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

February 3, 2023

Abstract

We analyze the price and liquidity effects in the U.S. corporate bond market caused by the Covid-19 crisis. We carefully consider the different impact of social distancing measures on firms. We find significant effects, i.e., bonds of firms that are more affected by these measures show a much stronger increase in yield spreads by 40.9 bp. Controlling for these effects, we employ standard credit and liquidity risk factors to explain yield spread changes. In addition, we explicitly consider the rollover risk channel. Although, we find a highly significant impact of liquidity measures as discussed in the previous literature, our results show that for firms highly affected by social distancing measures credit risk is the dominant factor.

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 social distancing 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 a measure 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. Thus, 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. 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. Note, that this time window is before the Fed announcements to directly intervene in the corporate bond market. In an additional analysis, we study a much longer time window impacted by the crisis going until mid-June, when the majority of U.S. states started reopening phases.

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 subindustry scores between 0 and 100 based on the share of workers affected by social distancing. This estimation of the affected share is based on description data of occupations measuring the reliance on human interaction and physical presence, which makes distancing more costly. We argue that (mandatory) stay-at-home policies, 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 exactly 2,000 outstanding bonds, representing 52% of the total trading volume in March 2020. We cover the year 2020 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 16 to 20, 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 this week. 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 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 40.9 bp more compared to an unaffected bond between weeks nine and twelve, based on the results of our 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 an important proxy for credit risk in the crisis, but not 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 and we find basically no significant results after 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, strengthening the view that social distancing impacts the credit risk of a firm and indicating that the observed liquidity crisis concerned the whole market including 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 12 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 that if the nature of the crisis is carefully considered by controlling for social distancing effects, then credit risk is the dominate factor for affected firms, whereas for unaffected firms the liquidity component is more important. Considering all effects together, a one standard deviation change in credit risk leads to an increase in yield spreads of 113.9 bp for affected firms and 73 bp for unaffected firms. In comparison, liquidity has an impact of 84 bp. These results shed light on the mixed results found in the existing literature

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 and stocks during the pandemic. The show that CDS spreads increased and share prices decrease for firms with higher rollover risk. Friewald et al. (2022) document the rollover channel in stock markets before the start of 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 credit spreads were driven by risk factors via the credit, liquidity and rollover channel.

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

2 Covid-19 and the U.S. Corporate Bond Market

In this section, we provide the timeline of the Covid-19 pandemic and discuss its consequences on the U.S. corporate bond market, motivating our analysis. Figure 1 presents this timeline starting at the beginning of 2020. 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 Centers for Disease Control and Prevention (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. Given the rising number of cases, states in the U.S. declare a state of emergency directing their agencies to prepare for the outbreak of Covid-19, starting on February 29, 2020 with Washington. In the week March 2 to 8, nine more U.S. states make their declaration including California and New York, while the other states follow in the next week.

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. 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 non-essential workplaces to close and ban all non-essential gatherings.

In this same week the VIX hits its all-time high of 82.69 signaling increased economic and market uncertainty. The Fed reacts to these developments and introduces the Primary Dealer Credit Facility (PDCF) to start on March 20. On March 23, the Fed announces the Secondary Market Corporate Credit Facility (SMCCF) and the Primary Market Corporate

Credit Facility (PMCCF). The SMCCF directly aims at the corporate bond market and is the first credit facility in the Federal Reserve's history to purchase investment-grade U.S. corporate bonds from the secondary market. On April 9, the Federal Reserve expands the SMCCF to include fallen angels that were downgraded after March 22 with at least a BB-/Ba3 rating.

During this time, governors across the country issue executive orders with increased frequency, limiting the ability for businesses to operate at a normal capacity by introducing travel restrictions, non-essential business closures, WFH, and general social distancing measures. By March 26, a total of 22 U.S. states have issued stay-at-home orders. The economic consequences of all these measures is enormous. 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. Towards the beginning of the summer, the crisis situation eases and social distancing measures are relaxed. By mid-June, basically all states started to lift their mandates and phase reopening.

Our paper analyzes the price and liquidity effects of this crisis in the U.S. corporate bond market. Based on the presented timeline of events, we define a benchmark period before the impact and compare it to the peak of the crisis period. This selection is challenging as there was quite a long build-up phase of protective measures against the Covid-19 outbreak and the severity and consequences of these measures were not clear right from the beginning. However, the benchmark period should be as close as possible to the crisis avoiding the influence of other structural differences, e.g., different interest rate environments. Thus, we define the trading week February 24 to 28, 2020 as our benchmark period, representing the week before official measures were taken. Thereafter, governors across the U.S. started to declare a state of emergency and it became increasing likely that protective measures would be implemented.

As the crisis period, we define the time where the full extent of protective measures was evident to market participants, representing the peak of the crisis. However, this choice is again challenging, as the Fed intervened directly in the U.S. corporate bond market for the first time in its history and announced this on March 23, 2020. This intervention had significant impact on prices and liquidity (see, e.g., O'Hara and Zhou (2021)). Therefore, we select a time period before the announcement of this direct intervention. Thus, our crisis period represents the trading week March 16 to 20, 2020 which started with the announcement of social distancing guidelines by the president of the United States and with federal agencies setting significant steps to counteract the pandemic. Therefore, it became evident that the closure of non-essential businesses and/or stay-at-home mandates will be introduced throughout the country. In this week, the Fed also announced their first response (PDCF) to the crisis, showing that markets already reacted significantly to the new crisis. However, as O'Hara and Zhou (2021) show, the PDCF itself did not have an immediate effect on the corporate bond market and, thus, does not affect our crisis period. Our choice is also in line with the VIX index, showing no reaction in our benchmark period and peaking in our crisis period. As this is a critical choice, we provide additional analyses covering the whole year of 2020 until March 2021 and present different choices of relevant time periods in our robustness tests.[1] In these additional analyses, we employ a longer time window for the crisis beginning on March 16 and going to June 12, i.e., ending in the week before U.S. states started to reopen.

A second challenge when analyzing the Covid-19 pandemic is that the crisis response occurred on multiple levels of government from local, state, to federal. These reactions were introduced starting in March 2020 and many of the social distancing measures were unprecedented in U.S. history. Given this 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 when analyzing credit and liquidity risk implications of the crisis. For example, airplanes were grounded and, hence, were basically out of business, whereas pharmaceuticals were expected

[1] Note that any potential information concerning the Fed's intervention that leaked to the market before its announcement would bias our results against finding significant effects.

to profit from the pandemic and were less affected by these measures since they were classified as essential businesses. These differences have to be considered before analyzing standard credit and liquidity factors.

Thus, we employ the measure of Koren and Pető (2020) to address this issue, which models a firm's exposure to these policies by evaluating the percentage of occupations in a firm that rely on working with colleagues, interacting with customers, and operating machines (see Section 4 for a detailed discussion). This measure gives essential information about firms during the weeks of uncertainty in March 2020 that a credit rating and other risk measures would be unable to provide. Namely, it has information on how likely a firm will be affected by these social distancing measures. This measure has been used before in the context of Covid-19 crisis by Pagano et al. (2021) and Fahlenbrach et al. (2021).

As a result of the policies implemented by the U.S. government and the strong impact the pandemic had on the U.S. economy, it seems reasonable to assume that social distancing measures will lead to cross-sectional differences across firms in the considered time window. A firm's capacity to respond and adjust to new policy measures that limit its normal operations becomes increasingly relevant as the severity of the pandemic increases. Thus, we expect credit spreads to increase more for bonds of firms that are heavily affected by social distancing measures, as implementing such measures is a difficult and costly task for these firms. We expect that social distancing affects the default risk during the pandemic shock, as it potentially has a severe impact on the earnings situation of affected firms. This factor has to be considered before analyzing standard credit and liquidity factors and evaluating their impact. Overall, considering the impact of the social distancing measures and including rollover risk provides us with a more detailed view on the price and liquidity effects on the U.S. corporate bond market compared to the existing literature.

3 Data

In this section, we present the data we use for our analysis. We employ bond data for the year 2020. We use bond characteristics from Mergent FISD and transaction data from TRACE. We filter our bond sample based on characteristics to plain vanilla bonds that can have either a put or call option. Thus, we remove all bonds with coupons that are non-fixed, zero-coupon, or those that are subject to change. We also exclude rule 144a bonds, bonds that are exchangeable, convertible, or have enhancements, and bonds that are asset-backed, defaulted, or defeased. We focus on bonds with an issue size greater than 10 million USD and a maturity that is less than 30 years. These filters leave us with 6,485 bonds.

For all of these bonds we remove trades that are non-institutional or occur on non-trading days. 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, leaving us with 5,676 bonds. To aggregate prices at a weekly level we compute the volume-weighted price in each week. In this step, we require that a particular bond is at least traded two-times per week.

In our main analysis, we focus on weeks nine (February 24 to 28) and twelve (March 16 to 20) of 2020 to capture the specific drivers of credit spreads during the onset of the crisis. In the following, we focus our presentation of the data set on this time window. However, the data structure and availability is very similar for the other weeks in our time window. As we analyze yield spread changes, bonds have to trade in both weeks for our main analysis. Overall, 3,419 bonds fulfill this requirement. We further restrict this sample to bonds for which we observe all relevant control variables, i.e., bond characteristics and rating data from Mergent FISD (see Section 4 for details) and Compustat information. We employ standard Compustat control variables used in the literature, i.e, firm size, cash, leverage, income, and bond financing lagging them by six months (as in Nagler (2020)). This leaves us with 2,374 bonds.

In the next step, we acquire the score we use to proxy a firm's ability to social distance from Koren and Pető (2020) which is supplied at their github page.[2] Specifically, we use the 'affected_share' to classify firms according to ability to cope with social distancing measures. We only keep bonds that have this score measuring the social distancing effects. This provides us with exactly 2,000 bonds for our main analysis.

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 spreads for the bonds (see Section 4 for details).

For this sample, we provide descriptive statistics on the bond and firm level. All summary statistics represent the variable values of week nine in 2020, i.e., representing the pre-crisis levels. In Table 1 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 (28 vs. 13 trades per week), but standard measures of liquidity show that there are substantially higher transaction costs and smaller trading volumes. Also, the average yield spread is higher by more than three percentage points for speculative grade bonds. 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 a lower yield spread. The group of not affected bonds tends to have slightly more bonds belonging to higher quality rating classes, but both groups have a median rating of BBB+. 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

[2]We download the data from https://github.com/ceumicrodata/social-distancing/ on September 5, 2021.

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 5% of outstanding bond volume maturing in the first year after the onset of the crisis. Firms not affected by social distancing measures are slightly larger than affected firms. Refinancing intensity, debt dispersion and volatility are about the same for the two groups. In terms of income affected and not affected firms are also comparable. The average amount of bond financing is above 60% in both groups with the not affected firms tending to have a higher amount of bond financing.

4 Methodology

4.1 Social Distancing Variable

In this section, we provide the details concerning the social distancing variable used to describe whether a firm is affected by social distancing measures, (mandatory) stay-at-home policies, 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. We use a score from Koren and Pető (2020), who model a firm's cost of social distancing by measuring the reliance on communication and machine dependent jobs on a subindustry level. They use job description data from O*NET and sort the tasks listed in these descriptions by activities that require close communication with other workers and customers, and to machines (physical proximity). Using this ranking and applying cut-off values allows them to define occupations that are affected by social distancing measures. In addition they use Current Employment Statistics (CES) from the U.S. Bureau of Labor Statistics for February 2020 to find the employment share of all 809 occupations for 3-digit NAICS industries (i.e., subindustries). Based on these inputs, they provide the percentage of affected workers in each subindustry, called the *affected share* (denoted by s_i in our paper).

We identify a firm as being affected if this score is above its median value across all firms in our sample and represent the social distancing ability as an indicator variable $s_{d,i}$. In our view, a dummy representation is the most consistent approach, as the affected share itself is constructed based on a dummy representation to identify affected occupations and is not directly represented by the percentage of affected activities within a certain occupation.[3] As described, we determine the median based on the firms in our sample. Note that an alternative would be to derive a median score across subindustries. However, simply equally-weighting the subindustries would not be optimal, as they differ significantly in size. Using alternative weights instead, e.g., based on firm size (or number of firms) in the Compustat universe or based on the number of employees per subindustry would result in very similar medians. In addition, the resulting median (see below) is close to 50%, which could be considered as a reasonable choice in economic terms.

Based on this definition, Table 4 presents summary statistics based on SIC major industry group levels, i.e., representing an aggregation of the subindustries. We show the number of total and affected firms (and bonds) and the range of the score per industry. 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 63.5% of firms are affected. The span of s_i has its maximum at 91 and its minimum at 18. The firm-level median is 47.

It is evident that several alternatives exist how to parameterize affected firms. Thus, in our robustness section we show that employing such alternatives provide the same results. In particular, we use the affected share directly as the numerical variable. In addition, Koren and Pető (2020) present alternative scores and sub-scores in their paper. One important alternative is the *interact affected share*. For this score, a stricter definition for identifying affected tasks is used, giving more weight to tasks requiring physical presence of workers.

[3]In general, a linear interpretation of the affected share, i.e., using s_i directly in the analysis, seems not be an optimal choice, as for example, a change from 100% to 75% of affected workers might not impact the overall situation of a firm much, whereas a change from 50% to 25% makes a significant difference.

Thus, we also employ this alternative score in our robustness tests. Furthermore, in many of their analyses Koren and Pető (2020) explore two sub-scores, i.e., the communication share based on tasks that are teamwork dependent or facing customers ($s_{com,i}$) and the presence share based in the physical proximity to machines ($s_{pres,i}$). We also employ these two sub-scores in our robustness tests.

4.2 Bond Risk Factors

We measure the riskiness of a bond along three dimensions: default risk, liquidity risk and rollover 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.

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

$$\text{Price Dispersion}_t = \sqrt{\frac{\sum_{k \in K_t} v_k (p_k - \bar{p})^2}{\sum_{k \in K_t} v_k}}, \tag{1}$$

where K_t is the set of all trades in week t, p_k and v_k are the price and volume of trade k 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., Nagler (2020), Friewald et al. (2022) 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) and calculate it each week:

$$\text{Debt dispersion}_j = -\log\left(\frac{1}{m_j^{max}}\sum_{m=1}^{m_j^{max}}\left(w_{j,m} - \frac{1}{m_j^{max}}\right)^2\right), \tag{3}$$

where $w_m = \frac{x_m}{\sum_m x_m}$ is the outstanding amount of bond debt in maturity bucket m over the total amount outstanding in all maturity buckets and m_j^{max} represents the maximum outstanding bond maturity of firm j. The choice of m_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 Yield Spreads and Regression Analysis

In our main analysis, we quantify the impact of rising economic and pandemic uncertainty on bond yield spreads. To measure yield spreads, $ys_{i,t}$, we compute the yield-to-maturity of bond i in week t, $y_{i,t}$, and subtract the rate of a duration-matched treasury security. We calculate the yield-to-maturity for bond i in week t by using the volume-weighted average price of all transactions for this bond in this week. Our main variable of interest is then the bond-specific difference between the averages of week nine and twelve, providing the yield spread change Δys_i of bond i.

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

$$\Delta ys_i = \alpha + \beta_1 s_{d,i} + \beta_2 X_i^{\text{risk}} + \beta_3 X_i^{\text{bond}} + \beta_4 X_i^{\text{firm}} + \varepsilon_i \tag{4}$$

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 affected by social distancing measures, X_i^{risk} is the vector of risk factors, X_i^{bond} represents the bond characteristics and X_i^{firm} firm control variables, respectively. The risk factor vector contains refinancing intensity, debt dispersion, price dispersion and credit rating measured in week nine. The bond characteristics are represented by the coupon rate, the offering amount as well as the maturity also measured in week nine. As firm control variables we follow Nagler (2020) and use the amount of bond financing, size, cash and leverage measured two quarters earlier. Table A5 in the appendix gives a technical definition of the control variables used. In this regression, we use firm-level clustering of standard errors. In the robustness section, we present results using different time windows over which we consider the change in yield spreads and provide alternative clustering of standard errors.

To provide additional evidence, we employ our full sample period from January 2020 until March 2021 and use panel data regressions as an alternative approach compared to the cross-sectional analysis. This also allows us to better understand the influence of the individual variables over time, especially the social distancing variable. Thus, we analyze whether social distancing differences are already priced before the crisis or whether social distancing is only a risk factor in the pandemic itself. We estimate the following panel regression:

$$ys_{i,t} = \alpha + \beta_\tau \tau_t^{\text{shock}} + \beta_s s_{d,i} + \beta_{\tau\times s} s_{d,i}\tau^{\text{shock}} + \gamma_1 X_{i,t}^{\text{risk}} + \gamma_2 X_{i,t}^{\text{bond}} + \gamma_3 X_{i,t}^{\text{firm}} + \varepsilon_{i,t}, \quad (5)$$

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 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-four as shock weeks; these are the weeks of March 16 to June 12 (see Section 2). Thus, in the panel setup we apply a dummy representing a three month window of pandemic induced market distress. This also allows us to add an interaction term with the social distancing variables. $X_{i,t}^{\text{risk}}$ is the vector of credit- and liquidity risk of bond i in week t, and $X_{i,t}^{\text{bond}}$ and $X_{i,t}^{\text{firm}}$ are vectors containing bond and firm control variables, respectively. We also provide an additional analysis based on this setup. Instead of using a panel regression, we use a cross-sectional regression for each week and explore the time-series of the resulting parameters.

5 Results

5.1 Descriptive Analysis of the Covid-19 Pandemic

We start our empirical analysis with a descriptive analysis of prices and market liquidity in the U.S. corporate bond market. Figure 2 shows the average yield spread and price dispersion during the year 2020. Both credit and liquidity risk increase drastically in March 2020 and stay at high levels in the months following. We find that average weekly bond yield spreads are around 1.1% at the beginning of the year and reaches 5.4% in the week of March 16 to 20, 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 this week. On average, liquidity improved more quickly than yield spreads after the peak of the crisis given the Fed's interventions.

In the next step, we split firms by their ability to cope with social distancing measures.

Figure 3 reveals that affected firms experienced a larger increase in yield spreads by 88 bp from week nine to twelve, i.e., the credit risk for firms affected by social distancing measures increased more than their unaffected counterparts. Interestingly, we do not observe any difference in the price dispersion measure between firms, indicating that the ability to deal with social distancing measures affects the credit risk, but has no effect on the liquidity of bonds.

Table 5 shows the change in yield spread for affected and not affected bonds over different time windows covering the whole crisis period (see Section 2). The difference between the two groups decreases with the length of the time window and is statistically significant in all time windows. We interpret this as importance of the social distancing becoming significantly less pronounced over time. This can have several reasons, for example, firms adjust to the social distancing measures or these measures are less important as after week 24 almost all states have begun to reopen.

As a comparison, Table 6 shows the stock returns for both groups over the same time windows. Again, we find that firms that are more 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 in the bond market are observed, we find that the difference in change in bond yield spreads is comparable in magnitude to the difference in stock returns. Note that we cannot directly compare changes is yield spreads to stock returns. In addition, we calculate the bond returns for affected and unaffected firms based on our sample. We find bond price returns of -8.41% and -11.81% for the unaffected and affected groups, respectively. Thus, the difference in returns is 3.4% and nearly identical to the 3.2% difference we observe in the stock market. However, for longer time windows we find that these differences drift apart, i.e., bond prices for affected firms start to improve with the yield spread difference reducing from 91 bp to 31 bp till week 24, whereas the stock return differences between unaffected and affected are more persistent and even increase till week 24. This is an interesting effect, as it shows that the perceived credit risk reduced significantly after the outbreak of the pandemic over time, whereas pure earnings effects where considered to be more long lasting.

5.2 Regression Analysis of 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. corporate bond market. We analyze the change between 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 our cross-sectional regression model (see Section 4.3). We present four different variations of this analysis. 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 social distancing dummy.

In our analysis, we focus on Model (1) containing all variables and controls. We find a statistically significant parameter for the social distancing dummy, confirming the results of our descriptive analysis. Including all controls, we find a difference of 40.9 bp between affected and unaffected firms. This difference is also highly significant in economic terms. In addition, this regression setup allows us to analyze the impact of the defined bond risk factors. A one standard deviation increase in rating or price dispersion increases the change in yield spreads by 61 bp and 84 bp, respectively. Both results are highly significant in statistical and economic terms. Before we assess the relative impact of credit and liquidity risk on changes in yield spreads, we take rollover risk into account. A one standard deviation increase in refinancing intensity leads to an increase of 12 bp change in yield spreads. Thus, firms that have to refinance more of their bond debt in the near future show significantly higher yield spread increases. In addition, the debt dispersion variable shows the expected negative sign, indicating that a lower overall debt concentration leads to lower yield spreads in the cross-section. However, it is not significant in all specifications. Considering a one standard deviation increase in all these variables together, the total credit risk change is 73 bp for unaffected firms and 113.9 bp for affected firms, where the difference is due to the social distancing dummy. Thus, for affected firms credit risk is the dominant factor in this crisis, whereas for unaffected firms the liquidity component is more important with an effect of 84 bp. These results show the importance of explicitly considering the effects of social distancing and also allow to shed light on the mixed results found in the existing literature.

In the following, we compare these results with the great financial crisis. For example, Nagler (2020) reports in his main results that a decrease in rating and liquidity by one standard deviation corresponds to a 404 bp and 45 bp increase in yield spreads, respectively. Moreover, firms that have a refinancing intensity of 10% or larger experience an additional increase of 158 bp in yield spreads. The overall effects that we find for the pandemic crisis are smaller. However, the increase of the yield spread occurred in a matter of weeks and never reached the levels seen in the financial crisis, also due to the Fed's intervention. The results also show that the relative and absolute importance of liquidity is much higher in the pandemic crisis, indicating that the liquidity component was more important compared to the specific case of the financial crisis.

Analyzing the rollover results, we find that the rollover risk increased the economic significance of credit risk by around 40% in the financial crisis, i.e., 158 bp for rollover risk versus 404 bp for credit ratings. In our sample, we find an effect of half the size for the pandemic crisis, i.e., 12 bp versus 61 bp. Thus, rollover risk is again an important risk component. However, it may not have reached its full impact due to the Fed's intervention. Overall, these results show that rollover risk is an important part of the overall risk and is not limited to the financial crisis.

In the next part of our analysis, we compare our results to Model (2), where we do not control for a firm's social distancing ability. Interestingly, the parameters for rating and liquidity stay at the same level (as do the ones of the controls), indicating that neither credit nor liquidity variables can pick-up the difference between affected and unaffected firms. In addition, we observe a reduction of the rollover risk parameter by 7%, when not including the social distancing dummy. This shows that during this pandemic-driven crisis, it is necessary to control for a firm's ability to social distance. Otherwise, disregarding differences across firms due to social distancing measures, one runs the risk of over-/underestimating the credit and liquidity components of the firms.

Finally, comparing Models (3) and (4), the models without control variables, to Models (1) and (2) reveals that our setup is robust to the inclusion of other potentially relevant bond and firm information. In particular, the coefficient of the social distancing indicator stays at the same level. Moreover, the change in coefficients when including the social distancing indicator is basically equal for the models with and without controls.

5.3 Yield Spreads Before, During and After the Shock

In this section, we employ a panel regression setup to analyze our full sample (see Section 4.3). This analysis allows us to confirm the results of the previous section and provides us with the opportunity to study whether the effects of the social distancing dummy are relevant for the whole crisis period and whether the social distancing dummy has a significant effect before and after the crisis.

Table 8 shows the estimation results of our panel regression analysis. Model (1) contains the social distancing dummy and the shock indicator, as well as, the risk, bond and firm controls, i.e., Model (1) has the same structure as our analysis in the previous section. As expected, we find a positive and significant parameter for the crisis dummy with a value of 65.8 bp indicating that, unconditionally, yield spreads were significantly higher during the crisis. Most importantly we find that affected firms experienced an additional 50.3 bp increase in yield spreads during the shock period, measured by the interaction term between the social distancing and crisis dummy. This result confirms the finding of the previous section. Interestingly, the social distancing dummy, measuring the impact on affected firms unconditionally, is insignificant. This indicates that before and after the crisis period affected firms do not have higher yield spreads. Model (2) uses a different set of controls, documenting that our results are not dependent on the particular choice of input variables. Model (3) shows that we find the same results regarding the social distancing dummy when we include time-fixed effects.

In a further analysis, we use the above setup, but instead of estimating one model based on the whole panel, we estimate a cross-sectional regression per week and analyze the time-series of the resulting parameters. This allows us to analyze the impact of the social distancing dummy in more detail. The results are summarized in Figure 4. The lower panel of this figure displays the absolute value of the effect sizes of the relevant variables relative to each other, including the social distancing dummy. The upper panel of the Figure 4 shows the coefficient of partial determination for the social distancing dummy $s_{d,i}$. The highlighted bars indicate a statistical significance on the 10% level. Both panels of Figure 4 show that the social distancing score of firms is a determinant of changes in yield spreads during the pandemic shock but not before or after. The coefficient of partial determination shows its highest values in weeks eleven to fourteen, i.e., around the announcement of the Fed's quantitative easing measures and slowly fades out thereafter. The coefficient is consistently significant starting in week eleven till mid-June, when almost all U.S. states had reopened. Interestingly, we find some weeks with significant results for the social distancing dummy again at the end of 2020, when Covid-19 case numbers reached a new all-time high after the calm summer period. Analyzing the lower panel of Figure 4 allows us to explore the relative importance of the social distancing dummy in comparison to the bond risk factors. In particular, the importance of the social distancing dummy in weeks eleven to fourteen is confirmed. Furthermore, these results show that rollover risk is more important in this period compared to the rest of the sample period.

5.4 Robustness Tests

5.4.1 Time Horizons and Regression Specifications

In this section, we analyze the robustness of our results to different time window selections and regression specifications. In Table A1 we report the results of estimating our cross-sectional regression model using different time windows. In Model (1) we use changes in yield spreads from week seven to week twelve. 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. Thus, we vary the week that is considered as the non-crisis benchmark. We are not changing the crisis week itself, as our descriptive analysis documents that this is clearly the most affected week in terms of yield spreads and transaction costs. The results are inline with our main analysis. The average change in yield spreads is decreasing over the time windows 320 bp vs. 166 bp (compared to 296 bp in the original specification), documenting that some measures in the pandemic where already taken in week eleven (e.g., announcement of travel restrictions or state of emergency declarations of individual states). The size of the coefficient of $s_{d,i}$ is larger (smaller) for the longer (shorter) time window which is intuitive, i.e., 43.3 bp vs. 23.6 bp (compared to 40.9 bp in the original specification). Table A2 reports the different regression specifications. Model (1) uses heteroskedasticity robust standard errors and Model (2) is based on standard errors employing industry levels as clusters. Both specifications show the same results as our base-line regression.

5.4.2 Investment grade vs. speculative grade

In this section, we investigate whether our findings regarding social distancing are only driven by either investment or speculative grade bonds. We estimate the main regression model for both groups of bonds separately and examine whether our results for the social distancing measure depend on one of the two rating categories. Table A4 shows the results of estimating Equation (4) for investment grade bonds (Models (1) and (2)) and speculative grade bonds

(Models (3) and (4)). We find statistically significant results for both groups of bonds. The effect that social distancing has on the change in yield spreads during the pandemic shock is larger for speculative grade bonds (147.7 vs. 36.4 bp), as expected. However, the relative impact on yield spread changes is of similar size, i.e., if we compare the impact of social distance to average yield spread changes of investment and speculative bonds, we find an effect of around 20% and 30%, respectively. Overall, we document that are results are not driven by particular rating grades.

5.4.3 Social Distancing Measure

In this section, we conduct robustness tests on the social distancing measure. Our employed social distancing score quantifies the fraction of employees in a subindustry that would have greater communication frictions as a result of government regulations that enforce social distancing and reduce close contact. In our main analysis, we focus on splitting our sample into two groups to analyze affected and unaffected firms based on equally-sized samples. In our first robustness test, we directly use the social distancing score s_i as explanatory variable instead. In our second robustness test, we use a different score presented by Koren and Pető (2020) to define whether a firm is affected or not. This measure is the *interact affected share*, where a stricter definition for identifying affected tasks is used, giving more weight to tasks requiring physical presence of workers, i.e., where work from home solutions are not really possible. In the third robustness test, we explore two sub-scores in Koren and Pető (2020), i.e., the communication share based on tasks that are teamwork dependent or facing customers ($s_{com,i}$) and the presence share based on the physical proximity to machines ($s_{pres,i}$). In this context, we consider a firm as being affected in case it is above the median value in at least one of these sub-scores.

Table A3 shows the estimation results of the three different specifications of the cross-sectional regression model. In all specifications the social distancing variable is statistically significant with similar results compared to the main specification. In Model (1) using directly the numerical score, we find that a one standard deviation change in the social distancing score is associated with a 14 bp increase in change in yield spreads. Put differently, increasing the social distancing score by 50 points results in yield spread increase of 45 bp. In Model (2), the results shows that bonds of affected fims have a yield spread increase of 62.1 bp. This version of the score uses a stricter definition for affected occupations in the score construction. Interestingly, the observed coefficient is larger by about 20 bp compared to our main specification. Model (3) is based on two different dimensions of social distancing and we find that the resulting effect for bonds of affected bonds is basically identical to our main specification. Overall, we document that our results do not rely on the specific definition of our social distancing measure.

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 social distancing policies and firms that were less affected by using a social distancing measure. 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 40.9 bp more compared to an unaffected bond. Thus, 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. Considering the effects of all relevant factors, we find that for affected firms credit risk is the dominant risk factor, whereas for unaffected firms liquidity is the more important risk factor. These findings allow to explain the mixed results in the existing literature. In addition, we document the importance of considering rollover risk, as this factor increases the effect of credit risk by around 20% in the crisis. 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 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*.

Fahlenbrach, R., Rageth, K., and Stulz, R. M. (2021). How valuable is financial flexibility when revenue stops? evidence from the covid-19 crisis. *The Review of Financial Studies*, 34(11):5474–5521.

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.

Friewald, N., Nagler, F., and Wagner, C. (2022). Debt refinancing and equity returns. *The Journal of Finance*, 77(4):2287–2329.

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. Working Paper 27809, 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

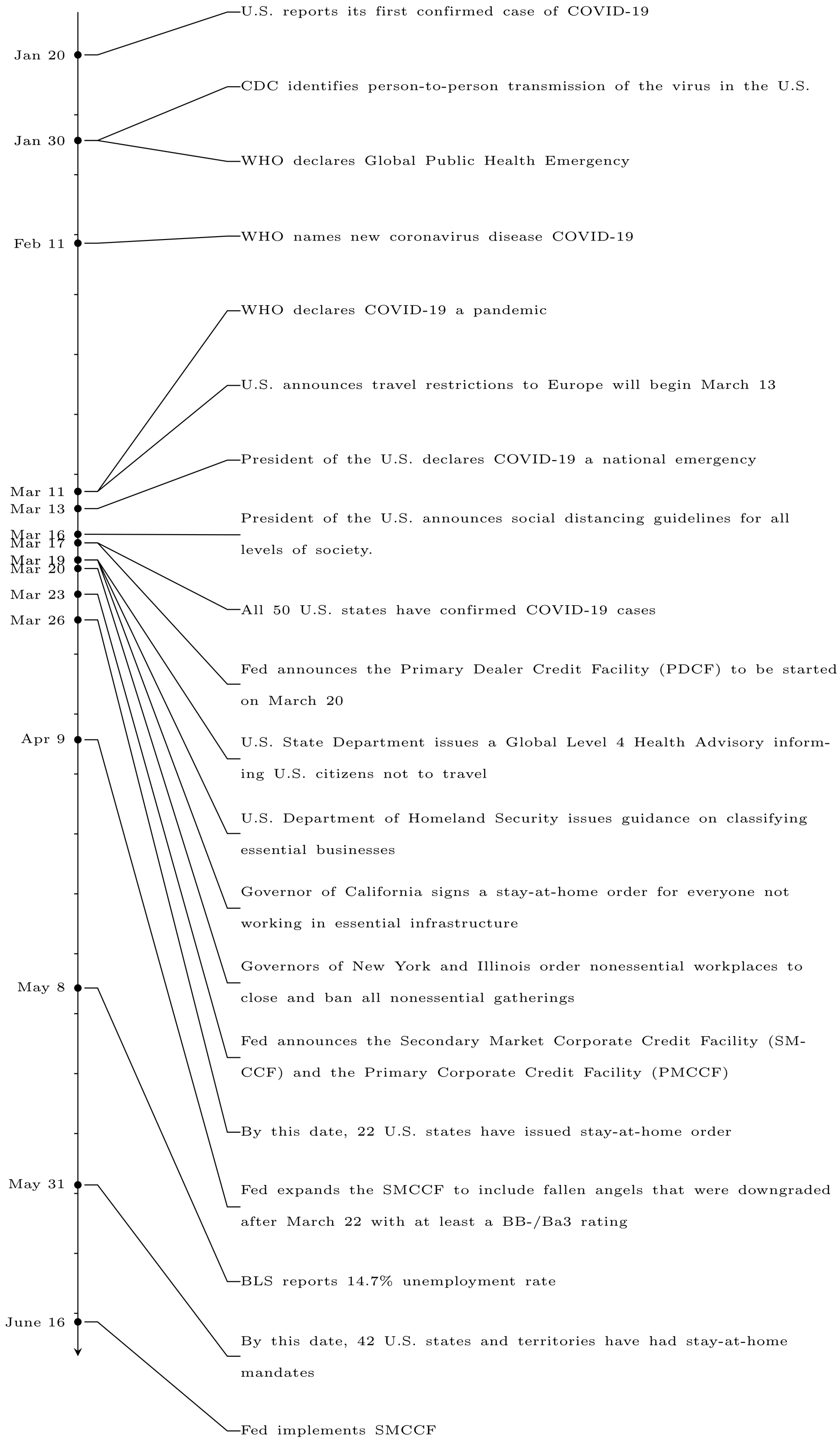

Figure 1: This figure shows a timeline of significant events in the U.S. during the progression of Covid-19 from January 2020 to mid-June 2020. Sources for each event are documented in chronological order in the appendix.

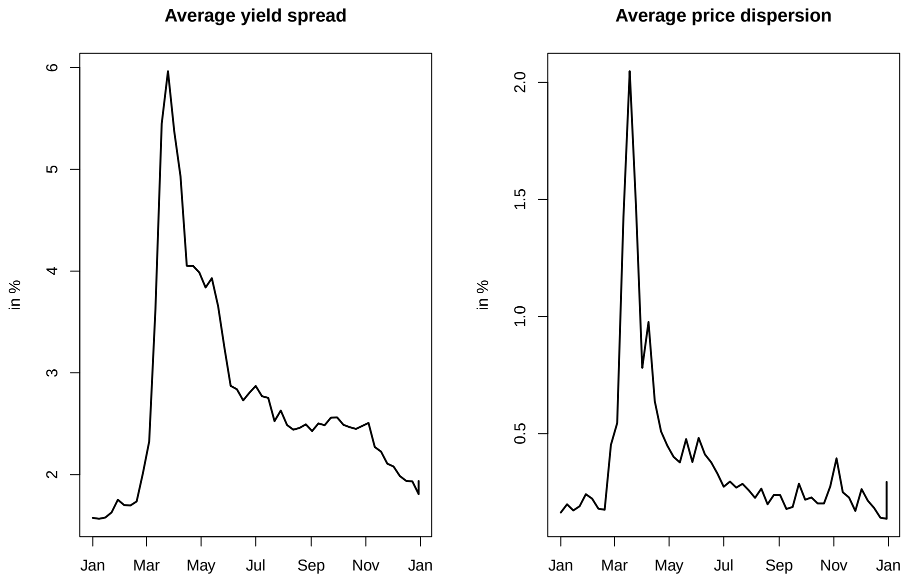

Figure 2: Average yield spread and price dispersion. This figure shows the average yield spread and price dispersion based on all bonds in the sample. We use the trading volume to compute the weighted average of yield spreads and price dispersion of each bond aggregated on firm level and present weekly averages.

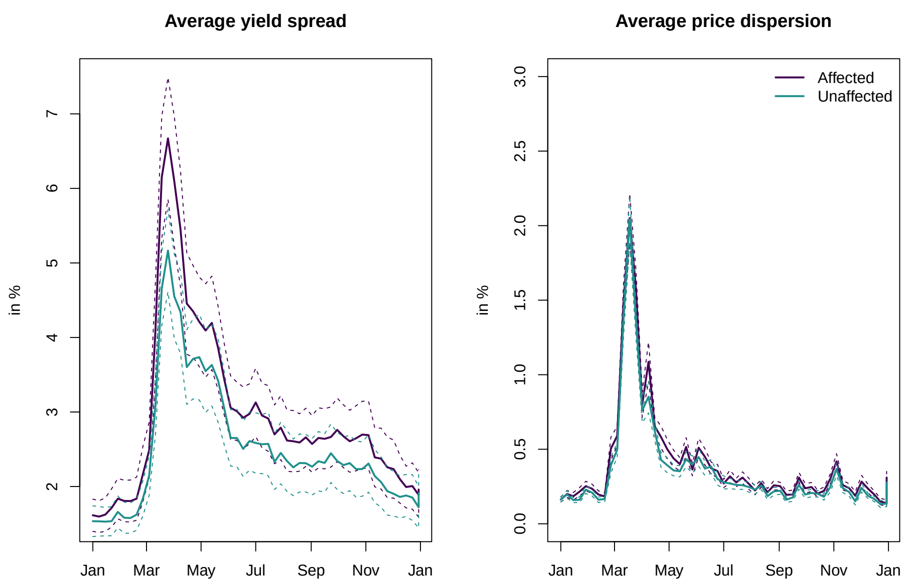

Figure 3: Average yield spread and price dispersion by social distancing exposure. This figure shows the average yield spread and price dispersion based on all bonds in the sample split on their ability to cope with social distancing measures. We use the trading volume to compute the weighted average of yield spreads and price dispersion of each bond aggregated on firm level and present weekly averages.

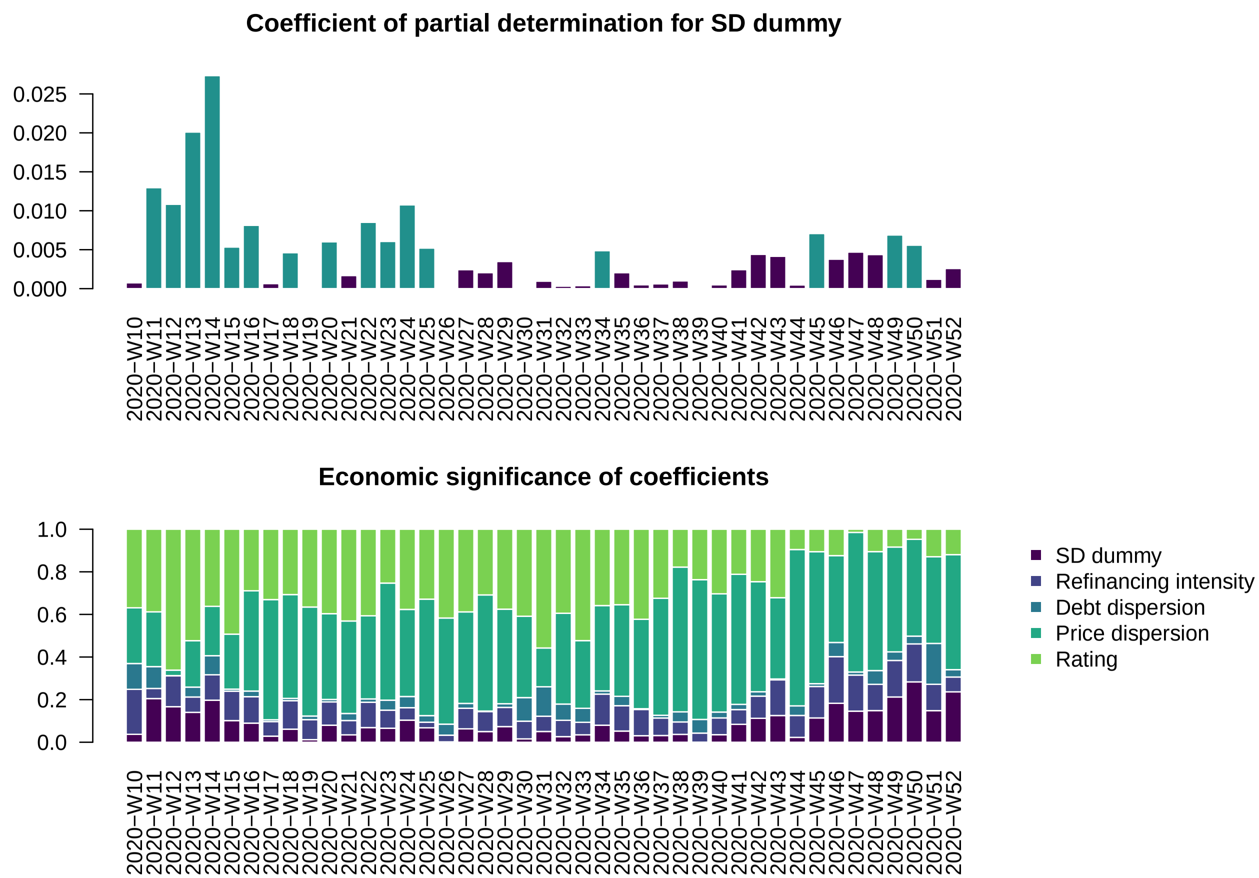

Figure 4: Importance of social distancing exposure over time. This figure shows in the upper panel the coefficient of partial determination for the social distancing dummy $s_{d,i}$ for a series of cross-sectional regressions. Turquoise colored bars indicate a significant F-test on the 10% level. The 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 changes in yield spread (relative to week nine) 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.

Table 1: Summary statistics for bonds by rating. The summary statistics represent the pre-crisis values of the variables in our sample (week nine). Amount issued and traded volume per week are in millions of USD. Coupon, yield spread and price dispersion are presented in %. Rating is encoded in numbers where AAA=1, AA+=2, . . . D=22. Duration is given in years.

	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	20.24	7.92	38.50	0.55	78.44	2000
Trades per week	15.57	10.00	17.43	2.00	47.00	2000
Coupon	3.81	3.60	1.25	2.20	6.13	2000
Yield spread	1.39	0.88	1.75	0.24	4.18	2000
Price dispersion	0.37	0.23	0.51	0.02	1.32	2000
Rating	8.11	8.00	2.96	3.00	14.00	2000
Duration	5.09	4.54	3.54	0.71	12.73	2000
Panel B: Investment grade bonds						
Amount issued	907.31	750.00	654.51	300.00	2250.00	1704
Traded volume per week	17.64	6.99	35.01	0.51	71.15	1704
Trades per week	13.34	9.00	13.21	2.00	37.00	1704
Coupon	3.50	3.40	0.97	2.15	5.20	1704
Yield spread	0.91	0.78	0.61	0.22	2.07	1704
Price dispersion	0.29	0.20	0.40	0.02	0.80	1704
Rating	7.22	8.00	2.09	3.00	10.00	1704
Duration	5.24	4.67	3.69	0.70	13.16	1704
Panel C: Speculative grade bonds						
Amount issued	697.87	532.50	498.96	250.00	1562.50	296
Traded volume per week	35.22	16.59	52.02	0.99	117.69	296
Trades per week	28.39	20.00	29.29	3.00	84.00	296
Coupon	5.58	5.50	1.23	3.75	7.66	296
Yield spread	4.13	3.58	3.13	1.37	8.82	296
Price dispersion	0.86	0.61	0.75	0.07	2.63	296
Rating	13.20	13.00	1.90	11.00	16.25	296
Duration	4.28	4.03	2.29	1.12	8.10	296

Table 2: Summary statistics for bonds by social distancing exposure. The summary statistics represent the pre-crisis values of the variables in our sample (week nine). Amount issued and traded volume per week are in millions of USD. Coupon, yield spread and price dispersion are presented in %. Rating is encoded in numbers where AAA=1, AA+=2, ... D=22. Duration is given in years.

	Mean	Median	Sdev	$q_{0.05}$	$q_{0.95}$	N
Panel A: Affected by social distancing measures						
Amount issued	837.77	650.00	645.53	300.00	2000.00	1034
Traded volume per week	22.67	8.15	43.06	0.55	93.71	1034
Trades per week	16.43	10.00	19.53	2.00	53.00	1034
Coupon	3.96	3.75	1.28	2.39	6.45	1034
Yield spread	1.57	0.99	2.04	0.31	4.31	1034
Price dispersion	0.43	0.24	0.60	0.02	1.60	1034
Rating	8.56	8.00	2.84	4.00	14.00	1034
Duration	5.30	4.72	3.59	0.88	13.07	1034
Panel B: Not affected by social distancing measures						
Amount issued	917.57	750.00	627.84	300.00	2250.00	966
Traded volume per week	17.65	7.81	32.75	0.57	67.74	966
Trades per week	14.65	10.00	14.81	2.00	39.00	966
Coupon	3.64	3.40	1.21	2.05	5.90	966
Yield spread	1.18	0.76	1.35	0.19	3.93	966
Price dispersion	0.31	0.21	0.38	0.02	1.03	966
Rating	7.62	8.00	3.01	2.00	13.00	966
Duration	4.88	4.29	3.47	0.66	12.33	966

Table 3: Firm descriptives conditional on social distancing exposure. The summary statistics represent the pre-crisis values of the variables in our sample (week nine). 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 represents the dispersion of the debt maturity profile with respect to the maximum maturity of all bonds of a firm. Volatility is the daily stock volatility over the last month, i.e. February, in %. Income is defined as income before extraordinary items divided by assets, cash as cash and short-term equivalents over assets and bond financing as the sum of outstanding bond debt divided by the sum of short and long term debt.

	Mean	Median	Sdev	$q_{0.05}$	$q_{0.95}$	N
Panel A: All firms						
Size	53.42	17.85	138.66	2.49	200.15	520
Leverage	0.38	0.36	0.21	0.10	0.67	520
Bonds	5.86	4.00	6.41	1.00	20.00	520
Refinancing intensity	0.05	0.00	0.10	0.00	0.23	520
Debt dispersion	4.40	4.71	1.18	1.84	5.82	520
Volatility	2.29	2.02	1.30	0.98	4.55	404
Income	0.01	0.01	0.02	-0.01	0.04	520
Cash	0.07	0.03	0.10	0.00	0.26	520
Bond financing	0.78	0.71	1.61	0.11	1.11	520
Panel B: Affected by social distancing measures						
Size	52.82	19.87	153.85	2.84	172.28	277
Leverage	0.41	0.38	0.25	0.10	0.72	277
Bonds	5.95	4.00	6.38	1.00	20.20	277
Refinancing intensity	0.05	0.00	0.11	0.00	0.24	277
Debt dispersion	4.40	4.70	1.14	1.96	5.79	277
Volatility	2.28	2.00	1.57	0.85	4.62	177
Income	0.01	0.01	0.02	-0.01	0.04	277
Cash	0.05	0.02	0.08	0.00	0.22	277
Bond financing	0.64	0.65	0.63	0.10	1.06	277
Panel C: Not affected by social distancing measures						
Size	54.11	16.79	119.33	2.18	243.33	243
Leverage	0.36	0.34	0.16	0.11	0.61	243
Bonds	5.75	4.00	6.45	1.00	18.90	243
Refinancing intensity	0.05	0.00	0.10	0.00	0.21	243
Debt dispersion	4.40	4.72	1.24	1.82	5.86	243
Volatility	2.30	2.03	1.05	1.25	4.22	227
Income	0.01	0.01	0.02	-0.01	0.04	243
Cash	0.10	0.06	0.11	0.01	0.34	243
Bond financing	0.94	0.75	2.25	0.14	1.43	243

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_i score for each industry in our sample. We map firms to industries using their SIC code and NAICS code for firms without SIC code.

	Bonds	Firms	Affected firms	s_i
Construction	30	10	2	[39,58]
Manufacturing	687	181	3	[18,62]
Mining	105	39	38	[39,76]
Retail trade	159	34	33	[35,91]
Services	470	107	68	[26,74]
Transportation	511	136	133	[25,78]
Wholesale trade	38	13	0	[26,41]
Total	2000	520	277	[18,91]

Table 5: Changes in yield spreads over different time windows. We report the change in average yield spreads in percentage points. Week nine is the trading week February 24 to 28, 2020, week twelve is March 16 to 20, week sixteen is April 13 to 17, week twenty is May 11 to 15 and week twenty-four is June 8 to 12. We winsorize all changes in yield spread on the 1% level. The statistical significance of the difference in yield spreads is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	W12 - W09	W16 - W09	W20 - W09	W24 - W09
	W12: Mar.16 - 20	W16: Apr.13 - 17	W20: May 11 - 15	W24: Jun.8 - 12
(Less)	*W09: Feb.24 - 28*	*W09: Feb.24 - 28*	*W09: Feb.24 - 28*	*W09: Feb.24 - 28*
Affected	3.32	1.74	1.68	0.77
Unaffected	2.40	1.16	1.11	0.46
Difference	0.91	0.58	0.57	0.31
St.Error	0.12***	0.08***	0.08***	0.04***

Table 6: Average firm stock return over different time windows. We report change in the average stock returns in percent based on all firms in our sample. Week nine is the trading week February 24 to 28, 2020, week twelve is March 16 to 20, week sixteen is April 13 to 17, week twenty is May 11 to 15 and week twenty-four is June 8 to 12. We winsorize all stock returns on the 1% level. 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	W20 - W09	W24 - W09
Affected	-33.97	-23.03	-21.19	-6.34
Unaffected	-30.79	-18.45	-16.53	-1.14
Difference	3.18	4.58	4.66	5.20
St.Error	2.14*	2.00**	2.22**	1.82***

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 affected by social distancing measures, X_i^{risk} is the risk profile of bond i, and $X_i^{\text{bond}}, X_i^{\text{firm}}$ are vectors containing bond and firm control variables, respectively. We winsorize all variables at the 1% level and report standard errors that are clustered on the firm level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
$s_{d,i}$	0.409**		0.476***	
	(0.159)		(0.156)	
Refinancing intensity	0.955**	0.892**	1.257***	1.116**
	(0.438)	(0.436)	(0.479)	(0.492)
Debt dispersion	−0.087	−0.103	−0.220**	−0.213**
	(0.104)	(0.104)	(0.104)	(0.106)
Price dispersion	1.831***	1.853***	1.474***	1.503***
	(0.309)	(0.312)	(0.300)	(0.304)
Rating	0.205***	0.204***	0.334***	0.343***
	(0.042)	(0.039)	(0.041)	(0.040)
α	1.222*	1.534**	0.392	0.527
	(0.662)	(0.632)	(0.723)	(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	0.355	0.351	0.286	0.279
Adjusted R^2	0.351	0.347	0.284	0.278
Residual Std. Error	2.255 (df = 1986)	2.262 (df = 1987)	2.368 (df = 1994)	2.379 (df = 1995)

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 affected by social distancing measures, 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. We winsorize all variables at the 1% level and report standard errors that are clustered on the firm level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:		
	$ys_{i,t}$		
	(1)	(2)	(3)
$s_{d,i}$	−0.060	−0.038	−0.055
	(0.124)	(0.125)	(0.124)
τ^{shock}	0.658***	0.542***	
	(0.100)	(0.104)	
$s_{d,i}\tau^{\text{shock}}$	0.503***	0.484***	0.498***
	(0.186)	(0.172)	(0.186)
Risk-profile	Yes	Yes	Yes
Bond, firm controls	Yes	No	Yes
Time fixed-effects	No	No	Yes
Observations	42,906	42,906	42,906
R^2	0.646	0.601	0.661
Adjusted R^2	0.646	0.601	0.661
Residual Std. Error	1.365 (df = 42890)	1.448 (df = 42898)	1.335 (df = 42839)

Appendix

Table A1: Time horizon robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Table 7 containing robustness checks. The table reports the results of the estimation of this regression model based on different time windows. In Model (1) the change in yield spreads is from week seven to week twelve, in Model (2) the change in yield spreads is from week eleven to week twelve and in Model (3) we present the specification from the main paper. We winsorize all variables at the 1% level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:		
	Δys_i		
	(1)	(2)	(3)
$s_{d,i}$	0.433^{**}	0.236^{**}	0.409^{**}
	(0.204)	(0.096)	(0.159)
Refinancing intensity	1.006^{*}	0.968^{***}	0.955^{**}
	(0.524)	(0.297)	(0.438)
Debt dispersion	−0.106	−0.041	−0.087
	(0.146)	(0.064)	(0.104)
Price dispersion	2.805^{***}	−0.002	1.831^{***}
	(0.859)	(0.053)	(0.309)
Rating	0.282^{***}	0.150^{***}	0.205^{***}
	(0.045)	(0.019)	(0.042)
Coupon	0.510^{***}	0.196^{***}	0.359^{***}
	(0.112)	(0.055)	(0.091)
Offering size	-0.0002^{**}	-0.0001^{*}	-0.0003^{**}
	(0.0001)	(0.0001)	(0.0001)
Maturity	-0.147^{***}	-0.075^{***}	-0.145^{***}
	(0.018)	(0.010)	(0.013)
Bond financing	0.017	-0.046^{*}	−0.111
	(0.087)	(0.024)	(0.086)
Firm size	0.0002	0.0002^{*}	0.0003
	(0.0003)	(0.0001)	(0.0002)
Income	−11.061	−1.298	−4.993
	(7.568)	(3.073)	(5.210)
Cash	−0.315	−0.391	−0.330
	(0.781)	(0.355)	(0.566)
Leverage	−0.434	−0.218	−0.140
	(0.539)	(0.262)	(0.489)
α	0.687	0.664^{*}	1.222^{*}
	(0.897)	(0.386)	(0.662)
Observations	1,933	2,013	2,000
R^2	0.334	0.229	0.355
Adjusted R^2	0.329	0.224	0.351
Residual Std. Error	2.393 (df = 1919)	1.397 (df = 1999)	2.255 (df = 1986)

Table A2: Standard error robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Models (1) of Table 7. Model (1) presents the results of using heteroskedasticity robust standard errors and Model (2) uses the national industry level, i.e., the NAICS code, as clusters. In Model (3) we present the specification from the main paper. is We winsorize all variables at the 1% level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:		
	Δys_i		
	(1)	(2)	(3)
$s_{d,i}$	0.409***	0.409*	0.409**
	(0.106)	(0.236)	(0.159)
Refinancing intensity	0.955***	0.955*	0.955**
	(0.340)	(0.507)	(0.438)
Debt dispersion	−0.087	−0.087	−0.087
	(0.078)	(0.089)	(0.104)
Price dispersion	1.831***	1.831***	1.831***
	(0.218)	(0.397)	(0.309)
Rating	0.205***	0.205***	0.205***
	(0.030)	(0.041)	(0.042)
α	1.222**	1.222*	1.222*
	(0.514)	(0.636)	(0.662)
Observations	2,000	2,000	2,000
R^2	0.355	0.355	0.355
Adjusted R^2	0.351	0.351	0.351
Residual Std. Error (df = 1986)	2.255	2.255	2.255

Table A3: Social distancing robustness: Cross-sectional regression models on changes in yield spreads. This table is a replication of Table 7 containing several robustness checks. In Model (1) the variable $s_{d,i}$ is substituted by its continuous score s_i. In Model (2) we use $s_{d,i}^{interact}$, a slight variation of $s_{d,i}$ using the 'affected interact' score as underlying variable. Model (3) uses two scores - 'communication interact' and 'presence interact' - to create the dummy $s_{d,i}^{2-dimensional}$. See Section 5.4 for details. We winsorize all variables at the 1% level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:		
	Δys_i		
	(1)	(2)	(3)
s_i	0.009*		
	(0.005)		
$s_{d,i}^{interact}$		0.621***	
		(0.164)	
$s_{d,i}^{2-dimensional}$			0.428***
			(0.130)
Refinancing intensity	0.967**	0.997**	1.024**
	(0.439)	(0.432)	(0.434)
Debt dispersion	−0.095	−0.106	−0.125
	(0.104)	(0.103)	(0.103)
Price dispersion	1.836***	1.759***	1.829***
	(0.310)	(0.311)	(0.312)
Rating	0.206***	0.213***	0.202***
	(0.041)	(0.043)	(0.040)
α	1.040	1.074	1.261*
	(0.718)	(0.682)	(0.651)
Observations	2,000	2,000	2,000
R^2	0.353	0.360	0.354
Adjusted R^2	0.349	0.356	0.350
Residual Std. Error (df = 1986)	2.259	2.247	2.257

Table A4: Rating robustness: Cross-sectional regression models on changes in yield spreads. This table reports the results of the regression model used in Table 7 only for investment grade bonds (Models (1) and (2)) and for speculative grade bonds (Models (3) and (4)). We winsorize all variables at the 1% level and report standard errors that are clustered on the firm level. The statistical significance is indicated by $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

	Dependent variable:			
	Δys_i			
	(1)	(2)	(3)	(4)
s_i	0.364**		1.477**	
	(0.168)		(0.701)	
Refinancing intensity	0.983**	0.872*	2.920	3.335
	(0.468)	(0.457)	(2.641)	(2.661)
Debt dispersion	−0.042	−0.084	0.166	0.243
	(0.117)	(0.114)	(0.401)	(0.389)
Price dispersion	0.957***	0.984***	2.208***	2.345***
	(0.344)	(0.366)	(0.579)	(0.612)
Rating	0.233***	0.228***	0.236	0.222
	(0.043)	(0.040)	(0.194)	(0.203)
α	0.658	1.110*	1.634	1.830
	(0.706)	(0.621)	(2.553)	(2.741)
Observations	1,704	1,704	296	296
R^2	0.202	0.196	0.292	0.273
Adjusted R^2	0.196	0.190	0.260	0.242
Residual Std. Error	1.812 (df = 1690)	1.819 (df = 1691)	3.808 (df = 282)	3.854 (df = 283)

Table A5: 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 A6: 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
21	Fed implements SMCCF	https://www.newyorkfed.org/newsevents/news/markets/2020/20200615