important to control for a firm's rollover exposure policy when trying to measure the effect of the rollover channel. Failing to do so might lead to biased results. To control for a firm's rollover exposure policy we employ the debt dispersion measure from Choi et al. (2018):

$$\text{Debt dispersion}_j = -\log\left(\frac{1}{t_j^{max}} \sum_{i=1}^{t_j^{max}} \left(w_{j,i} - \frac{1}{t_j^{max}}\right)^2\right),$$

where $w_i = \frac{x_i}{\sum_i x_i}$ is the outstanding amount of bond debt in maturity bucket i over the total amount outstanding in all maturity buckets and t_j^{max} represents the maximum outstanding bond maturity of firm j. The choice of t_j^{max} is firm j's strategic choice which is assumed to be optimal, hence this measure captures the distance to the firm's perfectly dispersed maturity profile, i.e., where an equal amount of debt is maturing in each point in time.

4.3 Measurement of the Covid-19 effect

In our main analysis we quantify the impact of rising economic and pandemic uncertainty on credit spreads/yield spreads. To measure yield spreads, $ys_{i,t}$, we compute the yield-to-maturity of bond i on day t, $y_{i,t}$, and subtract the rate of a duration matched treasury security. We obtain the yield-to-maturity for bond i on day t by computing the volume-weighted average yield-to-maturity of all transactions for this bond on that day.

To investigate the impact bond risk measures have had on the change in yield spreads during this specific crisis, we estimate the following cross-sectional regression model:

$$\Delta ys_i = \alpha + \beta_1 s_{d,i} + \beta_2 X_i^{\text{risk}} + \beta_3 X_i^{\text{bond}} + \beta_4 X_i^{\text{firm}} + \varepsilon_i \tag{3}$$

where Δys_i is the change in yield spread of bond i from week nine to week twelve, $s_{d,i}$ is an indicator set to one if the firm that issued bond i is likely to be affected by social distancing measures, X_i^{risk} is the risk vector of bond i which includes refinancing intensity, debt dispersion, price dispersion and credit rating, and X_i^{bond}, X_i^{firm} are vectors containing bond and firm control variables respectively. Refinancing intensity, debt dispersion, price dispersion and credit rating are measured in week nine. We use the coupon rate, the offering amount as well as the maturity of a bond as security specific control variables. As firm control variables we follow Nagler (2020) and use the amount of bond financing, size, cash and leverage measured two quarters earlier. Table 14 in the appendix gives a technical definition of the control variables used. To alleviate concerns about the chosen time window, we present results using different time windows over which we consider the change in yield spreads in the robustness section.

To understand whether the social distancing ability of a firm is a driver of yield spreads or, as hypothesized, only during a pandemic shock we estimate the following panel regression:

$$ys_{i,t} = \alpha + \beta_\tau \tau_t^{\text{shock}} + \beta_s s_{d,i} + \beta_{\tau\times s} s_{d,i} \tau^{\text{shock}} + \gamma_1 X_{i,t}^{\text{risk}} + \gamma_2 X_{i,t}^{\text{bond}} + \gamma_3 X_{i,t}^{\text{firm}} + \varepsilon_{i,t}, \tag{4}$$

where $ys_{i,t}$ is the yield spread of bond i in week t, $s_{d,i}$ is an indicator set to one if the firm that issued bond i is likely to be affected by social distancing measures, τ_t^{shock} is an indicator set to one if week t is classified as a shock-week. We classify weeks twelve to twenty as shock weeks; these are the weeks centered around March 18 and May 13 respectively. Thus, in the panel setup we apply a two month window of pandemic induced market distress. $X_{i,t}^{\text{risk}}$ is the vector of credit- and liquidity risk of bond i in week t, and $X_{i,t}^{\text{bond}}, X_{i,t}^{\text{firm}}$ are vectors containing bond and firm control variables respectively. We measure $X_{i,t}^{\text{risk}}$ and $X_{i,t}^{\text{bond}}$ in week t and lag firm controls by two quarters.

5 Empirical Analysis

5.1 Effect of social distancing ability in the U.S. bond market

We start our empirical analysis with the observation that credit and liquidity risk increased during the pandemic crisis. Figure 2 shows the average yield spread and price dispersion in the U.S. corporate bond market during the year 2020. Both credit and liquidity risk increase drastically in March 2020 and stay at high levels in the months following. On average, liquidity improved more quickly than credit risk. Splitting firms by their social distancing ability Figure 3 reveals that affected firms experienced a larger increase in yield spreads, i.e., the credit risk for firms prone to social distancing measures increased more than for their counterparts. However, we do not observe any difference in the price dispersion measure between firms that are likely affected and not affected by social distancing measures. Table 5 shows the change in yield spread for likely affected and not affected bonds over different time windows. The difference between the two groups decreases from 103 bp to 26 bp with the length of the time window but is statistically significant. We interpret this as a fading out of the importance of the social distancing ability over time. This fading out can have several reasons, for example, firms adjust to social distancing measures or real economic effects of these measures are better understood by market participants. Table 6 shows the cumulative stock returns for both groups over the same time windows. Again, we find that firms that are likely affected by social distancing measures experience a worse downturn than their counterparts. These results are also qualitatively similar to Pagano et al. (2021). For the first time window, week nine to twelve, where the largest market reactions are observed, we find that the difference in change in bond yield spreads is comparable in magnitude to the difference in cumulative stock returns. The change in yield spreads correspond to bond returns of 17.51% and 11.19% for the affected and not affected groups respectively and thus, the difference in returns is 6.32% and nearly identical to the 6.33% difference we observe in the stock market. However, for longer time windows we find that these differences drift apart.

5.2 Change in corporate bond yield spreads

In this section, we examine the driving factors of the change in yield spread during the onset of the Covid-19 crisis in the U.S. We analyze weeks nine and twelve, the weeks right before and at the peak of the crisis. As a result of the Fed's intervention, the shock to financial markets was short-lived which is why we want to isolate the difference between these two key weeks. Table 7 shows the estimation results of a few variations of the cross-sectional regression model (3). In models (1) and (2) we run cross-sectional regressions with bond and firm control variables and in models (3) and (4) without. In models (1) and (3) we add the indicator for social distancing ability.

When leaving out the indicator for social distancing ability, we already observe results similar to previous literature on the global financial crisis that bonds' credit, liquidity and rollover risk measures have a significant, positive effect on a bond's change in yield spread during crisis periods. Bonds that have lower liquidity, lower credit rating and higher rollover risk experienced a greater increase in yield spread. Debt dispersion measures firms' rollover exposure policy and is argued by Nagler (2020) that it is essential to control for this measure when estimating a firm's rollover risk. A lower value in this measure means that a firm's debt is less dispersed and more concentrated. So it is unsurprising that we find a negative sign for this measure in all models since a more dispersed debt structure in times of a liquidity shock will lessen the effect of rollover risk. When we do not consider the social distancing ability, then a one standard deviation increase in a bond's rating increases the change in yield spreads by 60 bp. A one standard deviation increase in price dispersion leads to a 85 bp increase in change in yield spreads and a one standard deviation increase in the refinancing intensity to a 11 bp increase. Comparing this with the great financial crisis we find that the overall effects are smaller, but the importance of the liquidity channel is larger during the pandemic crisis. Nagler (2020) reports in his main results that a decrease in rating (liquidity) by one standard deviation corresponds to a 404 bp (45 bp) increase in yield spreads. Moreover, firms that have a refinancing intensity of 10% or larger experience an additional increase of 158 bp in yield spreads. Although Nagler (2020) investigates a quarterly change in yield spread and his illiquidity measure is not directly comparable to ours, we conclude that the relative importance of the credit- and rollover risk channel is larger in the great financial crisis than during the 2020 pandemic shock.

Most importantly, when we control for a firm's social distancing ability in models (1) and (3) we observe that rollover risk, as measured by refinancing intensity, has an even greater impact on the change in yield spread. This shows that during this pandemic-driven crisis, it is necessary to control for a firm's ability to social distance. Otherwise, the coefficient of rollover risk measure is underestimated by about 27%. Further, we analyze this as being a determinant of a bond's default risk since it significantly impacts the rollover risk measure. This follows the specific type of default risk that bonds take on during this crisis as bond ratings are sticky, a firm's ability to social distance reflects the risks that firms have operating under stay-at-home policy constraints. A one standard deviation increase in rating or price dispersion increases the change in yield spreads by 61 bp and 81 bp respectively. When including the social distancing ability indicator the contribution of rollover risk to total credit risk increases from 15% to 19% and from 7.0% to 8.8% for total bond risk. We see that leaving out social distancing ability in this particular crisis overestimates the impact of liquidity and credit risk relative to rollover risk. The contribution of rollover risk to credit risk (total bond risk) was about 28% (26%). We attribute this difference to different length of the two shocks. The effect of the rollover risk channel is expected to be larger for longer lasting crisis since for more firms large exposures to rollover risk materialize.

5.3 Corporate bond yield spreads before, during and after the shock

Table 8 shows the estimation results of several model variants. Model (1) only contains the social distancing and the shock indicator as well as the bond-risk variable vector $X_{i,t}^{\text{risk}}$. Unsurprisingly, we find a positive and significant β_τ with a value of 0.610 indicating that, unconditionally, yield spreads were higher by about 61 bp during the crisis. Moreover, affected firms experienced an additional 73 bp increase in yield spreads during the shock period in comparison to average yield spreads during the same time. Model (2) includes the bond and firm controls coupon, offering size, maturity, amount of bond financing, firm size, leverage, income and cash. Controlling for these yields a β_τ that is higher by 11 bp and a slightly larger $\beta_{\tau\times s}$ of 0.746, both are again highly statistically significant. Moreover, including time fixed effects (Model (3)) does not change the size or significance of $\beta_{\tau\times s}$. In all models β_s is insignificant. This confirms our hypothesis that the social distancing ability of a firm is an important determinant of credit risk during pandemic times. However, it is only important when there is uncertainty about the real effects of social distancing measures on a firm.

The lower panel of Figure 4 displays the absolute value of the effect sizes of bond risk variables and the social distancing indicator relative to each other. The upper panel of Figure 4 shows the coefficient of partial determination for $s_{d,i}$. The turquoise bars indicate a significant F-test on the 5% level. Both panels of Figure 4 show that the social distancing ability of firms is a determinant of yield spreads if a pandemic shock hits the market but not otherwise. We measure a non-zero $\rho_{s,t}$ only during times of (pandemic related) market distress with a maximum of 1.2% in week thirteen, i.e., the week of the announcement of the Fed's quantitative easing measures. Looking at the lower panel, it becomes clear that the standard bond risk factors play an important role in the determination of credit spreads in the weeks that are not during the height of the pandemic shock. However, as soon as the liquidity shock hits the market, liquidity is no longer a significant determinant of credit spreads in the cross-section as the liquidity of all bonds suffers. We find that around this time the importance of a firm's social distancing ability in explaining the cross-section of credit spreads increases. This confirms our hypothesis that the social distancing ability of a firm is an important determinant of credit risk during pandemic times as long as there is uncertainty on the real effects of social distancing measures on a firm. Notice the significant impact in the beginning of 2021. We relate this to the increased uncertainty surrounding the change governing parties in the U.S. federal administration which, arguably, affected firms already in pandemic related distress.

5.4 Robustness

5.4.1 Standard errors

In this section, we address concerns regarding the choice of clustering level. Table 4 shows that the firms belonging to the mining, retail trade and transportation industry are almost all affected. This raises the question if our results are merely industry driven. We run several robustness checks to alleviate these concerns. We start by estimating the models (1) and (3) from Table 7 but instead of computing standard errors on the firm level we use standard errors clustered on the industry level (models (1) and (2)) and the subindustry level (models (3) and (4)). Moreover, we also report the coefficients on the control variables for the interested reader. A technical definition of the control variables can be found in the appendix. Table 9 shows the results of these models, the interpretation of the results is basically unchanged. Given that the social distancing measure is constructed using the subindustry level we consider our results to be very robust given different standard error clustering specifications.

5.4.2 Different time horizon

Next, we address the question if our results are robust to different time windows. In Table 10 we report the results of estimating the regression model (3) using a longer and a shorter time window respectively. In model (1) we use changes in yield spreads from week seven until week twelve and in model (2) from week eleven to week twelve. Week seven is the trading week from February 10 to 14 and week eleven is from March 9 to 13. The qualitative results are inline with our main analysis. The size of the coefficient of $s_{d,i}$ is larger (smaller) for the longer (shorter) time window which is intuitive. We also observe a non-significant coefficient for price dispersion in the regression with the shorter time window which is inline with our results in section 5.3. Moreover, the coefficient for the rating variable increases with the length of the time window. A one standard deviation increase in rating in the regression with the longest time window implies an 89 bp change. Similarly, a one standard deviation increase in rating in the main regressions, i.e., model (4) in Table 7 implies a 61 bp change and in the model with the shortest time window a 15 bp change. On the other hand, the increase in change in yield spreads for a one standard deviation increase in the refinancing intensity is roughly constant across models — 13 bp vs. 14 bp vs. 13 bp for the models decreasing in the length of the time window. The average change in yield spreads is also decreasing over the three time windows (320 bp vs. 296 bp vs. 166 bp) and thus, the relative price impact of rollover risk gets larger the closer we zoom in to the liquidity shock.

5.4.3 Social distancing measure

Lastly, we conduct a robustness test on the social distancing measure. First, we run a set of regressions where we employ the scores from Koren and Pető (2020) directly. Second, we estimate model (3) for investment and speculative grade bonds separately to examine whether our results are driven by one of the two groups of bonds.

Table 11 shows the estimation results of three different specifications of the cross-sectional regression model given by Equation (3). In the first two models we substitute $s_{d,i}$ by the scores used to construct the indicator, $s_{comm,i}$ (model (1)) and $s_{pres,i}$ (model (2)). In model (3) we use the interaction of the two instead of $s_{d,i}$. Note, that we center $s_{comm,i}$ and $s_{pres,i}$ to make the interpretation of the interaction term in model (3) straight forward. In line with our reasoning in Section 4, we observe insignificant social distancing coefficients in model (1) and (2) and only when we include the interaction term do the social distancing measures become significant. This underlines the importance that the *communication* and the *presence* channel have to be taken into account simultaneously. The results of this estimation are in line with the results presented above.

Table 12 and 13 show the results of model (3) for investment grade bonds and speculative grade bonds separately. The effect social distancing ability has on the change in yield spreads during the pandemic shock is larger for speculative grade bonds, but is also observable for investment grade bonds. Note that we excluded CCC rated bonds in this setup because the refinancing intensity variable is constant for all bonds within these rating classes. Figure 5 illustrates this. We emphasize that this neither affects the significance nor the magnitude of $s_{d,i}$.

6 Conclusion

In this paper, we explore the price impact of the Covid-19 crisis in the U.S. corporate bond market. We provide a detailed analysis of the main risk factors, while carefully considering the effects of social distancing measures on firms in the pandemic. Our focus is on the period of intense market distress in March 2020, presenting a perfect quasi-natural experiment to analyze shocks to default and liquidity risk. We distinguish between firms that were most impacted by the social distancing measures and firms that were less affected by using a social distancing measure based on Koren and Pető (2020). In addition to standard credit and liquidity risk factors, we cover the rollover channel, by considering the notional amount of bonds outstanding that have to be refinanced short-term at the onset of the pandemic.

Our results show that firms that are more affected by social distancing experience a stronger increase in yield spreads. On average, a bond of an affected firm increased by 103 bp more compared to an unaffected bond. Furthermore, we find that a firm's ability to cope with social distancing is an important determinant of bond yield spreads during the crisis but not before the crisis and after the implementation of Fed's quantitative easing programs. Overall, we document an important cross-sectional difference in the exposure of firms to the Covid-19 crisis that has to be considered before employing standard risk factors. In our main regression analysis, we employ credit and liquidity risk factors to explain yield spread changes. Although, we find a highly significant impact of liquidity measures as discussed in the previous literature, our results show that credit and liquidity risk have effects of similar size, once we consider differences in rollover risk across firms. Thus, it is important to include rollover risk, as this factor accounts for around 20% of the overall credit risk effect.

Overall, we contribute to the literature by showing the impact of social distancing measures for the U.S. corporate bond market. In addition, our results document that the importance of rollover risk is not limited to the particular case of the financial crisis 2007/08. Furthermore, we quantify the importance of default, liquidity and rollover risk for bond yield spreads in the pandemic, providing new insights on the impact of the individual risk factors.

References

Cejnek, G., Randl, O., and Zechner, J. (2021). The covid-19 pandemic and corporate dividend policy. *Journal of Financial and Quantitative Analysis*, 56(7):2389–2410.

Choi, J., Hackbarth, D., and Zechner, J. (2018). Corporate debt maturity profiles. *Journal of Financial Economics*, 130(3):484–502.

Choi, J., Hackbarth, D., and Zechner, J. (2021). Granularity of corporate debt. *Journal of Financial and Quantitative Analysis*, 56(4):1127–1162.

Dick-Nielsen, J. (2009). Liquidity biases in trace. *The Journal of Fixed Income*, 19(2):43–55.

Dick-Nielsen, J. (2014). How to clean enhanced trace data. *Available at SSRN 2337908.*

Friewald, N., Jankowitsch, R., and Subrahmanyam, M. G. (2012). Illiquidity or credit deterioration: A study of liquidity in the us corporate bond market during financial crises. *Journal of Financial Economics*, 105(1):18–36. To see the final version of this paper please visit the publisher's website. Access to this article requires a subscription.

Friewald, N., Nagler, F., and Wagner, C. (2021). Debt refinancing and equity returns. *Journal of Finance, Forthcoming.*

Gilchrist, S., Wei, B., Yue, V. Z., and Zakrajšek, E. (2020). The fed takes on corporate credit risk: An analysis of the efficacy of the smccf. Technical report, National Bureau of Economic Research.

Haddad, V., Moreira, A., and Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fed's response. *The Review of Financial Studies*, 34(11):5309–5351.

Halling, M., Yu, J., and Zechner, J. (2020). How did covid-19 affect firms' access to public capital markets? *The Review of Corporate Finance Studies*, 9(3):501–533.

Jankowitsch, R., Nashikkar, A., and Subrahmanyam, M. G. (2011). Price dispersion in otc markets: A new measure of liquidity. *Journal of Banking & Finance*, 35(2):343–357.

Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O., and Zúñiga, D. (2021). Corporate bond liquidity during the covid-19 crisis. *The Review of Financial Studies*, 34(11):5352–5401.

Koren, M. and Pető, R. (2020). Business disruptions from social distancing. *Plos one*, 15(9):e0239113.

Liu, Y., Qiu, B., and Wang, T. (2021). Debt rollover risk, credit default swap spread and stock returns: Evidence from the covid-19 crisis. *Journal of financial stability*, 53:100855.

Nagler, F. (2020). Yield spreads and the corporate bond rollover channel. *Review of Finance*, 24(2):345–379.

Nozawa, Y. and Qiu, Y. (2021). Corporate bond market reactions to quantitative easing during the covid-19 pandemic. *Journal of Banking & Finance*, 133:106153.

O'Hara, M. and Zhou, X. A. (2021). Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis. *Journal of Financial Economics*, 142(1):46–68.

Pagano, M., Wagner, C., and Zechner, J. (2021). Disaster resilience and asset prices. *Center for Financial Studies Working Paper*, (673).

Schestag, R., Schuster, P., and Uhrig-Homburg, M. (2016). Measuring liquidity in bond markets. *The Review of Financial Studies*, 29(5):1170–1219.

Figures & Tables

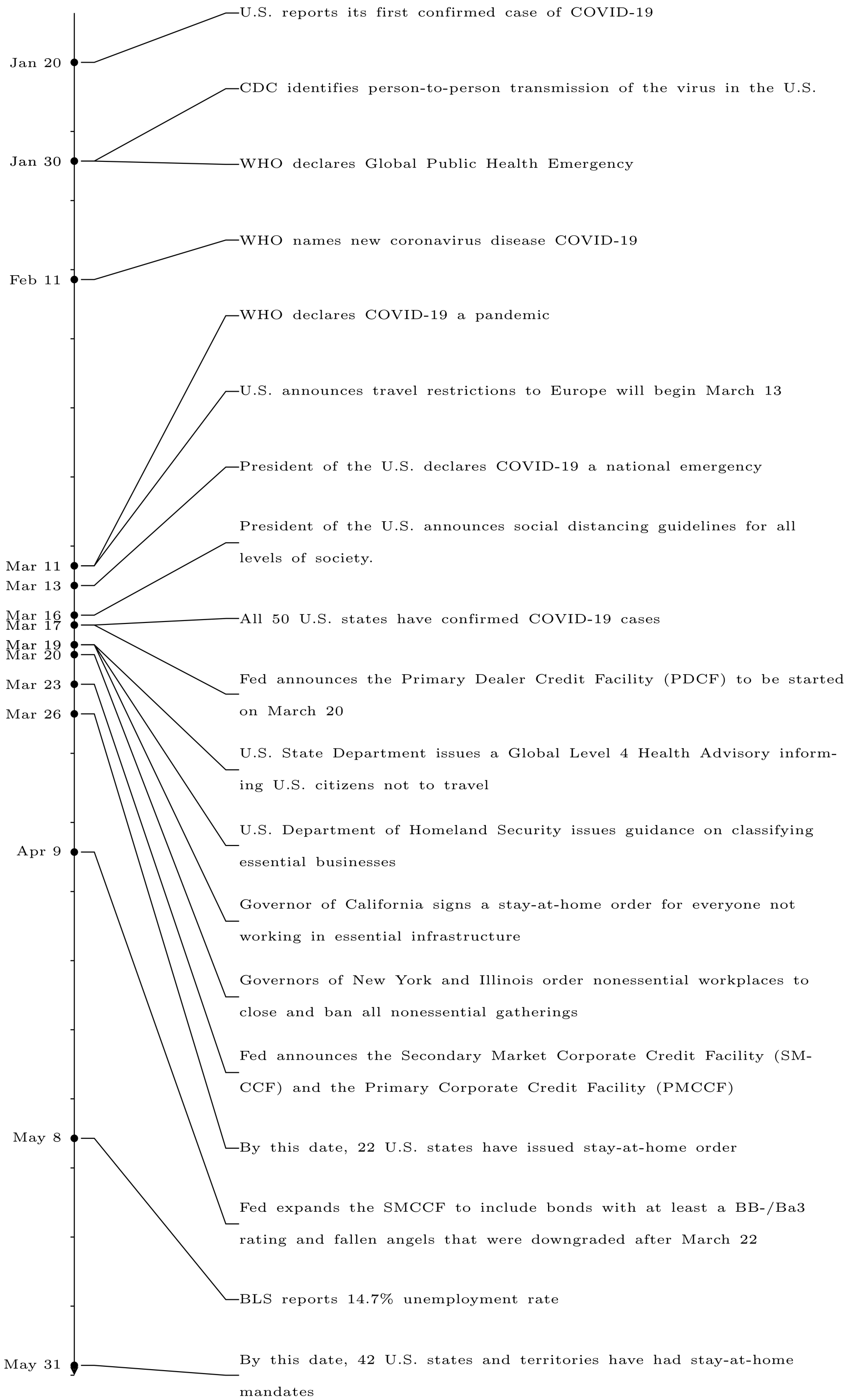

Figure 1: This figure shows a timeline of significant events in the U.S. during the progression of COVID-19 from January 2020 to the end of May 2020. Sources for each event are documented in chronological order in the appendix.

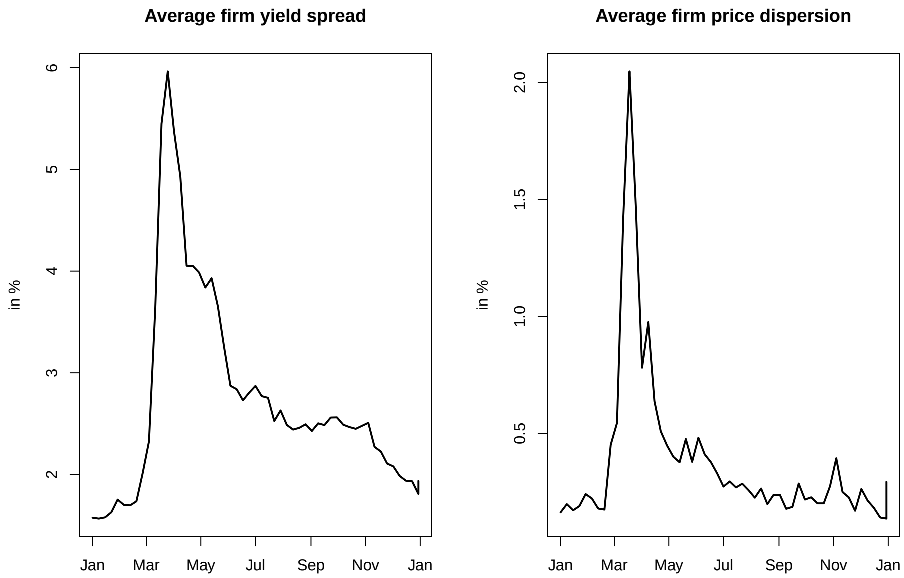

Figure 2: Average yield spread and price dispersion. This figure shows the average yield spread and price dispersion for all firms in the sample. We use the trading volume to compute the weighted average of yield spreads and price dispersion for each firm, and average over all firms.

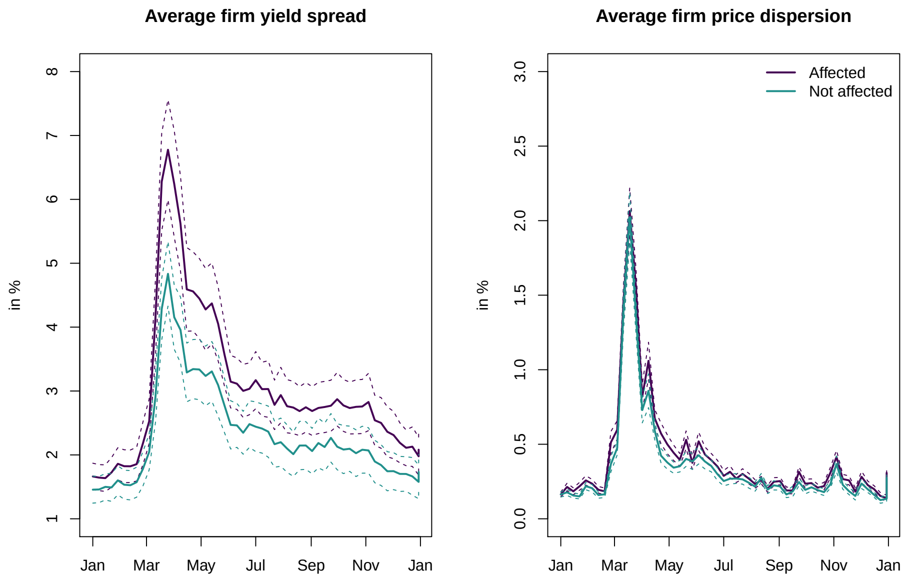

Figure 3: Average yield spread and price dispersion by social distancing ability. This figure shows the average yield spread and price dispersion for all firms in the sample split on their ability to cope with social distancing measures. Section 4 details the classification of affected and not affected by social distancing measures. We use the trading volume to compute the weighted average of yield spreads and price dispersion for each firm, and average over all firms.

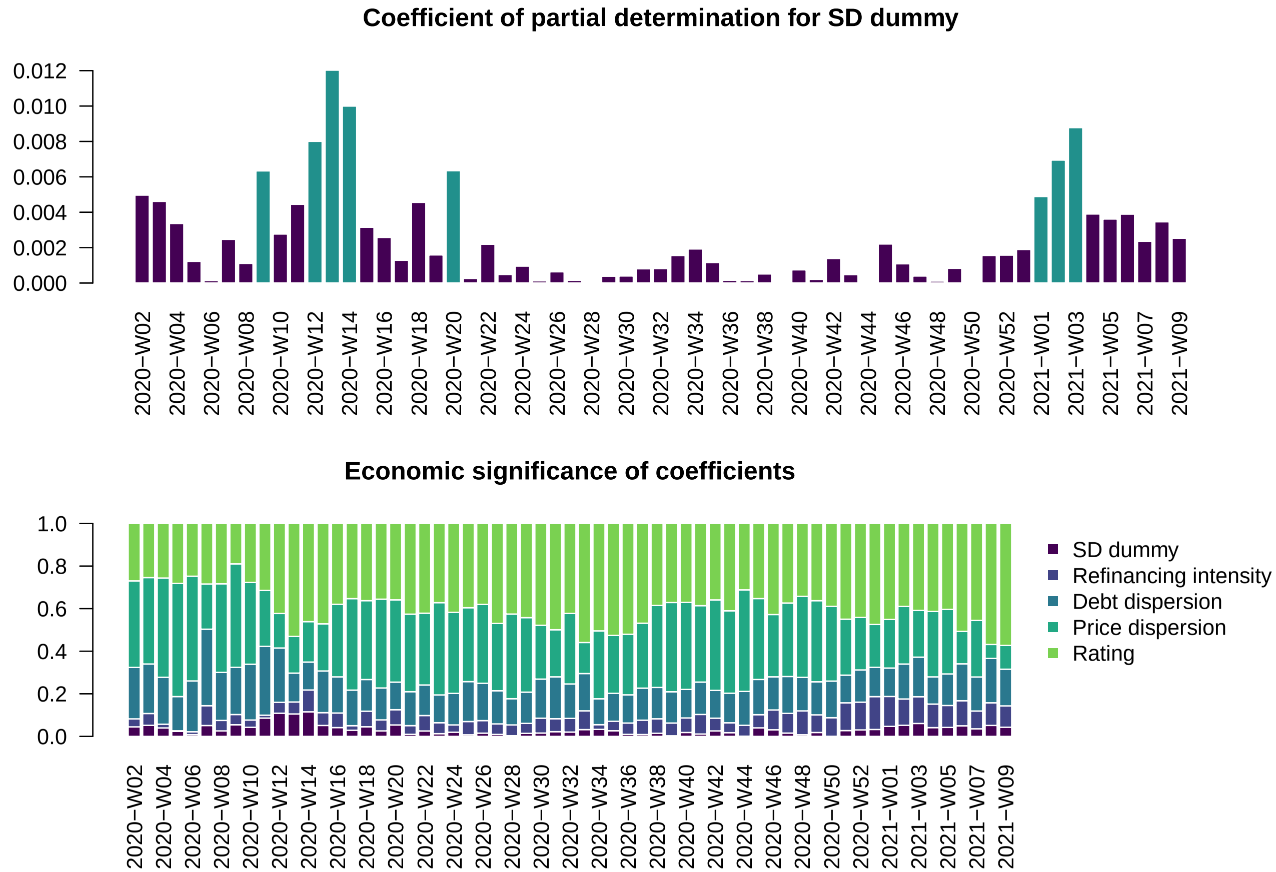

Figure 4: Importance of social distancing ability over time. This figure shows in the upper panel the coefficient of partial determination for the social distancing dummy $s_{d,i}$ for a series of cross-sectional regressions. Turquoise colored bars indicate a significant F-test on the 5% level. The coefficient of determination is given by the relative increase in R^2 of a model using $s_{d,i}$ to a model without. The lower panel shows the economic significance of $s_{d,i}$ and other risk related coefficients. We run a series of cross-sectional regressions of yield spread on $s_{d,i}$ and $\bar{X}^{\text{risk}}_i$, the standardized form of X_i^{risk}, as well as bond and firm controls and adjust the coefficient of $s_{d,i}$ by the respective standard deviation. The figure displays the relative magnitude of the absolute standardized coefficients.

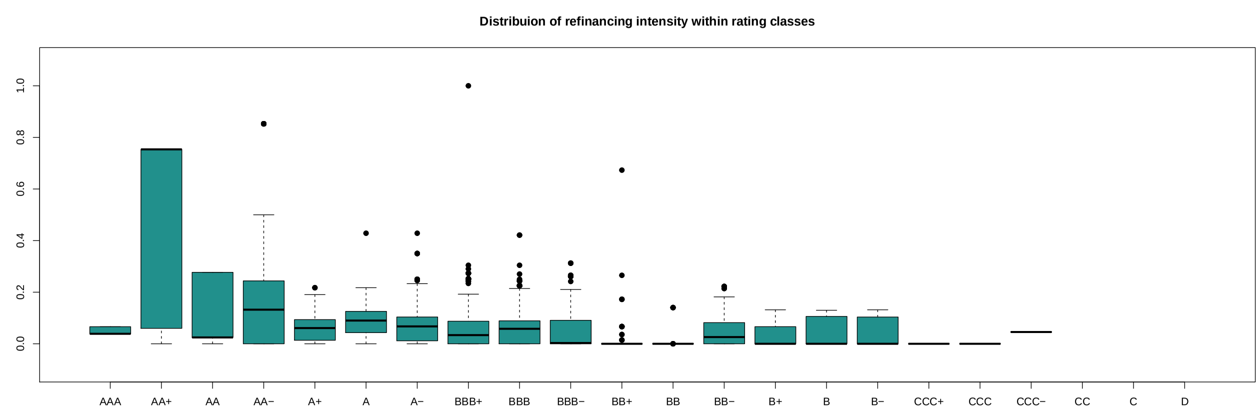

Figure 5: Distribution of the refinancing intensity within rating classes. This figure shows the boxplots for the refinancing intensity for each rating class. Section 4 details the calculation of this variable.

Table 1: Summary statistics for bonds by rating. Amount issued and traded volume per week are in millions of USD. The Amihud measure is multiplied with 10^7. Yield spread, price dispersion, Amihud and Roll measure are computed over the year 2019. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Rating is encoded in numbers where AAA=1, AA+=2, ... D=22.

	Mean	Median	Sdev	$q_{0.05}$	$q_{0.95}$	N
Panel A: All bonds						
Amount issued	876.32	700.00	638.14	300.00	2000.00	2000
Traded volume per week	15.67	10.00	18.36	2.94	45.20	2000
Trades per week	12.32	9.47	9.41	3.66	30.68	2000
Coupon	3.81	3.60	1.25	2.20	6.13	2000
Yield spread	1.34	1.00	1.19	0.27	3.65	1946
Price dispersion	0.21	0.18	0.12	0.06	0.46	1946
Amihud	0.08	0.07	0.06	0.03	0.19	1946
Roll	0.30	0.26	0.17	0.11	0.65	1946
Rating	8.18	8.00	2.94	3.00	14.00	2000
Duration	5.00	4.43	3.42	0.96	12.50	2000
Panel B: Investment grade bonds						
Amount issued	903.31	750.00	648.75	300.00	2249.32	1766
Traded volume per week	15.70	9.38	26.54	2.87	43.70	1766
Trades per week	11.92	9.07	11.50	3.55	28.59	1766
Coupon	3.55	3.45	1.00	2.15	5.33	1766
Yield spread	1.04	0.89	0.68	0.26	2.46	1707
Price dispersion	0.19	0.17	0.11	0.06	0.43	1707
Amihud	0.08	0.07	0.05	0.03	0.18	1707
Roll	0.29	0.25	0.17	0.11	0.64	1707
Rating	7.37	8.00	2.08	3.00	10.00	1766
Duration	5.16	4.59	3.56	0.95	12.82	1766
Panel C: Speculative grade bonds						
Amount issued	707.94	582.52	483.46	262.40	1500.00	375
Traded volume per week	36.40	14.32	131.81	3.47	71.93	375
Trades per week	19.31	13.34	21.92	4.67	44.65	375
Coupon	5.38	5.38	1.30	3.30	7.62	375
Yield spread	3.26	2.98	1.65	1.20	6.26	311
Price dispersion	0.29	0.26	0.16	0.10	0.57	311
Amihud	0.10	0.08	0.07	0.03	0.25	311
Roll	0.38	0.33	0.18	0.17	0.72	311
Rating	12.94	12.57	1.90	11.00	16.18	375
Duration	4.44	4.11	2.44	1.03	9.18	375

Table 2: Summary statistics for bonds by social distancing exposure. Amount issued and traded volume per week are in millions of USD. The Amihud measure is multiplied with 10^7. Yield spread, price dispersion, Amihud and Roll measure are computed over the year 2019. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Rating is encoded in numbers where AAA=1, AA+=2, ... D=22.

	Mean	Median	Sdev	$q_{0.05}$	$q_{0.95}$	N
Panel A: Affected by social distancing measures						
Amount issued	801.05	625.00	592.54	300.00	1750.00	1175
Traded volume per week	15.77	9.70	20.36	2.86	46.13	1175
Trades per week	11.86	8.90	9.64	3.54	30.30	1175
Coupon	3.89	3.70	1.28	2.25	6.38	1175
Yield spread	1.42	1.06	1.25	0.31	3.86	1143
Price dispersion	0.21	0.19	0.13	0.06	0.48	1143
Amihud	0.08	0.07	0.06	0.03	0.20	1143
Roll	0.31	0.26	0.18	0.11	0.66	1143
Rating	8.55	8.30	2.83	4.95	14.35	1175
Duration	5.18	4.53	3.56	0.98	12.85	1175
Panel B: Not affected by social distancing measures						
Amount issued	983.51	750.00	684.17	300.00	2290.00	825
Traded volume per week	15.52	10.55	15.06	3.12	41.67	825
Trades per week	12.98	10.46	9.03	3.91	31.24	825
Coupon	3.70	3.50	1.21	2.12	5.95	825
Yield spread	1.23	0.91	1.08	0.24	3.45	803
Price dispersion	0.20	0.18	0.11	0.06	0.42	803
Amihud	0.08	0.07	0.05	0.03	0.18	803
Roll	0.30	0.26	0.16	0.11	0.61	803
Rating	7.65	8.00	3.02	2.00	13.00	825
Duration	4.74	4.30	3.21	0.92	11.96	825

Table 3: Firm descriptives conditional on social distancing ability (at the beginning of March). Size is in billions of USD. Leverage is defined as total debt over total assets. Refinancing intensity is the sum outstanding of all bonds that mature within one year over the total sum outstanding of all bonds. Debt dispersion is defined in section 4. Volatility is the daily stock volatility over the last month, i.e. February, in %. Income is defined as income before extraordinary items dividid by assets, cash as cash and short-term equivalents over assets and bond financing as the sum of outstanding bond divided by the sum of short and long term debt. Firms, i.e. their bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded.

	Mean	Median	Sdev	$q_{0.05}$	$q_{0.95}$	N
Panel A: All firms						
Size	53.53	17.85	138.79	2.49	201.20	519
Leverage	0.38	0.36	0.21	0.10	0.67	519
Bonds	6.26	4.00	6.87	1.00	20.05	520
Refinancing intensity	0.06	0.00	0.12	0.00	0.24	520
Debt dispersion	4.41	4.69	1.19	1.84	5.83	520
Volatility	4.57	3.91	2.50	2.55	9.00	403
Income	0.01	0.01	0.02	-0.01	0.04	519
Cash	0.07	0.03	0.10	0.00	0.26	519
Bond financing	0.80	0.71	1.99	0.11	1.11	519
Panel B: Affected by social distancing measures						
Size	52.28	20.06	111.60	2.51	218.01	303
Leverage	0.40	0.38	0.23	0.14	0.70	303
Bonds	6.76	4.00	7.09	1.00	21.85	304
Refinancing intensity	0.05	0.00	0.11	0.00	0.24	304
Debt dispersion	4.48	4.78	1.14	1.98	5.81	304
Volatility	5.03	4.18	3.13	2.56	11.05	201
Income	0.01	0.01	0.02	-0.01	0.04	303
Cash	0.04	0.02	0.07	0.00	0.16	303
Bond financing	0.84	0.69	2.57	0.10	1.10	303
Panel C: Not affected by social distancing measures						
Size	55.30	15.90	170.03	2.48	167.75	216
Leverage	0.36	0.34	0.17	0.08	0.63	216
Bonds	5.57	3.00	6.50	1.00	19.00	216
Refinancing intensity	0.06	0.00	0.12	0.00	0.24	216
Debt dispersion	4.30	4.55	1.26	1.74	5.86	216
Volatility	4.11	3.72	1.54	2.55	7.82	202
Income	0.01	0.01	0.02	-0.01	0.04	216
Cash	0.11	0.07	0.12	0.01	0.39	216
Bond financing	0.73	0.74	0.44	0.15	1.20	216

Table 4: Summary statistics for industries. This table shows the number of bonds, firms, firms affected by social distancing measures as well as the range of the s_{comm} and s_{pres} score for each division in our sample. We map firms to division using their SIC code and NAICS code for firms without SIC code.

	Bonds	Firms	Affected firms	s_{comm}	s_{pres}
Construction	30	10	1	[12, 17]	[1, 36]
Manufacturing	687	181	43	[6, 31]	[0, 41]
Mining	105	39	37	[10, 31]	[1, 61]
Retail trade	159	34	33	[10, 90]	[0, 23]
Services	470	107	50	[6, 67]	[0, 33]
Transportation	511	136	135	[7, 48]	[0, 66]
Wholesale trade	38	13	5	[10, 16]	[4, 13]
Total	2000	520	304	[6, 90]	[0, 66]

Table 5: Changes in yield spreads over different time windows. We report the change in yield spread in percentage points. Week nine is the trading week 24-28.2.2020, week twelve is 16-20.3.2020, week sixteen is 13-17.4.2020 and week thirty is 20-24.7.2020. We only include firms that have bonds with a valid rating at least once during the sample period (1.1.2019 - 30.6.2021). We also remove firms that only have bonds in default and bonds with a maturity larger than 30 years.

	W12 - W09	W16 - W09	W30 - W09
	W12: Mar.16 - Mar.20	W16: Apr.13 - Apr.17	W30: Jul.20 - Jul.24
(Less)	*W09: Feb.24 - Feb.28*	*W09: Feb.24 - Feb.28*	*W09: Feb.24 - Feb.28*
Affected	3.38	1.79	0.50
Not affected	2.36	1.13	0.24
Difference	1.03***	0.66***	0.26***
St.Error	0.14	0.10	0.05

Table 6: Average firm stock return over different time windows. We report the average of firm stock returns in percent. Week nine is the trading week 24-28.2.2020, week twelve is 16-20.3.2020, week sixteen is 13-17.4.2020 and week thirty is 20-24.7.2020. We compute stock returns using adjusted prices in the middle of the week. Firms are included in the sample if they have outstanding bonds that are rated, not in default and have a maturity of less than 30 years. The statistical significance of the difference in stock returns is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	W12 - W09	W16 - W09	W30 - W09
Affected	-35.06	-23.24	-6.76
Not affected	-28.73	-16.89	0.98
Difference	6.33***	6.36***	7.73***
St.Error	2.15	2.20	2.49

Table 7: Cross-sectional regression models on changes in yield spreads. This table reports the results of the following multivariate regression model:

$$\Delta ys_i = \alpha + \beta_1 s_{d,i} + \beta_2 X_i^{\text{risk}} + \beta_3 X_i^{\text{bond}} + \beta_4 X_i^{\text{firm}} + \varepsilon_i,$$

where Δys_i is the change in yield spread of bond i from week nine to week twelve, $s_{d,i}$ an indicator set to one if the firm that issued bond i is likely to be affected by social distancing measures (as described in section 4), X_i^{risk} is the risk profile of bond i, and X_i^{bond}, X_i^{firm} are vectors containing bond and firm control variables respectively. A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 1% level where meaningful, i.e., we set the lowest (highest) 1% of observations to their respective quantile, and report standard errors that are clustered on the firm level. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
$s_{d,i}$	0.584***		0.516***	
	(0.157)		(0.151)	
Refinancing intensity	1.132***	0.892**	1.388***	1.116**
	(0.435)	(0.436)	(0.506)	(0.492)
Debt dispersion	−0.124	−0.103	−0.244**	−0.213**
	(0.103)	(0.104)	(0.106)	(0.106)
Price disperson	1.811***	1.853***	1.467***	1.503***
	(0.307)	(0.312)	(0.298)	(0.304)
Rating	0.207***	0.204***	0.333***	0.343***
	(0.041)	(0.039)	(0.040)	(0.040)
α	1.214*	1.534**	0.456	0.527
	(0.649)	(0.632)	(0.717)	(0.714)
Bond controls	Yes	Yes	No	No
Firm controls	Yes	Yes	No	No
Observations	2,000	2,000	2,000	2,000
R^2	0.359	0.351	0.287	0.279
Adjusted R^2	0.355	0.347	0.285	0.278
Residual Std. Error	2.248 (df = 1986)	2.262 (df = 1987)	2.367 (df = 1994)	2.379 (df = 1995)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 8: Panel regression on yield spreads. This table reports the results of the following multivariate regression model:

$$ys_{i,t} = \alpha + \beta_\tau \tau_t^{\text{shock}} + \beta_s s_{d,i} + \beta_{\tau\times s} s_{d,i}\tau^{\text{shock}} + \gamma_1 X_{i,t}^{\text{risk}} + \gamma_2 X_{i,t}^{\text{bond}} + \gamma_3 X_{i,t}^{\text{firm}} + \varepsilon_{i,t},$$

where $ys_{i,t}$ is the yield spread of bond i in week t, $s_{d,i}$ an indicator set to one if the firm that issued bond i is likely to be affected by social distancing measures (as described in section 4), τ_t^{shock} an indicator set to one if week t is classified as a shock-week, $X_{i,t}^{\text{risk}}$ is the risk profile of bond i in week t, and $X_{i,t}^{\text{bond}}$, $X_{i,t}^{\text{firm}}$ are vectors containing bond and firm control variables respectively. A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 1% level where meaningful. The yield spread is winsorized on a weekly basis all other variables are winsorized on the whole sample. We report standard errors that are clustered on the firm level. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing.

	Dependent variable:		
	$ys_{i,t}$		
	(1)	(2)	(3)
$s_{d,i}$	−0.036	−0.018	−0.014
	(0.123)	(0.104)	(0.104)
τ^{shock}	0.610***	0.724***	
	(0.131)	(0.125)	
$s_{d,i}\tau^{\text{shock}}$	0.732***	0.746***	0.745***
	(0.228)	(0.237)	(0.236)
Risk-profile	Yes	Yes	Yes
Bond, firm controls	No	Yes	Yes
Time fixed-effects	No	No	Yes
Observations	48,131	48,131	48,131
R^2	0.604	0.646	0.662
Adjusted R^2	0.604	0.646	0.662
Residual Std. Error	1.398 (df = 48123)	1.322 (df = 48115)	1.292 (df = 48056)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 9: Standard error robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Table of models (1) and (3) of Table 7 using an industry based standard error clustering. Models (1) and (2) use industry level clusters and models (3) and (4) subindustry level clusters. The table reports the results of the estimation of the multivariate regression model (3) in section 5. A detailed description of how we compute all variables is in section 4 for the main variables of interest and in the appendix for the control variables. We winsorize all variables at the 1% level where meaningful. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing. Also in this table we show the estimated coefficients of the control variables.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
$s_{d,i}$	0.584***	0.516*	0.584**	0.516**
	(0.215)	(0.270)	(0.242)	(0.260)
Refinancing intensity	1.132**	1.388***	1.132**	1.388***
	(0.450)	(0.480)	(0.477)	(0.414)
Debt dispersion	−0.124	−0.244*	−0.124	−0.244**
	(0.146)	(0.129)	(0.103)	(0.103)
Price dispersion	1.811***	1.467***	1.811***	1.467***
	(0.375)	(0.449)	(0.428)	(0.440)
Rating	0.207***	0.333***	0.207***	0.333***
	(0.036)	(0.030)	(0.035)	(0.032)
Coupon	0.362***		0.362***	
	(0.040)		(0.081)	
Offering size	−0.00000***		−0.00000*	
	(0.00000)		(0.00000)	
Maturity	−0.145***		−0.145***	
	(0.015)		(0.019)	
Bond financing	−0.0002**		−0.0002**	
	(0.0001)		(0.0001)	
Firm size	0.00000***		0.00000***	
	(0.00000)		(0.00000)	
Income	−5.643		−5.643	
	(5.219)		(5.434)	
Cash	0.177		0.177	
	(0.240)		(0.666)	
Leverage	−0.143		−0.143	
	(0.708)		(0.510)	
α	1.214*	0.456	1.214**	0.456
	(0.738)	(0.464)	(0.596)	(0.420)
Observations	2,000	2,000	2,000	2,000
R^2	0.359	0.287	0.359	0.287
Adjusted R^2	0.355	0.285	0.355	0.285
Residual Std. Error	2.248 (df = 1986)	2.367 (df = 1994)	2.248 (df = 1986)	2.367 (df = 1994)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 10: Time-frame robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Table 7 containing several robustness checks. The table reports the results of the estimation of the multivariate regression model (3) in section 5. A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 1% level where meaningful. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing. Model (1) and (2) are as Model (4) in Table 7 with the difference that in model (1) of this table the change in yield spreads is from week 7 to week 12 and in model (2) from week 11 to week 12.

	Dependent variable:	
	Δys_i	
	(1)	(2)
$s_{d,i}$	0.613***	0.300***
	(0.197)	(0.103)
Refinancing intensity	1.089**	1.031***
	(0.511)	(0.302)
Debt dispersion	−0.127	−0.061
	(0.146)	(0.063)
Price dispersion	2.932***	0.003
	(0.886)	(0.053)
Rating	0.301***	0.149***
	(0.041)	(0.019)
α	0.383	0.689*
	(0.929)	(0.380)
Observations	1,933	2,013
R^2	0.334	0.231
Adjusted R^2	0.330	0.226
Residual Std. Error	2.391 (df = 1920)	1.395 (df = 1999)
Note:		*p<0.1; **p<0.05; ***p<0.01

Table 11: Social distancing robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Table 7 containing several robustness checks. The table reports the results of the estimation of the multivariate regression model (3) in section 5. A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 2.5% level where meaningful. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing. Model (1) reports the results of using bonds that do not belong to highly affected industries, i.e., mining, retail trade and transportation, standard errors are clustered on the division level. Model (2) excludes the same industries but instead of using a social distancing dummy we use a score, standard errors are again clustered on the division level. Model (3) and (4) are as Model (4) in Table 7 with the difference that in model (3) of this table the change in yield spreads is from week 7 to week 12 and in model (4) from week 11 to week 12.

	Dependent variable:		
	Δys_i		
	(1)	(2)	(3)
$s_{\text{comm},i}$	0.002		0.018**
	(0.004)		(0.008)
$s_{\text{pres},i}$		0.007	0.010*
		(0.006)	(0.006)
$s_{\text{comm},i} \times s_{\text{pres},i}$			0.002**
			(0.001)
Refinancing intensity	1.324**	1.341**	1.036*
	(0.636)	(0.637)	(0.619)
Debt dispersion	−0.069	−0.074	−0.054
	(0.099)	(0.098)	(0.097)
Price dispersion	1.711***	1.687***	1.660***
	(0.273)	(0.272)	(0.272)
Rating	0.196***	0.197***	0.193***
	(0.031)	(0.032)	(0.032)
α	1.229**	1.207**	1.152**
	(0.566)	(0.574)	(0.569)
Observations	2,000	2,000	2,000
R^2	0.384	0.385	0.392
Adjusted R^2	0.380	0.381	0.388
Residual Std. Error	1.816 (df = 1987)	1.814 (df = 1987)	1.805 (df = 1985)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 12: Investment grade robustness: Cross-sectional regression models on changes in yield spreads. This table reports the results of the multivariate regression model (3) for investment grade bonds. A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 1% level where meaningful and report standard errors that are clustered on the firm level. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
$s_{d,i}$	0.359**		0.293*	
	(0.170)		(0.156)	
Refinancing intensity	1.046**	0.872*	1.317**	1.146**
	(0.469)	(0.457)	(0.532)	(0.504)
Debt dispersion	−0.083	−0.084	−0.112	−0.104
	(0.114)	(0.114)	(0.119)	(0.119)
Price disperson	0.961***	0.984***	0.355	0.373
	(0.351)	(0.366)	(0.430)	(0.442)
Rating	0.234***	0.228***	0.326***	0.333***
	(0.042)	(0.040)	(0.040)	(0.041)
α	0.816	1.110*	0.214	0.302
	(0.664)	(0.621)	(0.750)	(0.742)
Bond controls	Yes	Yes	No	No
Firm controls	Yes	Yes	No	No
Observations	1,704	1,704	1,704	1,704
R^2	0.202	0.196	0.125	0.120
Adjusted R^2	0.196	0.190	0.122	0.118
Residual Std. Error	1.813 (df = 1690)	1.819 (df = 1691)	1.894 (df = 1698)	1.898 (df = 1699)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 13: Speculative grade robustness: Cross-sectional regression models on changes in yield spreads. This table reports the results of the multivariate regression model (3) for speculative grade bonds excluding CCC rated bonds (see Section 5). A detailed description of how we compute all variables is in section 4. We winsorize all variables at the 1% level where meaningful and report standard errors that are clustered on the firm level. Bonds have to be rated at least once during the sample period (1.1.2019 - 30.6.2021), bonds in default are removed and bonds with a maturity larger than 30 years are also excluded. Moreover, for a bond to be included in any of the reported models all explanatory variables have to be non-missing.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
$s_{d,i}$	2.406***		2.178***	
	(0.543)		(0.552)	
Refinancing intensity	4.488*	3.648	0.682	0.048
	(2.574)	(2.663)	(2.573)	(2.788)
Debt dispersion	−0.241	0.128	−0.374	−0.104
	(0.422)	(0.417)	(0.324)	(0.323)
Price disperson	2.067***	2.227***	2.214***	2.430***
	(0.572)	(0.622)	(0.586)	(0.623)
Rating	0.015	0.102	0.241	0.319*
	(0.187)	(0.193)	(0.159)	(0.165)
α	4.332*	3.328	0.765	−0.026
	(2.332)	(2.494)	(2.173)	(2.334)
Bond controls	Yes	Yes	No	No
Firm controls	Yes	Yes	No	No
Observations	281	281	281	281
R^2	0.298	0.237	0.222	0.170
Adjusted R^2	0.264	0.203	0.208	0.158
Residual Std. Error	3.693 (df = 267)	3.841 (df = 268)	3.830 (df = 275)	3.949 (df = 276)
Note:				*p<0.1; **p<0.05; ***p<0.01

Appendix

Table 14: Control variables

Coupon	The coupon in % as reported in the field `coupon` in the Mergent FISD.
Offering size	The offering amount of a bond in thousands of USD as reported in the field `offering_amt` in the Mergent FISD.
Maturity	The total time to maturity of a bond in years computed from using the fields `maturity` and `offering_dt` from the Mergent FISD as (`maturity-offering_dt`)/365.25
Bond financing	The sum of the amount outstanding of all bonds in the Mergent FISD divided by the sum of debt in current liabilities (`dlc`) and long term debt (`dltt`) from the Compustat database.
Firm size	Total asset (`at`) from the Compustat database.
Income	Defined as income before extraordinary items (`ib`) scaled by total assets (`at`) from the Compustat database.
Cash	Defined as cash and short term investments (`che`) scaled by total assets (`at`) from the Compustat database.
Leverage	Defined as the sum of debt in current liabilities (`dlc`) and long term debt (`dltt`) divided by the book value of total assets (`at`) from the Compustat database.

Table 15: Timeline sources

	Event	Source
1	First U.S. case	https://www.cdc.gov/media/releases/2020/p0121-novel-coronavirus-travel-case.html
2	Virus transmission identified	https://www.cdc.gov/media/releases/2020/p0130-coronavirus-spread.html
3	Global health emergency	https://www.who.int/publications/m/item/situation-report---11
4	Disease named COVID-19	https://www.who.int/emergencies/diseases/novel-coronavirus-2019/technical-guidance/naming-the-coronavirus-disease-(covid-2019)-and-the-virus-that-causes-it
5	Pandemic announcement	https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020
6	Europe travel restrictions	https://trumpwhitehouse.archives.gov/briefings-statements/remarks-president-trump-address-nation/
7	National emergency	https://trumpwhitehouse.archives.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/
8	Social distancing guidelines	https://trumpwhitehouse.archives.gov/articles/15-days-slow-spread/
9	All states have confirmed cases	https://www.defense.gov/Spotlights/Coronavirus-DOD-Response/Timeline/
10	Fed announces PDCF	https://www.federalreserve.gov/newsevents/pressreleases/monetary20200317b.htm
11	Global Level 4 Health Advisory	https://www.forbes.com/sites/carlieporterfield/2020/03/19/us-state-department-tells-americans-not-to-travel-abroad/
12	Essential business guidance	https://www.cisa.gov/identifying-critical-infrastructure-during-covid-19
13	California stay-at-home order	https://www.gov.ca.gov/2020/03/19/governor-gavin-newsom-issues-stay-at-home-order/
14	New York stay-at-home order	https://edition.cnn.com/2020/03/20/politics/new-york-workforce-stay-home/index.html
15	Illinois stay-at-home order	https://www2.illinois.gov/IISNews/21288-Gov._Pritzker_Stay_at_Home_Order.pdf
16	Fed announces PMCCF and SMCCF	https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm
17	22 states have stay-at-home orders	https://www.defense.gov/Spotlights/Coronavirus-DOD-Response/Timeline/
18	Fed expands SMCCF	https://www.federalreserve.gov/newsevents/pressreleases/monetary20200409a.htm
19	BLS unemployment rate	https://www.bls.gov/news.release/archives/empsit_05082020.pdf
20	42 mandatory stay-at-home orders	https://www.cdc.gov/mmwr/volumes/69/wr/mm6935a2.htm?s_cid=mm6935a2_w