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Corporate Bond Market Reactions to Quantitative Easing During the COVID-19 Pandemic

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Abstract

Using transaction data from the first half of 2020, we examine the reaction of corporate credit spreads to the Federal Reserve's monetary policy announcements. We find evidence that the bond markets are segmented across credit ratings, which led to different initial reactions across bonds with different credit ratings. The role of market segmentation, however, is temporary, and the effect of reduced default risk spread across different sectors of corporate bonds over the longer event window. To quantify the default risk channel of quantitative easing, we apply the variance decomposition approach to credit spreads and find that a significant fraction of credit spread changes indeed correspond to reduced default risk caused by the corporate bond purchase program. In contrast, we only find mixed evidence for the liquidity channel driving the market reaction.

JEL Classification: G12, G13

Keywords: Coronavirus, Event Study, Corporate Bond, Federal Reserve, Quantitative Easing, COVID-19 Pandemic

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1 Introduction

The impact of the novel coronavirus (COVID-19) on the global economy has yet to be fully revealed, but the forward-looking nature of the financial market sheds light on the market's anticipation of future economic growth. Among major issues facing the economy, the rising default risk of firms that encounter cash shortfalls due to the outbreak is a key concern. Corporate credit spreads, a market-based measure of default risk, increased sharply in March 2020 (see Figure 1). Given the soaring cost of borrowing and the increased difficulty in funding firms' operating expenses during the shut-down in the economy, malfunctions in the debt market can pose a threat to the survival of firms that run otherwise viable business operations.

The top panel of Figure 1 presents credit spreads and the S&P 500 index from December 1, 2019, to June 30, 2020. The figure shows that there are several distinct periods in the behavior of credit spreads. When the virus led to the first crisis in China (the Wuhan lockdown on January 23, 2020), the aggregate U.S. corporate credit spreads remained stable. Only after February 23, when Italy entered lockdown, did the U.S. credit spreads start to rise. As the number of reported cases rose sharply in the U.S., the credit spreads reached their peak in mid-March 2020, which was about 5% for BBB-rated corporate bonds and 11% for high-yield (HY) bonds. Though much higher than the historical averages, these levels of credit spreads were still below their historical highs during the Global Financial Crisis in 2008, when HY spreads rose above 20%. Credit spreads retreated significantly after March 23, when the Federal Reserve (Fed) announced a series of programs to provide liquidity and credit to the financial markets. Among these programs, the Fed announced a credit facility in which the Fed set up a special-purpose vehicle to purchase investment-grade (IG) corporate bonds and exchange-traded funds (ETFs) on those bonds. Corporate credit spreads decreased further on April 9, 2020, when the Fed expanded the purchase program to include certain HY bonds and HY-bond ETFs to jolt U.S. bond markets back to life.[1]

How did the Fed's March and April announcements of the corporate bond purchase program reduce credit spreads despite the rising number of defaults and bankruptcies? After the Fed's announcement, the aggregate credit spreads clearly went down, but the drivers for the change are not clear. The literature suggests that relevant forces through which quantitative easing affects credit spreads are the default risk channel and the liquidity channel. In the short run, however, the way these forces impact credit spreads may be distorted by market

[1]Corporate bond issuance has revived since the Fed unveiled the bond purchasing program. According to Moody's estimate, after withering to $4 billion in March, corporate bond issuance reignited to $35 billion in April and hit $38 billion in June.

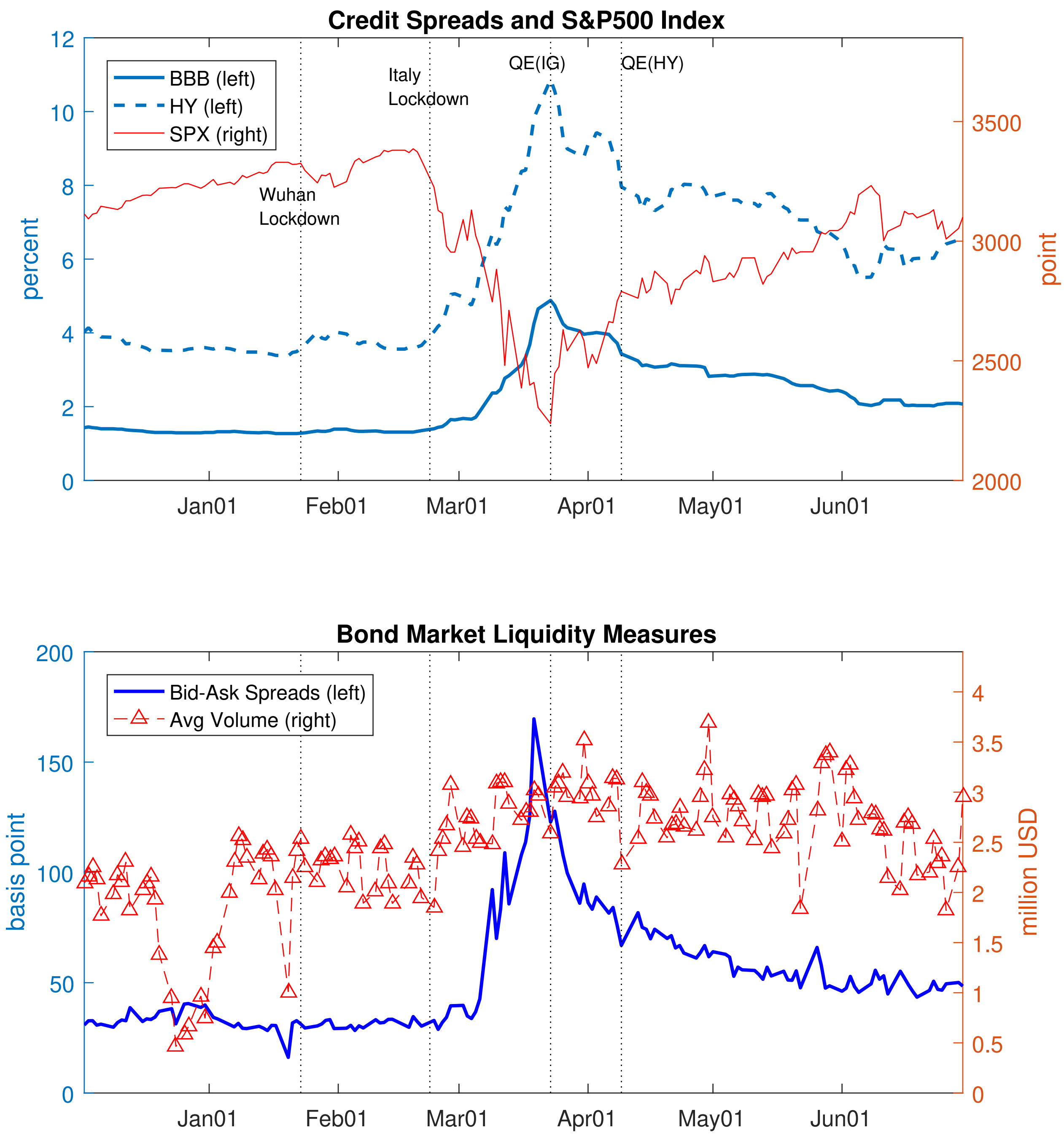

Figure 1: Credit Spreads, S&P500 Index and Bond Illiquidity Measures: December 2019 to June 2020

The top panel plots the ICE BofA option-adjusted credit spreads on corporate bonds and the S&P 500 index. Wuhan lockdown is on January 23, 2020, Italy lockdown is on February 23, and the Fed's QE announcements are on March 23 and April 9. The bottom panel plots the bond market illiquidity measures including the bid-ask spreads and dollar transaction volume for the average bond.

segmentation, which prevents arbitrage capital from flowing from one segment of the bond market to another. In this paper, we aim to empirically disentangle these effects from each other.

Specifically, we document heterogeneous reactions to the announcements across different subsamples of corporate bonds, show some evidence for market segmentation, and attribute credit spread reactions to the default and liquidity channels. To this end, we conduct event studies on security-level credit spread changes over the two-day windows. Because an event study requires accurate bond price data that reflect news promptly, we use transaction data in TRACE rather than the readily available bond index that reflects potentially stale quote prices.

We find that, after the March 23 announcement, credit spreads on IG bonds went down over the two-day window, but those on HY bonds remained unchanged. This finding suggests that the bond market is indeed segmented across credit ratings, and thus the program targeting IG bonds reduced IG credit spreads but not HY credit spreads. However, the gap in credit spread changes was temporary. If we calculate the credit spread changes over the two-week horizon (which still ends before April 9), the difference in the reactions between IG and HY bonds narrows. This narrowing of the difference suggests that, over time, arbitrage capital flows from one segment of the market to the other, equalizing the impact across various market segments.

In order to more cleanly identify the role of market segmentation, we employ an identification scheme based on a difference-in-differences approach. Specifically, we examine the issuers that are downgraded from BBB to BB between March 22 and April 9 with the issuers that are downgraded to BB before March 22. In the April 9 announcement, the former bonds are a part of the purchase targets, while the latter bonds are not. Thus, these two groups of bonds serve as treatment and control groups that have the same default risk but are treated differently in the purchase program. We find that credit spreads on bonds in the treatment group decrease more after the April 9 announcement than those in the control group. This finding further supports the argument that market segmentation affects the initial reaction of asset prices to the quantitative easing (QE) announcement.

Market segmentation does distort asset price reactions in the short run, but it does not explain the market-wide movements in credit spreads or their medium-term reaction to the news. These facts need to be attributed to changing default risk and liquidity. Thus, we quantify the default risk component of credit spreads by applying the variance decomposition approach of Nozawa (2017) to credit spreads and estimate the expected default loss and risk premium component of the spreads.

With this decomposition, we attribute about half of credit spread changes at the aggregate level to the March 23 and April 9 announcements to the expected default loss component, which reflects an investor's expectation of loss of investment value due to default. The remaining half reflects changing risk premiums, which could come from compensation for bearing default risk or illiquidity. This evidence from the decomposition suggests that the default risk channel of monetary policy plays an important role in explaining credit spread changes after the QE announcement.

The variance decomposition also reveals an interesting pattern in the term structure of credit spreads. After the March 23 announcement, short-term credit spreads fell more than long-term credit spreads. Unlike the difference between IG and HY bonds, these differences did not converge in the two-week window. According to the variance decomposition results, much of the difference in credit spread changes across maturities is attributed to the expected credit loss component rather than the risk premium component. Thus, the corporate bond purchase program reduced the (perceived) imminent default risk of borrowers due to temporary cash shortfalls, and thereby decreased short-term credit spreads via the default risk channel.

We study changes in corporate bond illiquidity measures after the QE announcement and find that bid-ask spreads fell after the March 23 announcement, while transaction volume did not change much. After the April 9 announcement, neither bid-ask spreads nor volume changed significantly. We explain the decrease in bid-ask spreads after the March 23 announcement with changes in corporate bond mutual fund flows. The QE announcement on March 23 significantly increased fund flows and thus reduced investors' urgent desire to sell corporate bonds. This reduction in liquidity demand alleviated the inventory constraints facing dealers, reducing the price charged for liquidity provision.

To quantify the liquidity channel of monetary policy, we regress daily credit spread changes on changes in bid-ask spreads and transaction volume during the Global Financial Crisis period, accounting for the heterogeneity in sensitivity in bonds across different credit ratings, maturities, and other bond characteristics. We then apply the estimated coefficients to changes in liquidity measures after the Fed's announcements in 2020. The fitted values of these regressions provide estimates for changes in credit spreads predicted from changes in illiquidity measures. We find that these fitted values are close to zero, suggesting that the reaction in illiquidity measures is not large relative to what was observed during the previous crisis, and thus quantitatively it does not fully explain the credit spread changes after the announcement.

The limited role of liquidity in explaining credit spread reactions to the QE announcement is surprising, given the emphasis in the literature (e.g. Bao et al. (2011)) on the link between illiquidity and credit spreads. However, our finding is consistent with the argument of Goldberg and Nozawa (2020), who decompose the corporate bond illiquidity measures into liquidity supply and demand and find that while liquidity supply affects bond prices, liquidity demand does not. If the QE announcement reduced bid-ask spreads primarily via reduced liquidity demand rather than increased supply, then the impact on credit spreads would be limited.

To sum up, the Fed's announcement that it would purchase corporate bonds and bond ETFs decreased credit spreads in aggregate, but the detailed look into segments suggests that the decrease is likely caused by the decreased default risk of borrowers rather than changes in bond illiquidity. This interpretation of the market reaction needs caution because market segmentation distorts the credit spread reaction in the short run, such that after the announcement, credit spreads on bonds that are direct targets of the purchase move more than those that are not. As time passes, the benefit of the purchase program extends beyond the borrowers that are direct targets for purchase to those that are not, because of the improved economic outlook and reduced default risk.

We contribute to the literature on the effect of monetary policy, in particular quantitative easing, on the financial market. Krishnamurthy and Vissing-Jorgensen (2011) document the reaction of the financial markets to the quantitative easing in 2011 and argue that the policy reduces the cost of borrowing for risky borrowers only when the Fed purchases risky debt, such as mortgage-backed securities (MBS). Abidi and Miquel-Flores (2018) and Zaghini (2019) document the financial market reaction to the European Central Bank's corporate bond purchase program introduced in 2016. Finally, Aramonte and Avalos (2020) document the reaction of the ETF discounts to the Fed's corporate QE announcement.

There is a growing literature that investigates the effect of COVID-19 on the bond market. D'Amico, Kurakula, and Lee (2020) examine the reactions of bond ETFs to the QE announcement, while Haddad, Moreira, and Muir (2020) study the discrepancy between corporate bonds and related markets during the market turmoil. He, Nagel, and Song (2020) build a term structure model with preferred habitat investors to explain the Treasury yield reactions to the pandemic.

More broadly on financial markets, Baker et al. (2020) and Ramelli and Wagner (2020) examine the relationship between the stock market and news release. Alfaro et al. (2020) estimate models of infectious disease and find that their model parameters explain daily stock returns in affected countries well. Gormsen and Koijen (2020) use dividend futures to measure the impact of the pandemic on investors' expectations for dividend growth. Barro, Ursúa, and Weng (2020) examine how past pandemics affected economic activities and stock prices.

Our work contributes to the nascent literature on the financial implications of the COVID-19 pandemic. Few asset pricing theories and industry experts can anticipate the extraordinary plunge-and-rebound in the bond and equity market in the first half of 2020. Through an unprecedented bond-buying program, the Fed has demonstrated its willingness to take action to prevent further liquidity spirals and disruption, and thus restore confidence and stability in financial markets. This paper exploits the cross-sectional heterogeneity of corporate bond market responses and dissects channels through which the Fed can provide support to the asset market.

The remainder of the paper proceeds as follows. Section 2 presents institutional background and theoretical discussion on why QE may affect asset prices. Section 3 explains our data, and Section 4 presents the main empirical results. Section 5 attributes credit spread reactions to the default and liquidity channels. Section 6 concludes.

2 Background

2.1 Institutional Background

COVID-19 started to be recognized as a potential threat to the global economy in January 2020, when it began spreading in China. Most notably, the rapid spread of the virus in Wuhan led to a lockdown of the city on January 23, 2020. As the lockdown in China took effect, reported cases of infections started to climb all over the world. A surge in cases in Italy led to the lockdown of Northern Italy in February 2020, which signaled the start of the pandemic. Table 1 lists the key developments regarding the COVID-19 crisis in early 2020.

In response to the worsening COVID-19 pandemic, the Fed took a series of policy actions in 2020. On March 3, the Federal Open Market Committee (FOMC) announced an emergency rate cut of 50 basis points (bps). On March 15, it reduced the federal funds rate to effectively zero and launched a QE program, purchasing Treasury securities and MBS. An unprecedented decision was announced on March 23, 2020, when the Fed introduced a series of programs to provide temporary credit to the private sectors. The programs included purchasing Treasury securities, MBS, newly issued IG-rated corporate bonds, commercial papers, and asset-backed securities based on corporate and consumer loans.[2] Among the

[2] In addition to expanding asset classes, the Fed removed the limit on the purchase amount of Treasury

new programs, the Fed launched the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF) to help stabilize the credit markets.[3] Under these programs, a special-purpose vehicle (SPV) funded by the Fed and the U.S. Treasury Department would purchase corporate bonds as well as ETFs that track the U.S. IG corporate bond market, including iShares Investment-Grade Corporate Bond ETF (LQD) and Vanguard Long-Term Corporate Bond ETFs. Initially, the Treasury Department committed $10 billion of equity investment in the SPV.

On April 9, the Fed expanded the previous QE program to include high-yield bond ETFs (HYG) and individual bonds that are rated at least BB-, and that were rated as IG as of March 22 as a target for purchase. Furthermore, the Treasury Department increased its equity investment to the SPV to $75 billion, expanding the scale of the program as well. These movements were significant, as the Fed committed to providing credit to private-sector borrowers, deviating from the traditional role of central banks in focusing on liquidity provision.

Because this QE program is new, the Fed did not start purchasing bonds immediately after the program was announced. In fact, the SPV did not begin purchasing ETFs until May 12, and individual bonds until June 15.[4]

We collectively refer to the new QE programs on corporate bonds announced on March 23 and April 9 as the corporate QE, differentiating it from the traditional QE announced on March 15, which focuses on Treasury securities and MBS. Other programs introduced by the Fed focus on liquidity provision in the short-term funding markets. Table 1 lists those programs. Because our aim is to study the corporate bond market reactions, we focus on the corporate QE in the analysis below.

As one of the massive targets of the Fed's corporate QE, iShares ETF tracks Markit iBoxx USD Liquid Investment Grade Index, which is a constituent of the Markit iBoxx USD Corporate Bond Index. This index consists of the U.S. dollar-denominated corporate bonds that (i) are issued by companies in developed markets, (ii) have an average credit rating of

securities and MBS on March 23.

[3]The Fed would slow the pace of buying, and even stop purchasing bonds altogether, if that aim were achieved. The SMCCF is supposed to stop buying bonds and ETFs after September 30, unless the Fed extends the operation.

[4]The actual transactions of SMCCF, as disclosed on July 10, include individual corporate bonds of household names such as Apple, AT&T, Boeing, Southwest Airlines, IBM, Microsoft, Walt Disney, and Warren Buffett's Berkshire Hathaway, with 42% rated AA, AA, or A. Another 55% went into BBB-rated credits, leaving just 3% in the BB category. In addition, the Fed plowed $7.97 bn as of June 30 into 16 corporate bond ETFs, including seven high-yield ETFs. Its biggest purchase was in the iShares iBoxx US Dollar Investment Grade Corporate Bond ETF. It invested close to $2.3 billion in the fund, buying around 16.8 million shares.

investment grade, (iii) are from issuers with at least $2 billion outstanding face value, (iv) have at least $750 million of outstanding face value, (v) have at least three years to maturity, and (vi) have at least three and a half years to maturity for new index inclusion. Though ETFs generally do not exactly track the underlying index, the announcement of the Fed may affect credit spreads of corporate bonds differently based on how likely these bonds are to be purchased under SMCCF.

To understand the economic significance of the corporate QE program, Table 2 compares the size of the U.S. corporate bond market with that of the program. The amount outstanding of the corporate bond market is around $9 trillion, and issuance per year was $1.4 trillion in 2018. The announced limit on the corporate QE is $750 billion, which is slightly less than 10% of the outstanding amount, and more than half of new issues in a year. Thus, the demand from the Fed can potentially impact corporate bond prices. However, the actual implementation of the purchase program is rather gradual. As of June 30, 2020, the SPV has purchased only $8.0 billion of ETFs and $1.6 billion of individual corporate bonds.[5]

2.2 Channels Through Which Quantitative Easing Affects Credit Spreads

Krishnamurthy and Vissing-Jorgensen (2011) discuss several channels through which QE affects yields on various bonds: (i) the signaling channel, (ii) the duration risk channel, (iii) the liquidity channel, (iv) the safety channel, (v) the prepayment risk channel, (vi) the default risk channel, and (vii) the inflation channel.

Among these theoretical channels, the most relevant channels for corporate credit spreads are (iii) the liquidity channel and (vi) the default risk channel. The liquidity channel affects corporate credit spreads in the following way: a central bank purchases bonds, which increases liquidity in the hands of investors. Goldberg and Nozawa (2020) show that there is supply and demand for market liquidity in corporate bonds, which jointly determine how liquid the corporate bond market is. In their framework, QE of a central bank likely reduces liquidity demand as investors are less likely to be forced to sell for liquidity reasons, which leads to lower costs of bond transactions. If liquidity is priced in corporate bonds (e.g. Bao et al. (2011)), then the QE will reduce credit spreads by improving market liquidity.

Though there are a variety of models that explain why liquidity affects asset prices, a common feature for those models is market segmentation. For example, a preferred habitat

[5]These data are taken from the Fed's website, which lists the outstanding amount for each security. See https://www.federalreserve.gov/monetarypolicy/smccf.htm.

view of asset pricing suggests that the bond market is segmented from the perspective of investors, and some investors like to hold a subset of bonds regardless of their risk and return trade-off. Then, an idiosyncratic liquidity shock to an investor can affect the price of the asset that she sells because arbitrage capital does not flow quickly enough to this segment of the market and liquidity provision is limited. If this holds true in the corporate bond market, QE will decrease credit spreads for all bonds as it improves the dealer's financial conditions, but the effects are more pronounced for bonds that are purchased as the purchase improves the liquidity for investors in the particular segment.

Market segmentation is a necessary condition for the liquidity channel to operate, but not a sufficient condition. We will show that there are signs of market segmentation in the corporate bond market, and yet the liquidity channel is unlikely to be a driver of market reaction to the QE announcement.

One caveat regarding the liquidity channel is that the bond purchase must be actually conducted, not merely announced. For traditional QE, the purchase follows nearly immediately after the announcement, and thus the distinction between announcement and implementation is negligible. For the corporate QE, however, there is a gap of more than a month between announcement and implementation, and thus distinguishing these two becomes more important.

In summary, the liquidity channel of QE predicts that credit spreads fall as liquidity improves due to QE. Furthermore, this channel implies that we should observe a more pronounced decrease in corporate credit spreads for bonds that are purchased in the program compared with others that are not purchased, and for bonds whose liquidity improves more than that of other bonds.

The default risk channel affects corporate credit spreads directly by reducing the quantity and price of default risk of borrowers. If QE improves the economic outlook and eases funding conditions to private-sector firms, then borrowers are less likely to default, reducing the quantity of default risk. Furthermore, the asset pricing model of Campbell and Cochrane (1999) suggests that the price of risk is generally lower in good times, and thus the improved economic outlook likely reduces the price of default risk as well. The improved outlook and easier funding conditions in turn affect the corporate bond market as a whole, and thus this channel of QE predicts that credit spreads fall across the board. Absent market segmentation, whether a specific corporate bond in question is actually purchased or not matters less in determining the asset prices.

In this article, we focus on the liquidity and default risk channels because other channels of QE are less relevant for corporate credit spreads. The signaling and duration risk channels affect risk-free rates with various maturities, and thus likely affect yields on corporate bonds. However, in this article, we study credit spreads, which is the difference in yields between corporate bonds and Treasury securities, and thus these channels are not relevant.[6] For the safety channel, the key announcements for the corporate QE on March 23 and April 9 do not involve major changes in purchases of Treasury and agency securities, and thus the announcement does not affect the supply of safe assets. Therefore, this channel does not play a role in our setup. The prepayment risk channel matters mainly for MBS, while the inflation channel in principle does not affect corporate credit spreads because expected inflation affects both nominal Treasury and corporate yields equally.

3 Data

For bond prices, we use transaction data for dollar-denominated U.S. corporate bonds from standard TRACE from July 2002 to June 2020. We use standard TRACE rather than the commonly used enhanced TRACE because enhanced TRACE is updated with a lag of at least six months, and we wish to use the latest information in the financial market. We follow Dick-Nielsen (2009) to clean the raw data. We then compute the volume-weighted average of daily transactions using transactions with a volume of at least $100,000 to obtain daily prices. We remove observations with a price below $5 or above $1,000 (per face value of $100), and for bonds with embedded options other than call options.

We use bond characteristic data from Mergent FISD. Specifically, we narrow down to the subset of bonds that meet our selection criteria described above using the information in Mergent FISD. In addition, we obtain the bond's maturity, coupon, credit rating, and issue size from this database. One caveat is that the database is updated annually, and the most recent update was in August 2019. Thus, for the fallen angel analysis below, we obtain the latest credit rating information from press releases of Moody's and S&P.

To measure the liquidity of bonds, we use TRACE data and calculate daily bid-ask spreads for bond i on day d as

$$BAS_{i,d} = \frac{Sell_{i,d} - Buy_{i,d}}{0.5(Sell_{i,d} + Buy_{i,d})} \tag{1}$$

[6]Technically, the risk-free rate affects credit spreads because credit spreads contain an option value component that is sensitive to risk-free rates. However, as in Collin-Dufresne, Goldstein, and Martin (2001), this component is small relative to other determinants of credit spreads.

where $Sell_{i,d}$ and $Buy_{i,d}$ is the equal-weighted average price for transactions where a dealer sells and buys. Furthermore, we calculate total trading volume for each bond.[7]

Stock returns are from Compustat North America, and Treasury constant maturity yields are obtained from FRED and used as a risk-free benchmark to compute corporate credit spreads. We focus on U.S. firms as identified by headquarters and place of incorporation in our main results, but we include bonds issued by non-U.S. firms in the identification exercise in Appendix A. Furthermore, we use Thomson Reuter's Tick History for intra-day transaction data of corporate ETFs. Lastly, we apply daily and weekly U.S. bond fund flow data from Informa Financial Intelligence.[8]

4 Credit Spread Reactions to the Quantitative Easing Announcements

In this section, we report the corporate bond market reaction to the corporate QE announcements. By examining the price movements in different segments of the bond market, we shed light on the drivers of the overall market reactions. Furthermore, we examine changes in proxies for default risk and liquidity after the announcements and try to attribute credit spread changes to these two components.

4.1 Intraday Changes in Event Window

Following Krishnamurthy and Vissing-Jorgensen (2011), we use the two-day event window to evaluate credit spread reactions to policy announcements. Specifically, if an event occurs on day d, then we examine changes in credit spreads from (business) day $d-1$ to day $d+1$. This event window is relatively wide because individual corporate bonds trade infrequently (e.g. Chordia et al. (2017)), and the reaction to news may not be impounded in bond prices immediately after the news release.

On the other hand, ETFs on corporate bonds are traded in exchanges and are likely to

[7] These liquidity measures are calculated using all transactions without imposing the \$100,000 cutoff. Furthermore, Standard TRACE truncates transaction volume at \$5 million for IG bonds and \$1 million for HY bonds. We treat such transactions as those with volume of \$5 million and \$1 million, respectively.

[8] Specifically, we use the Emerging Portfolio Fund Research (EPFR) fund flow and allocations data. EPFR tracks fund flows and asset allocation of more than 120,000 funds with over USD 38 trillion AUM from several thousand sources around the globe using a proprietary collection process. Previous literature uses EPFR fund flow data; see, for instance, Jotikasthira, Lundblad, and Ramadorai (2012) and Fratzscher, Lo Duca, and Straub (2018). We only focus on U.S. bond funds in the first half of 2020 in this study.

react quickly to the news. Thus, we first examine intra-day movements in corporate bond ETF prices and ensure that the price movements around the announcement are significant relative to movements in other times within the event window.

Figure 2 shows the minute-by-minute price of LQD and HYG from March 20 to March 24. The Fed's announcement occurred at 8:30 a.m. EST on March 23, which falls in after hours. Because there is no futures contract on LQD and HYG, we do not observe the price reaction at 8:30 a.m. Nonetheless, we can compare the price change from the close of March 20 to the opening of March 23 to evaluate the impact of the news. The top panel of Figure 2 shows prices for LQD, which exhibits a discrete upward jump from the close of March 20 to the opening of March 23, suggesting that the Fed's QE announcement positively surprised the IG-rated bond market. Though intra-day price changes are volatile over the event window, there are no other discrete changes comparable to the change from March 20's close to March 23's opening. In contrast, there is no visible jump for HYG, possibly because HYG is not included as a target for the Fed's purchase. The contrast between the LQD and HYG's reactions shows that the Fed's announcement was the primary driver for the jump over the weekend. If another announcement, such as fiscal policy, is the key driver of the ETF price changes, then we would expect HYG to rise as well.

Figure 3 shows the intra-day price changes around the Fed's April 9 announcement. This time, HYG is included as a target for purchase, and thus we see an upward jump for HYG as well as LQD after the announcement. Overall, Figures 2 and 3 support our claim that the Fed's announcement is the major driver of asset prices over the two-day window that we examine in the main results.

4.2 Comparing Credit Spread Reactions Across Announcements

We begin our event studies by examining credit spread changes around six events: the rate-cut announcement on March 3, the traditional QE announcement on Treasuries and MBS on March 15, the corporate bond QE announcement on March 23, the expansion of the corporate bond QE on April 9, the beginning of the actual purchase of corporate bond ETFs on May 12, and the beginning of the purchase of individual corporate bonds on June 15. Table 3 shows credit spread changes using all bonds and subsets of bonds categorized by credit rating and maturity.

On March 3, the impact of COVID-19 on the credit market had not yet been felt keenly, and thus the average credit spreads before the announcement remained low at 198 bps. After the announcement, the spread decreased 4 bps. Thus, the emergency rate cut on March 3 affected credit spreads little.

After the March 15 announcement of the traditional QE targeting Treasury bonds and MBS, credit spreads in fact increased. As the number of COVID-19 cases in the U.S. increased, the prospects for the U.S. economy deteriorated significantly. As a result, despite the Fed's announcement, credit spreads increased across the board, with an average increase of 65 bps. These findings go against the traditional view in which lowering risk-free rates reduces corporate credit spreads by alleviating the so-called external finance premium, a premium arising from the financial market frictions such as information asymmetry between lenders and borrowers (Bernanke and Gertler (1995)).

In contrast, on March 23 and April 9, the announcement of the corporate bond QE reduced credit spreads for the average bond by 47 bps and 71 bps, respectively. Thus, it appears that when the purchase program directly targets corporate bonds, firms' borrowing costs decrease. Zaghini (2019) reports that the effect of the announcement of the European Central Bank's corporate bond purchase program in March 2016 was about 30 bps on European corporate credit spreads.[9] The response of the U.S. corporate credit spreads is more pronounced than his estimates.

The contrast between the traditional QE on March 15 and the corporate QE on March 23 and April 9 is interesting because the default risk and liquidity risk channels of QE predict that corporate credit spreads will fall on all three dates. In reality, we observe a fall in credit spreads only after the corporate QE announcements, suggesting that there is market segmentation that prevents certain classes of investors from purchasing corporate bonds due to regulatory and other institutional constraints. With such a friction, funds created through the traditional QE do not flow into ultimate borrowers, and thus directly purchasing corporate bonds makes a difference.

Finally, the beginning of actual purchases of corporate bond ETFs and individual bonds in May and June had a smaller impact on credit spreads than the initial announcements in March and April. Specifically, the average credit spreads increased 13 bps on May 12 and decreased 21 bps on June 15. These findings suggest that corporate bond investors had priced the actual purchases in before the announcements. Therefore, in the next section, we

[9] This new program is called "Corporate Sector Purchase Programme" (CSPP). When CSPP was announced in March 2016, only an increase in monthly purchases of all types of bonds from EUR60 billion to EUR80 billion was mentioned. Thus, at the time of the announcement, the exact magnitude of the program was unknown, making the comparison with the Fed's purchase program difficult. Ex-post, Abidi and Miquel-Flores (2018) show that the ECB purchased about EUR90 billion one year after CSPP's implementation, which is relatively small compared with the size of the European nonfinancial corporate bond market, which is about EUR6 trillion reported in Çelik et al. (2020).

focus on the reaction on March 23 and April 9 and examine a more detailed breakdown of the credit spread changes.

4.3 Breakdown of Credit Spread Reactions

In order to evaluate how market segmentation in the corporate bond market affects credit spread reactions to the March 15 and April 9 announcements across different sectors of bonds, we examine the breakdown of bonds by credit rating, maturity, the bond's face value, issuer's size, and industry.

In Panel A of Table 4, we report the average credit spreads before and after the Fed's announcement on March 23. For the overall corporate bond market, credit spreads decrease from 544 bps to 497 bps. However, IG and HY bonds behave differently; credit spreads on IG bonds decrease from 439 bps to 380 bps, while credit spreads on HY bonds increase slightly from 1,099 to 1,115 bps. The difference by rating reflects the fact that in this announcement, the Fed was expected to purchase only IG bonds and ETFs based on IG bonds, not HY bonds. The small change in HY credit spreads is consistent with intra-day price changes for HY ETF in Figure 2, but may seem surprising given that the default risk channel and the liquidity risk channel both predict that HY credit spreads will fall.

However, as Ellul, Jotikasthira, and Lundblad (2011) show, there is evidence for market segmentation between IG and HY bonds due to regulatory constraints on major corporate bond investors such as insurance firms. Thus, from this perspective, the differential reaction between IG and HY bonds is anticipated. It is possible to argue that the size of the corporate QE is not large enough to save the economy, and the effect of QE did not spill over to HY bond issuers. However, HY bond issuers are generally small and more sensitive to changing prospects for economic growth than IG bond issuers. In fact, stock returns for HY issuers over the event window are 12.81%, which is higher than those for IG issuers (6.54%). Thus, a more plausible explanation for the differential reactions between IG and HY credit spreads is market segmentation.

Table 4 also presents the breakdown by the bond's maturity, the bond's face value, and the sum of face values at the issuer level. The effect of the announcement on bonds with different maturities is ex-ante not clear. The Fed would purchase individual corporate bonds with a remaining maturity of 5 years or less, while the ETFs are based on the index, which includes bonds with maturities of more than 3 years. In the data, the effect is more pronounced for short-term bonds than for medium- and long-term bonds; the credit spreads for bonds with maturities between 6 months and 1 year decline 115 bps, while those for bonds with maturities of 5 to 10 years decline 29 bps. The corporate bond market may be segmented across maturities as well, and thus credit spread reactions can vary across maturities. Though our findings are consistent with the market segmentation across maturities, it is also possible to argue that the Fed's announcement affects corporate credit spreads by reducing the eminent default risk of the borrower by committing to providing credit to borrowers experiencing temporary cash shortfalls. For such borrowers, default intensity would be high for the short horizon but low for the long horizon. Therefore, the Fed's announcement reduces the short-term default intensity and thus affects credit spreads on short-term bonds more than longer-term bonds. We argue that the latter is likely the better explanation in Section 4.5 and 5.1.

For the breakdown by the size of bonds and issuers, the QE announcement benefits large issuers and large issues more than smaller issuers. Credit spreads for bonds with face value less than $750 million fall 36 bps after the announcement, while they decrease 54 bps for larger bonds. Large bond issuers who are above the 70th percentile in terms of total issue size of bonds see their credit spreads fall 57 bps, while the decrease is only 7 bps for smaller issuers that are below the 30th percentile. The greater benefit for large issuers and issues may reflect the market segmentation or a greater reduction in default risk for large borrowers.

To evaluate the effect of the corporate bond QE across different industries, we classify issuing firms based on the Fama-French 5 industries. We split "manufacturing" in the Fama-French definition into energy sector and non-energy manufacturing, and split "others" into finance and other, non-finance industries. The breakdown by industry reveals that the high-tech, healthcare, and finance industries enjoy a greater decrease in credit spreads around the Fed's announcement than do other industries.

Development in the energy sector has garnered significant market attention during the COVID-19 pandemic, as the crude oil price declined sharply in 2020 Q1. Reflecting this trend, credit spreads on energy firms are much higher than other industries. The corporate QE lowers their credit spreads, but only as much as other industries. Thus, the unprecedented policy action still does not stimulate enough demand for the energy sector to recover.

Commercial banks (a part of the finance industry) see their credit spreads fall 68 bps, which is greater than other industries. This finding is interesting because with the SMCCF, the Fed bypasses commercial banks as lenders to private-sector borrowers and provides credit directly. This action may harm banks' profitability in the future by reducing credit spreads. However, if the Fed's action reduces the default risk of banks' existing loans, then banks also benefit from their improved balance sheet. In this case, the latter effect seems to dominate the former effect, and credit spreads for commercial banks fall after the announcement.

Panel B of Table 4 reports the event study for the April 9 announcement. The reaction to the announcement is similar to that after the March 23 announcement except for changes in HY bonds. Because the April 9 announcement includes ETFs on HY bonds and some individual HY bonds as potential targets of the purchase program, credit spreads on HY bonds fall 125 bps. This reaction again highlights the role of market segmentation across credit ratings, and thus directly targeting a category of bonds makes a difference in the initial reaction of credit spreads to the news.

Overall, the breakdown of credit spread reactions to the corporate QE announcement supports the significance of market segmentation in the bond market. However, to quantify the exact magnitude of credit spread changes due to QE under market segmentation, we need cleaner identification, which we turn to next.

4.4 Identification Exercise

To identify the effect of the corporate QE more clearly, we exploit exogenous differences in the issuer's characteristics. Specifically, we compare the credit spreads of firms that are downgraded from investment-grade to BB-rating before March 22 with those downgraded after March 22. On April 9, the Fed announced that it would purchase individual HY bonds if the issuers were rated as IG before March 22, 2020. Thus, there is a clear-cut difference in eligibility between firms that are newly downgraded to HY rating between March 22 and April 9 and firms that were already rated as HY as of March 22.[10] Thus, we use the first set of firms as a treatment group and the second set of firms as a control group to conduct a natural experiment.

We report firms in the control and treatment groups in Table 5. In our bond sample, we find six bond issuers that are downgraded from IG to HY rating between March 22 and April 9: Apache Corp., Continental Resources Inc., Delta Airlines Inc., Ford Motor Co., Hospitality Properties Trust, and Macy's Retail Holdings Inc. We then find firms that have the same credit rating (including "notches") after downgrade and four-digit SIC code as these six firms. As shown in Table 5, we find a total of seven bond issuers corresponding to Apache Corp., Continental Resources Inc., Delta Airlines Inc., and Hospitality Properties Trust. We do not find comparable bond issuers for Ford Motor Co. and Macy's Retail Holdings Inc, as issuers in these two industries are mostly rated IG as of March 22.[11]

[10] If a firm is rated by multiple rating agencies, they must be rated at least BBB-/Baa3 by two or more agencies as of March 22, 2020, to qualify.

[11] According to the Fed's disclosure, as of June 30, individual corporate bond holdings within the SMCCF program totaled around $1.6 billion, with just 3.1% invested in credits rated BB or less. That largely consists

Now we compare credit spread changes around the Fed's April 9 announcement on the corporate QE. Table 6 reports two-day changes in credit spreads and bid-ask spreads around the announcement for both treatment and control groups. The April 9 announcement decreases credit spreads on bonds issued by firms in the treatment group significantly. The credit spreads averaged across four firms in the treatment group that are matched to controls fall about 360 bps over the two-day window. In contrast, the credit spreads averaged within the control group decline about 200 bps. Thus, the analysis on this small sample suggests that credit spreads for the treatment group firms fall more than for other firms that share a similar default risk but that do not qualify for the purchase. The evidence in this small sample is consistent with our findings in the corporate bond market as a whole, in the sense that the bond market is segmented, and thus QE is more effective when the purchase program targets the market segment more directly.

In Appendix A, we compare U.S. and non-U.S. issuers because non-U.S. issuers may not be the target of the purchase program. However, we do not find significant differences between them, suggesting that such a difference was not recognized by bond investors at the time of the announcement.

4.5 Wider Event Window

As discussed above, the credit spread reaction over the two-day event window likely captures the impact of the monetary policy announcement relatively cleanly. Examining the changes over a wider event window such as two weeks, however, helps provide a better interpretation of the shocks. First, by comparing the response over the short run and over a longer term, we can get a sense of the persistence of the shock. Second, if the differential reaction of credit spreads across various types of bonds stems from market segmentation, then we expect the difference to shrink over time, as arbitragers (slowly) come in to equalize asset prices across segments.

Thus, we repeat the event study in Table 4 using the two-week event windows. Specifically, we examine the subset of bonds that have credit spreads on March 20 (pre-announcement date) and in the week of March 30, and use the transaction date closest to April 3 (which is two weeks after March 20) for the post-announcement credit spreads. Table 7 reports the credit spread changes for various types of bonds.

We find that credit spread reactions to the March 23 announcement are more pronounced

of $17.6 million bonds of Ford Motor (Ford Motor Company's and Ford Motor Credit Co.), $2.9 million bonds of Apache Corp., $2.9 million bonds of Delta Airlines, and $2.5 million bonds of Continental Resources.

over the two-week horizon than over the two-day horizon. The average credit spread falls 137 bps over the two-week horizon, which is larger than the 47 bps decline in Table 4. Notably, credit spreads for the average HY bond decline 103 bps over the two-week event window, even though the window ends before the April 9 announcement of including HY bonds in the QE program. The difference in credit spread changes between IG and HY bonds is 75 bps over the two-day window, but it shrinks to 33 bps over the two-week window. This narrowing gap implies that market segmentation initially drives a wedge between IG and HY bond credit spreads after the announcement, but as the economic outlook improves, the effect spills over from IG bonds to riskier segments of the market, reducing credit spreads on HY bonds as well. This convergence supports the view that market segmentation in the bond market exists, but its effect diminishes over time. These findings lead to a question on the fundamental drivers of credit spread reactions to the QE announcements that are consistent over both short-term and longer-term reactions in the data. We turn to this in the next section.

5 Dissecting Credit Spread Reactions

In this section, we attribute credit spread reactions to default risk and liquidity. To quantify the contribution of default risk, we use the variance decomposition approach of Nozawa (2017). We then try to explain credit spread reactions with changes in liquidity and stock prices.

5.1 Variance Decomposition

To directly quantify the impact of changing default risk on credit spread reactions to the monetary policy announcement, we decompose credit spreads into expected credit loss and risk premiums. Expected credit loss is equivalent to the probability of default times loss given default, and reflects an investor's expectation for the loss due to default in the future. Risk premiums reflect what investors require to bear the risk of investing in corporate bonds. The distinction between the two components is important in interpreting changes in asset prices after the policy announcement. For example, Bernanke and Kuttner (2005) study the stock market reaction to policy announcements and use variance decomposition of stock returns proposed by Campbell (1991) to distinguish the cash flow effect from the risk premium effect.

Following Bernanke and Kuttner (2005)'s approach, we adopt the variance decomposition of corporate credit spreads proposed by Nozawa (2017) and estimate the risk premium and expected credit loss components of credit spreads.

To implement the decomposition, we consider a vector of state variables,

$$X_t = \begin{pmatrix} r_t^e & s_t\tau_t & DD_t \end{pmatrix}' \tag{2}$$

where r_t^e is the logarithm of the average one-year return on week t in excess of those on matching Treasury bonds; s_t is the average credit spread; τ_t is the average duration; and DD_t is the average distance to default of bond issuers, constructed following Vassalou and Xing (2004). For week t bond price, we use the last observation for each bond in the week.

The law of motion for the state vector next year is given by

$$X_{t+52} = A_0 + AX_t + u_{t+52}, \tag{3}$$

where A is assumed to be constant.

Nozawa (2017) shows that the approximate log-linear identity holds for credit spreads,

$$s_t \approx \frac{1}{\tau_t} E_t \left[\sum_{j=0}^{\infty} \rho^j r^e_{t+52(j+1)} + \sum_{j=0}^{\infty} \rho^j l_{t+52(j+1)} \right] \tag{4}$$

where l_{t+j} is credit loss, and ρ is 0.992^{12}.[12]

The first term and the second term in the right-hand side of (4) are the risk premium and expected credit loss component of credit spreads, respectively, which can be written as

$$\begin{aligned} s_t^r &\equiv \frac{1}{\tau_t} E_t \left[\sum_{j=0}^{\infty} \rho^j r^e_{t+52(j+1)} \right] = \frac{1}{\tau_t} e_1 G X_t, \\ s_t^l &\equiv \frac{1}{\tau_t} E_t \left[\sum_{j=0}^{\infty} \rho^j l_{t+52(j+1)} \right] = \frac{1}{\tau_t} e_l G X_t, \end{aligned} \tag{5}$$

where e_m is a unit vector whose m-th entry is one, and $G = (I - \rho A)^{-1} A$. We estimate matrix A in (3) using OLS regressions over the full sample of overlapping weekly data to maximize the statistical precision, and infer the long-run predictive coefficients G from the one-year-ahead forecasts.

For event studies, we use the daily series of state variables, requiring bonds to trade on both a day before and after the event date. Using this loglinear identity, we decompose

[12] Nozawa (2017) uses $\rho = 0.992$ for monthly returns.

changes in credit spreads into two components,

$$\Delta s_t = \Delta s_t^r + \Delta s_t^l, \tag{6}$$

where the right-hand side variables are computed using the long-run prediction coefficients G and changes in state variables over the two-day event window. For brevity, we report estimated G coefficients in Table A4 in the Appendix.

Table 8 reports changes in credit spreads, state variables in (2), and changes in the risk premiums and expected credit loss components around the March 23 announcement on the corporate QE. Of the -47 bps change in the overall credit spreads, we find that the risk premium component explains -24 bps and the expected credit loss explains -23 bps. Thus, both default risk and default risk premiums are important drivers for the credit spread changes, and default risk explains about half of the credit spread reaction to the QE announcement. The fifty-fifty split applies to the market reaction to the April 9 announcement as well.

For the remainder of the results in Table 8, we repeat the decomposition exercise above using a subsample of bonds. For each subsample, we compute the simple average across bonds in each group to form a new vector of state variables as in (2), and re-estimate a VAR. This procedure allows long-run predictive coefficients in (5) to depend on the characteristics of bonds.

Table 8 presents the decomposition results for subsamples based on credit rating and maturity. For IG bonds, changes in the risk premium component are a dominant driver of credit spreads, explaining -51 bps out of a total change of -60 bps. This result is expected because IG bonds have relatively small default risk. In contrast, for HY bonds, the expected credit loss component is more important than risk premium components. On March 23, changes in expected credit loss largely account for credit spread changes for HY bonds, while it explains about 50% of credit spread changes on April 9.

The breakdown by maturity shows that the pronounced reaction of short-term bonds largely corresponds to expected credit loss changes rather than to risk premiums. For example, on March 23, expected credit loss decreases 87 bps for bonds with maturities of less than a year, while it decreases 5 bps for bonds with maturities of 10 years or longer. In contrast, changes in risk premium components do not vary significantly across maturity. As shown in Table 7, the difference in credit spread changes across maturities is less likely to be driven by market segmentation. Instead, the difference reflects the effect of corporate QE on the default risk of borrowers.

To sum up, the variance decomposition analysis shows that, despite market segmentation, the decreased default risk of borrowers explains a significant fraction of credit spread reactions to the QE announcements. The default risk channel of QE manifests itself in bond prices and reduces credit spreads of corporate bonds significantly.

5.2 Illiquidity Measures

Next, we study the role of the liquidity channel of the corporate QE. To this end, we examine changes in bond market liquidity measures, including bid-ask spreads and transaction volume, over the event window. Because calculating bid-ask spreads requires both dealer buys and sells to occur on the same day, not all bonds in our sample have this measure available. Thus, we take the average bid-ask spreads across available observations within each subsample of bonds.

The last three columns of Table 4 report the changes in these liquidity measures on March 23 (Panel A) and April 9 (Panel B). Unlike changes in default risk, the March 23 announcement led to the reduction of bid-ask spreads for IG bonds but not HY bonds, consistent with the direction of credit spread changes. Specifically, bid-ask spreads decreased 81 bps for IG bonds but increased 24 bps for HY bonds. On the day, transaction volume slightly increased for both IG and HY bonds. In contrast, the April 9 announcement had little effect on the two liquidity measures we study. Thus, changes in liquidity are unlikely to explain credit spread changes on April 9 but potentially account for part of the credit spread reactions on March 23.

To explain the changes in bid-ask spread, Table 10 further reports the changes in bond fund flows on March 23 (Panel A) and April 9 (Panel B) using EPFR flow data. Investors withdrew an astonishing \$21 billion from U.S. bond funds on March 20 — the largest outflow day in the first half of 2020 – with a high fraction of actively managed, IG, short-term, and institutional-oriented bond funds. The QE announcement on March 23 significantly reversed the run-for-exit and thus reduced investors' urgent desire to sell corporate bonds. In particular, bond fund flows increased \$12 billion for IG bonds but decreased \$160 million for HY bondsThis behavior of fund flows explains the changes in bid-ask spread in Table 4. Therefore, changes in liquidity during these event windows are likely driven by reduction in liquidity demand rather than increased liquidity supply.

To quantify the contribution of changing liquidity in understanding the credit spread reactions, we run a regression of credit spread changes on two-day changes in the liquidity measures,

$$\Delta s_{i,j,d} = b_0 D_{i,j,d} + b_1 D_{i,j,d} \Delta BAS_{i,j,d} + b_2 D_{i,j,d} \Delta VOL_{i,j,d} + u_{i,j,d}, \tag{7}$$

where $\Delta s_{i,j,d}$ is a change in credit spreads on bond i of issuer j on day d, $D_{i,j,d}$ is a vector of dummy variables that correspond to categories of bonds in Table 4, and $\Delta BAS_{j,d}$ and $\Delta VOL_{i,j,d}$ are the two-day changes in a bond's bid-ask spreads and trading volume, respectively.

We use daily stock and bond observations during the Global Financial Crisis period from July 1, 2007, to April 30, 2009, to estimate (7). The choice of the sample period is motivated by the observation in the literature that the risk of corporate bonds is generally state-dependent (e.g. Chen (2010) and Bhamra, Kuehn, and Strebulaev (2010)). Thus, it is not appropriate to use b estimated from normal times to predict credit spread changes in bad times, and we use the estimate from the stress period.[13] We include dummy variables for characteristics of bonds, such as credit rating, maturity, face value, and issuer size, which accounts for the potential dependence of parameter vectors b on the bond's characteristics, such as default risk and maturity of bonds.

Summary statistics for the variables in (7) are reported in Table A1 in the Appendix. Not surprisingly, both credit spreads and the illiquidity measures are volatile during the crisis period. Standard deviation for changes in credit spreads and bid-ask spreads are 108 bps and 241 bps, respectively.

The estimated coefficients are reported in Table A2 in the Appendix for brevity. Consistent with the previous literature on the effect of liquidity on corporate credit spreads (e.g., Bao et al. (2011)), a higher bid-ask spread is positively correlated with credit spread changes during the Global Financial Crisis. The relationship between changes in volume and credit spreads are more nuanced. For short-term bonds, changes in volume and credit spreads are positively related. Though this is somewhat counterintuitive, Goldberg and Nozawa (2020) show that the relationship between volume and liquidity can be positive or negative, depending on whether liquidity supply or demand drive the results. Furthermore, this positive correlation between volume and credit spread changes becomes weaker for longer-term bonds, and does not exist for bonds with maturities of more than 10 years.

Now, using the estimates for (7), we study the predicted credit spread changes due to changes in liquidity measures on March 23 and April 9. We find that the predicted credit spread changes based on changes in liquidity measures after the announcement are rather

[13] For the exact start and end dates of the crisis, we use the definition in Bao et al. (2017).

small in magnitude. For example, on March 23, liquidity-implied credit spread changes are -3 bps for IG bonds and -1 bps for HY bonds. Even though bid-ask spreads for IG bonds fell 81 bps, the change is small compared with their variation during the financial crisis, and thus the predicted change is close to zero. On April 9, predicted credit spread changes are -1 bps and -2 bps for IG and HY bonds, respectively. Thus, based on the historical relationship between liquidity and credit spreads, changes in liquidity over the event window do not seem to explain changes in credit spreads. For robustness, we replace bid-ask spreads with imputed round-trip costs of Feldhutter (2012), and confirm that our results are not driven by the particular choice of liquidity proxies.

Furthermore, we also examine how CDS spreads in the CDX indices react to the corporate QE announcement. Examining CDS spreads is useful, as CDS spreads are less likely to be affected by the liquidity premium than corporate credit spreads. In Table 9, we report changes in CDS spreads for 3-, 5-, 7-, and 10-year CDX indices. After the March 23 announcement, CDS spreads decreased about 40 bps for IG-rated borrowers, while the changes for HY borrowers are not clear. On April 9, IG CDS spreads fell about 20 bps, while HY CDS spreads decreased around 90 bps. These changes in CDS spreads are roughly consistent with changes in corporate credit spreads. These facts also support our claim that bond market liquidity was not the major driver for credit spread changes after the announcement.

In sum, the liquidity measures we use do not support the view that the liquidity channel played an important role in understanding the credit spread reactions to the corporate QE announcement. Given the strong evidence for market segmentation, the limited role played by liquidity is surprising. One explanation is that the announcement of corporate QE did not entail immediate implementation and primarily affected liquidity demand rather than liquidity supply (i.e. the dealer's inventory absorption capacity). For the liquidity channel to work, it may be necessary to actually provide liquidity and not just promise to provide it in the future.

5.3 Comparing with the Stock Market Reaction

The variance decomposition approach provides direct estimates for the default risk component but depends on VAR specifications. To address this concern, we also employ a more simple framework to estimate the contribution of default risk. Specifically, we rely on the insight from Merton (1974), in which credit spreads and stock returns are tightly linked. Specifically, both default risk and stock value depend on the firm's asset value, and thus an increase in default risk should correspond to lower stock returns. Empirically, Schaefer and

Strebulaev (2008) show that the Merton (1974) model correctly captures the hedge ratio, or the sensitivity of bond returns to the issuer's stock returns. Furthermore, since stocks are generally more liquid than corporate bonds, stock returns are less likely to be affected by shocks to bond market liquidity. Thus, we aim to capture the default risk component for credit spread changes by multiplying stock returns by credit spreads' sensitivity to stock returns.

To estimate the sensitivity parameter, we run a pooled OLS regression of daily changes in credit spreads on stock returns and dummy variables,

$$\Delta s_{i,j,d} = b_0 D_{i,j,d} + b_1 D_{i,j,d} r_{j,d} + u_{i,j,d}, \tag{8}$$

where $\Delta s_{i,j,d}$ is a change in credit spreads on bond i of issuer j on day d, $D_{i,j,d}$ is a vector of dummy variables that correspond to categories of bonds in Table 4, and $r_{j,d}$ is the issuer's stock return on day d.

To save space, we report the estimated coefficients b_0 and b_1 in Table A2 in the Appendix, but briefly summarize our findings here. As predicted by the Merton (1974) model, the coefficient b_1 is generally negative, indicating that a higher stock return reflects an improved valuation of the issuer's asset, which results in lower default risk and thus credit spreads.

Based on the estimates for b_0 and b_1, we construct predicted changes in credit spreads during the event window,

$$\Delta \hat{s}_{i,j,d} = \hat{b}_0 + \hat{b}_1 r_{j,d}. \tag{9}$$

Table 4 presents predicted changes for the average bonds using the full sample as well as subsamples. For the average bond issuer, stock returns during the event window are 7.6%, which implies an -12 bps change in credit spreads. Given the average changes in credit spreads of -47 bps, the default risk component implied by stock returns explains about one-fourth of the changes in credit spreads. The breakdown of samples by credit rating shows that the average stock returns are greater for HY issuers than for IG issuers, and thus the predicted credit spreads in (9) are more negative for HY bonds than for IG bonds. Based on this analysis, the increase in HY credit spreads appears puzzling, further cementing the argument for the bond market segmentation.

The stock returns and predicted credit spreads vary across issuer size. The small issuers have average stock returns of 14.7%, which leads to predicted credit spread changes of -30 bps. This predicted change in credit spreads is more pronounced than that for large issuers (-10 bps). The difference between large and small issuers in stock returns goes against the observed pattern in credit spread changes, because credit spreads fell more for large issuers than small issuers.

Furthermore, Panel B of Table 4 reports that the stock-return implied credit spread changes are close to zero for the April 9 announcement. These results reveal the limitation of this simple approach, which strongly depends on the intuition from a one-factor Merton model. To understand the unexplained residuals, we need a more general framework to allow multifactors to determine credit spreads, as we did in Section 5.1.

6 Conclusion

In this paper, we examine how the U.S. corporate bond market reacted to the Fed's corporate bond purchase program. We find that credit spreads on IG bonds decreased significantly after the March 23 announcement, while HY bonds did not. The market segmentation between IG and HY likely explains such differences in initial reactions, as the difference narrows in the wider event window.

Examining channels through which QE affects corporate credit spreads, we find evidence that the default risk channel explains a significant fraction of credit spread reactions across different segments of corporate bonds. In particular, the results from variance decomposition suggest that reduced default risk over the short-term well explains changing term structure of credit spreads upon the policy announcements. On the other hand, changing liquidity of corporate bonds does not seem to explain credit spread reactions. These corporate bond market reactions reflect the nature of the crisis arising from the COVID-19 pandemic which first affects the real economy and then spreads the shock to the financial market. The transmission is in stark contrast to what happened during the financial crisis in 2008, where liquidity problems in the financial market spilled over to the real economy.

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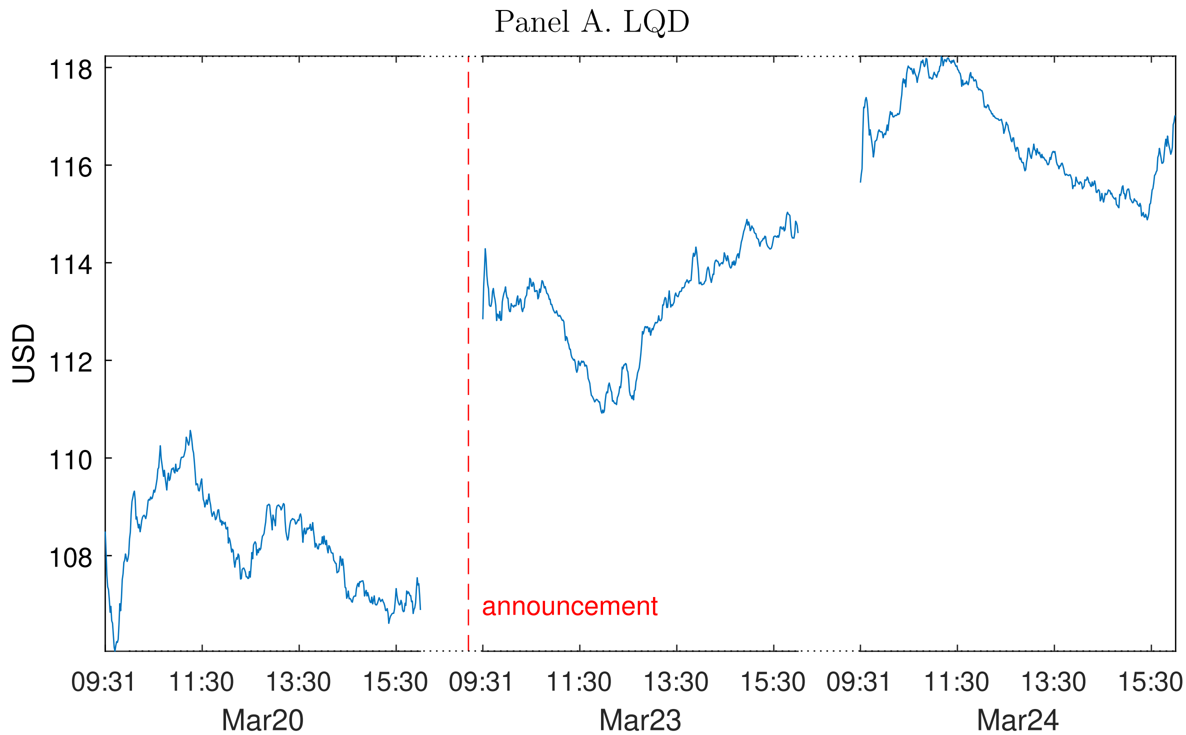
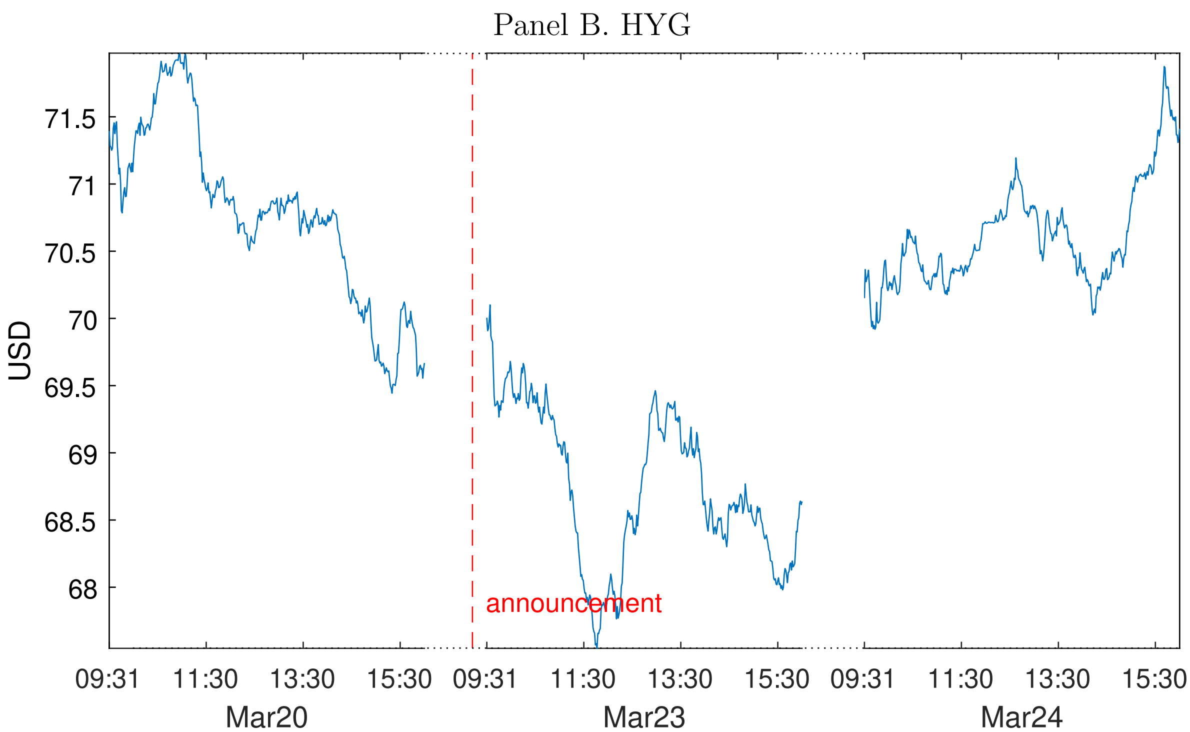
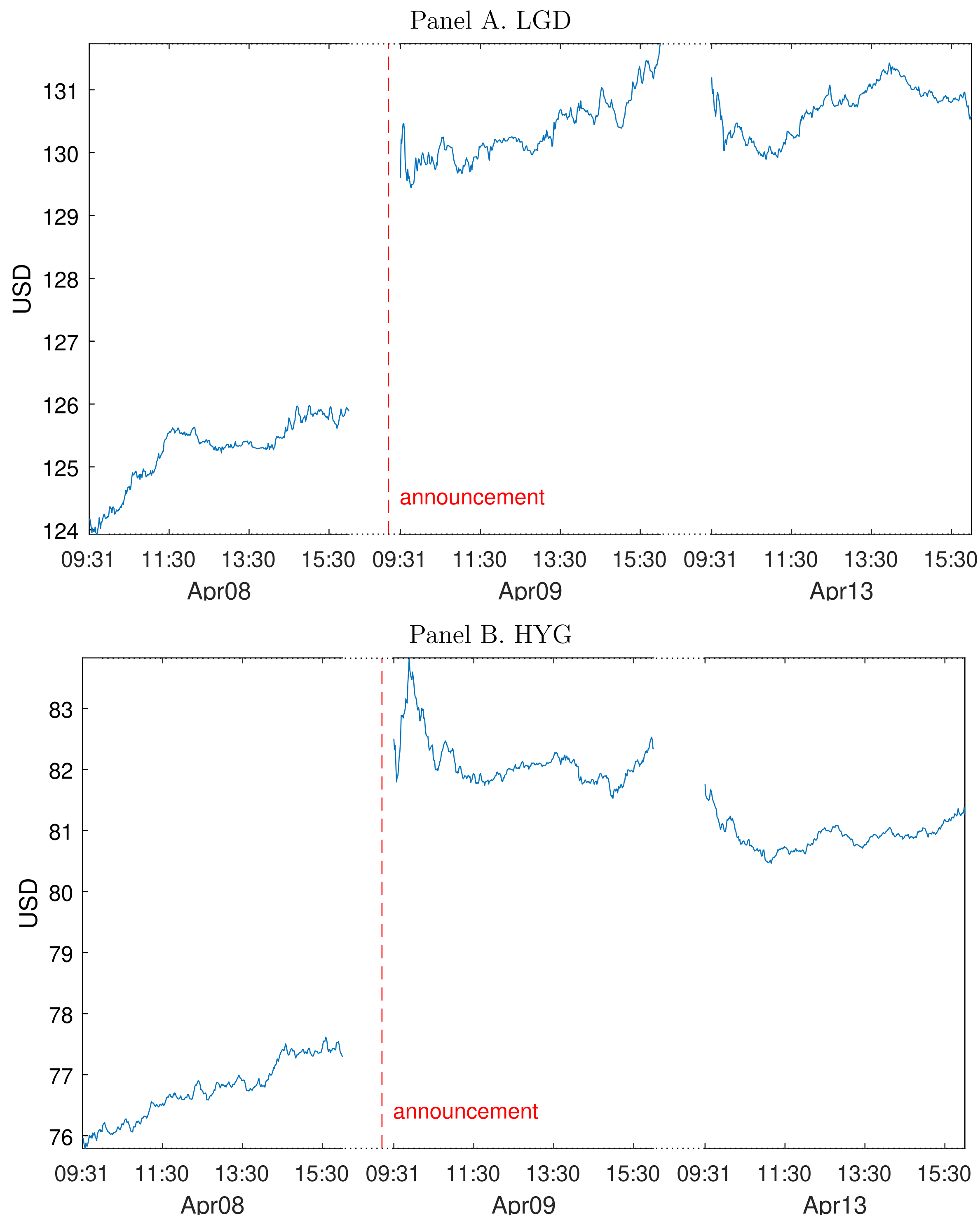
Figure 2: Intra-Day Prices for Corporate Bond ETFs Around March 23 Announcement





The figure plots intraday movements in price for the iShares IBoxx $ Invest Grade Corporate Bond Fund (LQD) and High-Yield Corporate Bond Fund (HYG). Using the second-level transaction price from Thomson Reuters Tick History database, we take the average at the minute level to plot.

Figure 3: Intra-Day Prices for Corporate Bond ETFs Around April 9 Announcement



The figure plots intraday movements in price for the iShares IBoxx $ Invest Grade Corporate Bond Fund (LQD) and High-Yield Corporate Bond Fund (HYG). Using the second-level transaction price from Thomson Reuters Tick History database, we take the average at the minute level to plot.

Table 1: Key Developments in the COVID-19 Pandemic and Monetary Policy in 2020

Date	News and Events
January 23	China implements travel bans or lockdowns in Wuhan and the other four cities in the Hubei province.
February 23	Italy sees a major surge in coronavirus cases and officials lock down towns, signaling the second phase of the coronavirus pandemic.
March 3	The FOMC announces an emergency rate cut of 50 bps.
March 15	Emergency FOMC meeting to lower rates to effectively zero and purchase Treasuries and MBS. The Fed lowers the primary credit rate in the discount window, and lowers the required reserve ratio to zero.
March 17	The Fed announces a Commercial Paper Funding Facility and a Primary Dealer Credit Facility.
March 18	The Fed announces a Money Market Mutual Fund Liquidity Facility.
March 19	The Fed announces a temporary U.S. dollar swap arrangement with 9 central banks.
March 23	The Fed announces the corporate bond purchase programs (PMCCF, SMCCF), with the Treasury Dept., committing an equity investment of $10bn. CMBS is included in the QE on MBS. The Term Asset-Backed Securities Facility is introduced.
March 25	The U.S. Senate passes a 2 trillion fiscal package to stimulate the economy.
March 31	The Fed announces a temporary repurchase agreement facility for foreign central banks.
April 9	The Fed expands the target of the corporate bond purchase programs to include High-Yield ETFs and issuers downgraded to BB/Ba before March 22. The Treasury Dept. increases equity investment to $75bn.
May 11	The Fed announces that it will start purchasing corporate bond ETFs on May 12.
June 15	The Fed announces that it will start purchasing individual corporate bonds to form a diversified portfolio of bonds.

Table 2: Size of the U.S. Bond Market and Fed's Quantitative Easing Program

	Amount (USD bil)	Date	Source
Corporate bond market outstanding	9,466.9	as of June 30, 2019	SIFMA
Corporate bond issues	1,338.2	in year 2018	SIFMA
Size of the Q.E. program announced	750.0	as of March 23, 2020	FRB
Balance for ETFs	8.0	as of June 30, 2020	FRB
Balance for individual bonds	1.6	as of June 30, 2020	FRB

Size of the Q.E. program announced is the sum of the purchase in the primary market (PMCCF) and the secondary market (SMCCF). Balance for ETFs and individual bonds is the outstanding values of securities purchased under SMCCF as of June 30, 2020.

Table 3: Changes in Credit Spreads Around the Fed's Monetary Policy Announcement in 2020

		Pre (bps)	Post (bps)	Δs (bps)	Pre (bps)	Post (bps)	Δs (bps)
		Panel A. March 3			Panel B. March 15		
All		198	194	-4	364	428	65
By rating	IG	130	126	-4	238	282	44
	HY	501	494	-7	844	988	144
By maturity	6m-1y	102	105	4	561	633	72
	1-2y	146	152	5	313	402	89
	2-3y	182	178	-4	371	454	84
	3-5y	235	232	-3	434	519	85
	5y-10y	206	201	-6	375	440	66
	10y-	199	190	-8	278	308	30
		Panel C. March 23			Panel D. April 9		
All		544	497	-47	386	315	-71
By rating	IG	439	380	-59	281	221	-60
	HY	1,099	1,115	16	915	790	-125
By maturity	6m-1y	681	566	-115	364	278	-86
	1-2y	553	480	-74	359	258	-101
	2-3y	549	485	-64	429	334	-95
	3-5y	663	616	-47	437	353	-84
	5y-10y	556	527	-29	413	352	-61
	10y-	408	373	-36	299	254	-45
		Panel E. May 12			Panel F. June 15		
All		404	417	13	313	292	-21
By rating	IG	235	236	1	170	153	-17
	HY	1,156	1,224	68	911	874	-36
By maturity	6m-1y	1,130	1,244	114	1017	1010	-7
	1-2y	315	328	14	255	231	-24
	2-3y	438	458	20	316	282	-34
	3-5y	384	389	5	278	253	-25
	5y-10y	386	388	2	297	278	-19
	10y-	276	278	2	242	226	-16

This table reports the average changes in credit credit spreads around the Fed's announcement in early 2020. For an event on day d, we take the average of the bond-level changes in credit spreads from $d-1$ to $d+1$, excluding zero change observations.

Table 4: Panel A, Changes in Credit Spreads Around March 23 QE Announcement

		Credit Spreads			Stock Returns		Bond Liquidity		
		Pre (bps)	Post (bps)	Δs (bps)	Returns (%)	$\Delta \hat{s}_s$ (bps)	BAS (bps)	Volume (mil)	$\Delta \hat{s}_l$ (bps)
All		544	497	-47	7.60	-12	-62	0.30	-2
By rating	IG	439	380	-59	6.54	-8	-81	0.27	-3
	HY	1,099	1,115	16	12.81	-30	24	0.54	-1
By maturity	6m-1y	681	566	-115	7.40	-23	-42	0.27	-6
	1-2y	553	480	-74	7.27	-15	-73	-0.62	-4
	2-3y	549	485	-64	6.80	-12	-91	0.02	-5
	3-5y	663	616	-47	7.51	-12	-58	0.31	-2
	5y-10y	556	527	-29	8.36	-12	-37	0.97	-2
	10y-	408	373	-36	7.29	-8	-89	0.04	0
By face value	-750 mil	646	610	-36	8.52	-14	-41	0.55	-3
	750 mil-	487	433	-54	7.08	-11	-71	0.16	-2
By issuer size	70%-tile	467	411	-57	6.78	-10	-67	0.18	-2
	30%-70%	755	740	-15	9.74	-16	-43	0.72	-3
	-30%-tile	1,150	1,143	-7	14.71	-30	-47	0.88	1
By industry	Cnsmr	559	518	-41	7.51	-15	-85	0.34	-2
	Energy	1,355	1,319	-36	10.42	-7	-22	1.03	0
	Manuf	470	446	-24	6.80	-8	-30	0.34	-2
	HiTec	438	368	-69	6.13	-7	-78	-0.13	-4
	Hlth	386	334	-52	2.08	-4	-78	0.58	-1
	Finance	486	426	-60	8.31	-14	-49	0.28	-3
	Other	722	686	-37	13.52	-26	-69	0.52	-2
Within Finance	Banks	430	362	-68	6.61	-12	-101	-0.86	-4
	Nonbanks	499	441	-58	8.72	-14	-34	0.56	-3

This table reports the average of the bond-level changes in credit spreads from March 20 to March 24 (Panel A), and from April 8 to April 13 (Panel B), excluding zero change observations. Stock returns are measured over the two-day event window accordingly. $\Delta \hat{s}$ is stock-implied credit spread changes computed as $\hat{b_0} + \hat{b_1} \times$ ret, where $\hat{b_0}$, $\hat{b_1}$ are estimated using a pooled OLS regression of credit rate changes on stock returns amid the Global Financial Crisis period. BAS is the bid-ask spread. For all bonds that have buys and sells on the same day, we compute the bid-ask spread as (S-B)/0.5(S+B), where S (B) is the average sell (buy) price on a day for bond. Volume is daily transaction volume for each bond at each day using all transactions in the TRACE data. Issuer size is the sum of total face values of outstanding bonds at the issuer level. (To be continued.)

Table 4, Panel B: Changes in Credit Spreads Around April 9 QE Announcement

		Credit Spreads			Stock Returns		Bond Liquidity		
		Pre (bps)	Post (bps)	Δs (bps)	Returns (%)	$\Delta \hat{s}$ (bps)	BAS (bps)	Volume (mil)	$\Delta \hat{s}$ (bps)
All		386	315	-71	0.75	-1	2	-0.49	-1
By rating	IG	281	221	-60	0.66	-1	0	-0.60	-1
	HY	915	790	-125	1.18	0	13	0.13	-2
By maturity	6m-1y	364	278	-86	0.38	-5	-12	0.06	-4
	1-2y	359	258	-101	0.34	-1	4	-0.29	1
	2-3y	429	334	-95	1.00	-2	22	-0.60	-2
	3-5y	437	353	-84	1.15	-2	-1	-0.21	-2
	5y-10y	413	352	-61	0.51	0	-3	-0.72	-2
	10y-	299	254	-45	0.88	-1	6	-0.56	0
By face value	-750 mil	550	466	-84	1.06	-2	8	-0.26	-3
	750 mil-	297	233	-64	0.58	-1	0	-0.61	-1
By issuer size	70%-tile	301	239	-62	0.62	-1	0	-0.66	-1
	30%-70%	606	510	-96	1.16	-1	12	0.20	-2
	-30%-tile	836	721	-114	1.17	-2	-1	-0.32	-1
By industry	Cnsmr	428	344	-84	0.37	-1	5	0.34	-1
	Energy	1,107	970	-137	4.29	-5	70	-0.53	1
	Manuf	378	308	-70	1.40	-2	-5	-0.25	-1
	HiTec	262	210	-53	0.12	0	8	-1.34	-2
	Hlth	235	183	-52	-0.80	1	-12	-0.19	-2
	Finance	281	224	-57	1.33	-3	-1	-0.77	-2
	Other	515	421	-94	-0.23	2	-20	-0.38	-1
Within Finance	Banks	211	163	-47	3.71	-6	4	-2.39	-2
	Nonbanks	299	239	-60	0.71	-2	-2	-0.35	-2

We apply Fama-French 5 industry classification based on four-digit SIC codes: Cnsmr (Consumer Durables, Nodurables, Wholesale, Retail, and Some Services), Manuf (Manufacturing, Energy, and Utilities), HiTec (Business Equipment, Telephone and Television Transmission), Hlth (Healthcare, Medical Equipment, and Drugs), and Other. We divide 'Other' into Finance (SIC code between 6000 and 6999) and Nonfinance sectors. The finance sector is split into commercial banks (with the first three SIC digits of 602) and nonbanks.

Table 5: Firms Downgraded to High Yield Between March 22 and April 8

Treatment group				Control group	
Permno	Name	Rating after downgrade	SIC	Permno	Name
39490	Apache Corp	BB+	1311	70332	ANADARKO PETE CORP
91983	Continental Resources	BB+	1311	79915	NEWFIELD EXPL CO
				87137	ENLINK MIDSTREAM PARTNERS LP
				89134	NEWFIELD EXPL CO
91926	Delta Airlines	BB	4512	91103	UNITED CONTL HLDGS INC
81917	Hospitality Properties	BB+	6798	85234	CORRECTIONS CORP AMER
				87289	SENIOR HSG PPTYS TR
77462	Macy's Retail Holdings	BB+	5311		n.a.
25785	Ford Motor Co	BB	3711		n.a.

The treatment group is five bond issuers that were downgraded from IG to HY between March 22 and April 8. Firms in the control group are in the same industry as the treatment group defined by 4-digit SIC codes, and have the same credit rating as of April 8, but were not downgraded to HY between March 22 and April 8.

Table 6: Changes in Credit Spreads and Bid-Ask Spreads on April 9 Announcement

	Credit Spreads (bps)			Liquidity	
	Pre	Post	Δs	BAS (bps)	Volume (mil)
Apache Corp	1,604	1,117	-488	47	-2
Control	2,023	1,742	-281	-5	-1
Continental Resources	1,295	951	-344	11	-6
Control	2,023	1,742	-281	-107	-1
Delta Airlines	1,054	730	-323	95	-2
Control	1,181	990	-191	-22	1
Hospitality Properties	1,506	1,210	-296	52	0
Control	717	632	-85	-150	0
Macy's Retail Holdings	1,774	1,226	-548	-85	-1
Ford Motor Co	818	515	-303	37	0

For each firm, we take the average of credit spreads and bid-ask spreads for bonds issued by the firm to compute the firm-level values on April 8 and April 13. Δs is the change in firm-level credit spreads over the period. Ctrl is the average of the firm-level credit spreads in controlling groups, defined in Table 5.

Table 7: Changes in Credit Spreads Around March 23 QE Announcement: 2-Week Window

		Credit Spreads			Stock Returns		Bond Liquidity		
		Pre (bps)	Post (bps)	Δs (bps)	Returns (%)	$\Delta \hat{s}$ (bps)	BAS (bps)	Volume (mil)	$\Delta \hat{s}$ (bps)
All		573	437	-137	8.12	-10	-104	-0.77	-4
By rating	IG	433	296	-136	8.63	-9	-125	-0.82	-4
	HY	1,201	1,098	-103	5.46	-11	-16	-0.54	-2
By maturity	6m-1y	669	385	-284	6.88	-19	-80	-1.93	-11
	1-2y	697	551	-146	7.77	-14	-93	-0.96	-6
	2-3y	565	401	-164	7.24	-10	-159	-0.06	-8
	3-5y	681	505	-175	6.66	-7	-84	-0.46	-2
	5y-10y	592	471	-121	8.24	-8	-87	-0.72	-3
	10y-	407	324	-83	9.75	-8	-140	-1.03	0
By face value	-750 mil	666	548	-119	8.68	-10	-68	0.09	-4
	750 mil-	502	352	-150	7.69	-10	-124	-1.42	-4
By issuer size	70%-tile	487	333	-155	8.53	-10	-124	-1.04	-4
	30%-70%	731	613	-117	6.86	-8	-73	0.02	-4
	-30%-tile	1,085	1,104	19	7.41	-13	44	-0.17	2
By industry	Cnsmr	542	434	-108	6.36	-12	-110	-0.75	-3
	Energy	1,747	1,660	-87	13.94	-7	-73	0.07	3
	Manuf	456	357	-99	10.24	-10	-77	0.06	-3
	HiTec	447	289	-158	6.93	-7	-96	-1.97	-5
	Hlth	402	267	-135	9.77	-8	-111	-1.23	-2
	Finance	555	356	-199	6.91	-9	-127	-1.06	-6
	Other	695	549	-146	7.04	-13	-122	-0.20	-4
Within	Banks	415	239	-176	2.59	-4	-165	-1.94	-7
Finance	Nonbanks	586	382	-204	7.87	-10	-116	-0.86	-6

This table reports the average changes in credit risk and liquidity measures between March 20 and the last daily observation in the period from March 30 to April 3. Stock returns for each firm are measured over the corresponding event window accordingly. Other details of the table can be found in the notes to Table 4.

Table 8: Decomposition of Credit Spread Changes on March 23 and April 9 Announcement

			Changes in State Variables			Decomposition	
		Δs (bps)	Δr (bps)	$\Delta s\tau$	ΔDD	Δs^r (bps)	Δs^l (bps)
Panel A. Reactions to March 23 Announcement							
All		-47	194	-253	1322	-24	-23
By rating	IG	-60	252	-351	1029	-51	-8
	HY	16	-25	53	2892	-4	20
By maturity	6m-1y	-114	79	-96	836	-28	-87
	1-2y	-74	78	-114	988	-24	-51
	2-3y	-65	184	-158	1407	-37	-27
	3-5y	-47	200	-175	1347	-37	-9
	5y-10y	-29	138	-170	1653	-19	-10
	10y-	-37	405	-354	1092	-31	-5
Panel B. Reactions to April 9 Announcement							
All		-71	358	-434	-296	-35	-36
By rating	IG	-60	309	-390	-261	-52	-8
	HY	-125	521	-531	-450	-65	-60
By maturity	6m-1y	-86	35	-55	-1540	2	-72
	1-2y	-101	75	-156	-306	-19	-87
	2-3y	-95	239	-241	556	-48	-53
	3-5y	-84	319	-302	-622	-62	-20
	5y-10y	-61	479	-368	-426	-38	-23
	10y-	-45	412	-586	8	-37	-8

This table reports the two-day changes in the credit spreads, state variables, as well as the variance decomposition results around March 23 and April 9, 2020. The vector of state variables (X_t) include average bond excess returns (r_t^e), the product of the average credit spreads and average duration ($s_t\tau_t$), and the average distance to default (dd_t). We multiply X_t by 10,000 so that the long-run expected returns (s_t^r), $e_r GX_t/\tau_t$, and the long-run expected credit loss (s_t^l), $e_l GX_t/\tau_t$, are expressed in basis points. The average changes in credit spreads and their components are reported using the whole sample as well as the subsamples grouped by rating and maturity. To compute changes over the two-day window, we restrict the bond sample to have valid price observations and stock returns on both March 20 and March 24, and on both April 8 and April 13, for the March 23 and April 9 announcements, respectively.

Table 9: **Reaction of Other Credit Instruments**

			March 23, 2020			April 9, 2020		
			Pre	Post	Change	Pre	Post	Change
Corporate bonds	IG		438	379	-60	281	221	-60
	HY		1101	1116	16	915	790	-125
CDX.IG		3 year	128	89	-39	97	72	-25
		5 year	152	108	-44	105	84	-21
		7 year	163	119	-44	118	102	-16
		10 year	172	132	-41	124	111	-14
CDX.HY		3 year	760	782	22	708	612	-96
		5 year	866	723	-143	625	555	-70
		7 year	849	849	0	737	648	-89
		10 year	847	842	-5	703	614	-88
Leveraged Loan Index			1,826	1,795	-31	2,089	2,138	49

The table reports the changes in corporate credit spreads, CDS spreads, and leveraged loan index around the March 23 and April 9 corporate QE announcements. CDS spreads are for CDX.NA.IG and CDX.NA.HY indices and expressed in bps, while Leveraged Loan Index is an index value (i.e. generally, a higher value corresponds to lower credit spreads).

Table 10: Daily Fund Flows to Corporate Bond Mutual Funds

		Pre (mil)	Post (mil)	$\Delta flow$ (mil)	Pre (mil)	Post (mil)	$\Delta flow$ (mil)
		Panel A. March 23			Panel B. April 9		
All		-21,371	-7,680	13,692	727	2,662	1,934
By style	Active-ETF	-1,656	-404	1,252	321	282	-39
	Active-Non ETF	-18,181	-8,180	10,000	-198	1,039	1,237
	Passive-ETF	-1,416	1,069	2,485	717	1,420	703
	Passive-Non ETF	-118	-164	-45	-113	-79	34
By rating	IG	-16,227	-4,016	12,211	347	-1,061	-1,408
	HY	-1,828	-1,988	-160	525	2,842	2,317
	Mixed	-3,317	-1,676	1,641	-145	880	1,025
By maturity	ST (0-4y)	-10,655	-873	9,782	492	2,992	2,500
	MT (4-6y)	-4,120	-3,650	470	-577	-4,097	-3,521
	LT (6y-)	-676	223	898	714	712	-2
	ST Corp	-443	-333	110	-1	318	319
	MT Corp	-396	-164	232	328	357	29
	LT Corp	522	1,684	1,163	885	680	-206
By investor type	Retail	-4,702	-4,925	-223	-165	321	486
	Institutional	-16,669	-2,755	13,915	893	2,341	1,449

This table reports the aggregate-level changes in bond fund flows from March 20 to March 24 (Panel A), and from April 8 to April 13 (Panel B), using EPFR fund flow data from Informa Financial Intelligence. The categorization of bond funds follows EPFR. Active includes only funds that are actively traded and not tied to a passive index/benchmark. Passive includes only funds that are tied to an index/benchmark and seek to mirror the index/benchmark's performance. IG (HY) bond funds are those that invest primarily (at least two-thirds of total assets) in investment-grade (high-yield) debt instruments. Mixed are bond funds that invest in both IG and HY without significant portfolio tilt. ST/MT/LT are funds with a mixture of government and corporate bonds focusing on bonds with duration of 0-4 yr / 4-6 yr / 6+ yr. Corporate Bond Funds (ST Corp, MT Corp, LT Corp) are funds with at least 65% allocation to corporate bonds. Retail includes only funds marketed to, or with a primary focus on, retail investors. Institutional includes only funds that are focused on institutional, or that have a minimum investment of $100,000.

A U.S. and non-U.S. Issuers

We begin by comparing the U.S. issuers with non-U.S. issuers. In the March 22 announcement, the Fed defines issuers eligible for purchase as "U.S. businesses with material operations in the United States." On April 9, the definition of U.S. firms is more clearly specified, which is "a business that is created or organized in the United States or under the laws of the United States with significant operations in and a majority of its employees based in the United States." This distinction between U.S. and non-U.S. firms suggests that the price pressure of the Fed purchase can be measured as a difference in credit spread changes between bonds issued by U.S. issuers and non-U.S. issuers. To identify non-U.S. issuers, we augment the data set in the main analysis by adding yankee bonds, which are bonds offered in the U.S. issued by non-U.S. corporations. Using the subsample of bonds issued by non-U.S. firms, we compute credit spread changes around the corporate bond QE announcement on March 23, and report the average across bonds.

Table A3 reports the reaction of credit spreads for non-U.S. bonds. For comparison, we also report the main results taken from Table 4. We find that, despite the much smaller sample of non-U.S. bonds, the magnitude of credit spread changes for non-U.S. bonds is similar to that of U.S. bonds in the main results. Notably, the average credit spread for U.S. bonds decreases 49 bps after the announcement, while the average for non-U.S. bonds decreases 45 bps. The breakdown by credit rating, maturity, size, and industry shows broadly the same pattern in credit spread changes between U.S. and non-U.S. issuers. The only exception is HY bonds: HY bonds issued by non-U.S. firms have -46 bps changes in credit spreads, which is lower than HY bonds by U.S. firms. This difference likely reflects the high estimation uncertainty for the average. Because the standard deviation in credit spreads for HY bonds is large, it is difficult to pin down the exact reaction.

The fact that we do not observe a significant difference between U.S. and non-U.S. firms suggests that the decline in credit spreads in response to the corporate QE is not a simple reflection of buying pressure of the Fed distorting the market price for the targeted bonds. Rather, the improved cash flows and business conditions in the U.S. due to the better funding condition is the likely contributor to the change in credit spreads. A caveat to this conclusion is that the distinction between U.S. and non-U.S. firms may not be obvious to investors, which would also explain this result.[14]

[14] The Bloomberg article "Fed's Power to Buoy Corporate Debt Market Curbed by Bailout Law" dated April 28, 2020, points out this ambiguity about the eligibility for purchase.

B Variance Decomposition of Credit Spreads

Table A4 reports the estimated long-run predictive regression coefficients for different subsamples of corporate bonds.

Table A1: Summary Statistics for the Panel Regressions of Daily Credit Spread Changes

Variables	N	Mean	Std	P1	P25	Median	P75	P99
				Full Sample				
Δs	195,112	0.77	108.02	-152.56	-10.98	-0.39	10.14	167.11
r	195,013	-0.02	4.87	-13.04	-1.80	-0.06	1.62	14.17
ΔBAS	36,285	-1.33	241.15	-692.51	-67.55	-0.03	65.95	689.66
ΔVOL	195,112	-0.06	9.54	-28.65	-2.11	0.00	2.00	27.87
				Stock Return Regression				
Δs	195,013	0.83	104.26	-149.88	-10.97	-0.38	10.13	165.73
r	195,013	-0.02	4.87	-13.04	-1.80	-0.06	1.62	14.17
				Liquidity Regression				
Δs	36,285	-1.10	148.60	-232.85	-15.83	-2.12	11.32	253.84
ΔBAS	36,285	-1.33	241.15	-692.51	-67.55	-0.03	65.95	689.66
ΔVOL	36,285	-0.12	11.50	-35.30	-3.13	-0.01	3.01	33.08

This table reports the summary statistics for daily credit spread changes (in bps) during the Global Financial Crisis period. Following Bao et al. (2017), we define the crisis period as from July 1, 2007, to April 30, 2009. To calculate credit spread changes, we require at lease two consecutive daily observations for bond prices. r is stock returns adjusted for delisting. ΔBAS is changes in bid-ask spreads, and ΔVOL is changes in trading volume.

Table A2: Panel Regressions of Daily Credit Spread Changes

	Stock Returns Regressions		Liquidity Regressions		
	Const.	Returns	Const.	ΔBAS	$\Delta Volume$
Intercept	-4.855***	-2.680***	-4.091	0.047	1.551***
	(-2.85)	(-4.92)	(-0.96)	(0.86)	(2.97)
D_{HY}	2.762***	-1.680***	0.212	-0.004	-0.071
	(2.94)	(-7.71)	(0.06)	(-0.46)	(-0.27)
D_{1-2y}	3.108*	0.587	3.892	0.002	-0.381
	(1.81)	(1.01)	(0.92)	(0.04)	(-0.69)
D_{2-3y}	3.872**	0.860	1.239	-0.015	-0.723
	(2.40)	(1.62)	(0.31)	(-0.25)	(-1.36)
D_{3-5y}	4.322***	1.259***	1.535	-0.051	-0.905*
	(2.69)	(2.61)	(0.38)	(-0.94)	(-1.71)
D_{5-10y}	4.306***	1.289***	1.594	-0.038	-1.217**
	(2.62)	(2.59)	(0.39)	(-0.67)	(-2.30)
$D_{>10y}$	4.198**	1.294**	2.905	-0.051	-1.337**
	(2.58)	(2.54)	(0.73)	(-0.91)	(-2.55)
$D_{>750m}$	1.205***	-0.241	1.697*	-0.002	-0.097
	(3.79)	(-1.60)	(1.96)	(-0.24)	(-0.98)
D_{Medium}	-0.522	0.274	-1.263	0.008	-0.012
	(-1.37)	(1.54)	(-0.87)	(1.02)	(-0.10)
D_{Low}	-1.056*	0.233	1.498	0.017	0.015
	(-1.81)	(1.02)	(0.59)	(1.23)	(0.05)
D_{Energy}	-0.847*	1.357***	1.307	-0.009	-0.133*
	(-1.84)	(6.51)	(0.96)	(-0.95)	(-1.67)
D_{Manuf}	-0.401	0.804***	1.078	0.004	0.285***
	(-0.99)	(3.95)	(1.02)	(0.41)	(3.11)
D_{HiTec}	-0.630	0.928***	-1.402	0.009	-0.182**
	(-1.51)	(3.65)	(-1.13)	(0.79)	(-2.24)
D_{Hlth}	-1.126**	1.105***	-1.067	-0.010	-0.107
	(-2.53)	(4.56)	(-0.89)	(-0.96)	(-1.29)
D_{Fin}	-0.241	0.375	-0.809	0.015	-0.201**
	(-0.46)	(1.59)	(-0.65)	(1.54)	(-2.52)
D_{NonFin}	-0.043	0.620**	1.102	0.005	0.659**
	(-0.06)	(2.20)	(0.42)	(0.35)	(2.36)

This table reports the estimated coefficients and t-statistics from the following pooled OLS regression of daily credit spread changes (in bps) for bond i issued by firm j on day d during the Global Financial Crisis period:

$$\Delta s_{i,j,d} = b_0 D_{i,j,d} + b_1 D_{i,j,d} r_{j,d} + u_{i,j,d}.$$

$$\Delta s_{i,j,d} = b_0 D_{i,j,d} + b_1 D_{i,j,d} \Delta BAS_{i,j,d} + b_2 D_{i,j,d} \Delta VOL_{i,j,d} + u_{i,j,d}$$

Following Bao et al. (2017), we define the crisis period as from July 1, 2007, to April 30, 2009. To calculate credit spread changes, we require at lease two consecutive daily observations for bond prices. The stock returns are adjusted for delisting. The regression coefficients are estimated in the whole sample as well as various subsamples based on credit rating, maturity, face value, issuer size, and industry. We cluster standard errors by calendar date and report t-statistics in parentheses. ***, **, and * correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Comparison Between U.S. and Non-U.S. Issuers

		U.S. Issuers				Non-U.S. Issuers			
		Pre (bps)	Post (bps)	Δs (bps)	N	Pre (bps)	Post (bps)	Δs (bps)	N
All		544	497	-47	1,852	724	681	-43	228
By rating	IG	438	379	-60	1,545	526	483	-43	175
	HY	1,101	1,116	16	292	1,404	1,363	-40	51
By maturity	6m-1y	681	567	-114	91	1,091	876	-215	9
	1-2y	553	479	-74	210	603	609	6	28
	2-3y	549	485	-65	215	645	590	-55	30
	3-5y	663	616	-47	327	1,092	1,000	-92	52
	5y-10y	556	527	-29	559	527	497	-30	59
	10y-	408	372	-37	450	625	628	3	50
By face value	-750 mil	646	610	-36	666	960	932	-29	42
	750 mil-	487	433	-54	1,186	671	625	-46	186
By issuer size	70%-tile	467	411	-57	1,434	566	526	-39	137
	30%-70%	757	740	-18	360	948	907	-41	81
	-30%-tile	1,118	1,112	-5	58	1,091	979	-112	10
By industry	Cnsmr	554	512	-42	337	497	445	-52	15
	Energy	1,392	1,349	-43	84	1,280	1,244	-36	37
	Manuf	473	449	-24	379	797	737	-60	13
	HiTec	438	369	-69	372	695	651	-44	43
	Hlth	385	333	-52	137	554	507	-47	25
	Finance	486	425	-61	352	515	442	-73	64
	Other	724	688	-36	191	750	776	26	31
Within Finance	Banks	430	362	-68	68	527	453	-74	37
	Nonbanks	499	440	-59	284	499	427	-72	27

This table reports the average of the bond-level changes in credit spreads from March 20 to March 24, excluding zero change observations. Stock returns are measured over the two-day event window accordingly. $\Delta \hat{s}$ is stock-implied credit spread changes computed as $\hat{b_0} + \hat{b_1} \times \text{ret}$, where $\hat{b_0}$, $\hat{b_1}$ are estimated using a pooled OLS regression of credit rate changes on stock returns amid the Global Financial Crisis period. Issuer size is the sum of total face values of outstanding bonds at the issuer level. We apply Fama-French 5 industry classification based on four-digit SIC codes: Cnsmr (Consumer Durables, Nodurables, Wholesale, Retail, and Some Services), Manuf (Manufacturing, Energy, and Utilities), HiTec (Business Equipment, Telephone and Television Transmission), Hlth (Healthcare, Medical Equipment, and Drugs), and Other. We divide 'Other' into Finance (SIC code between 6000 and 6999) and Nonfinance sectors. The finance sector is split into commercial banks (with the first three SIC digits of 602) and nonbanks.

Table A4: Estimated Long-Run VAR Coefficients

	All			IG			HY		
	r_t	st_t	dd_t	r_t	st_t	dd_t	r_t	st_t	dd_t
erG	-0.04	0.62	-0.01	-0.04	0.84	0.00	0.04	0.63	-0.01
elG	0.04	0.38	0.01	0.04	0.16	0.00	-0.04	0.37	0.01

	6m - 1y			1 - 2y			2 - 3y		
	r_t	st_t	dd_t	r_t	st_t	dd_t	r_t	st_t	dd_t
erG	-0.16	0.52	0.00	-0.13	0.50	0.00	-0.09	0.77	0.00
elG	0.16	0.48	0.00	0.13	0.50	0.00	0.09	0.23	0.00

	3 - 5y			5 - 10y			10y -		
	r_t	st_t	dd_t	r_t	st_t	dd_t	r_t	st_t	dd_t
erG	0.02	0.80	0.00	0.04	0.66	0.00	-0.08	0.81	-0.01
elG	-0.02	0.20	0.00	-0.04	0.34	0.00	0.08	0.19	0.01

This table reports the VAR-implied long-run coefficients for long-run excess returns, e_rG, and long-run credit loss, e_lG, where $G = (I - \rho A)^{-1}A$. The three state variables are average bond excess returns (r^e_t), the product of the average credit spreads and average duration ($s_t\tau_t$), and the average distance to default (dd_t). The sample period is weekly from July 2003 to Mar 2020.