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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 but spread across various 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.

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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 face 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 Fig. 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 Fig. 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 (SPV) 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 were not clear. The literature suggests...

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1 Corporate bond issuance has revived since the Fed unveiled the bond purchasing program. According to the Securities Industry and Financial Markets Association (SIFMA), U.S. corporate bond issuance in 2020 hit higher by 60.1% to $2,276.9 billion ($1,856.1 billion for investment grade and $420.9 billion for high yield).
that relevant forces through which quantitative easing (QE) 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 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 indices that reflect 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. Even though the various events that occurred during this longer window makes the results difficult to interpret, one can view this narrowing of the difference as evidence for arbitrage capital flowing from one segment of the market to the other, equalizing the impact across various market segments.

In order to more clearly identify the role of market segmentation, we employ an identification scheme based on a difference-in-differences approach. Specifically, we examine the issuers that were downgraded from BBB to BB between March 22 and April 9 with the issuers that were 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 QE announcement.

Market segmentation does distort asset price reactions in the short run, but it does not explain the market-wide movements in

Fig. 1. Credit Spreads, the S&P 500 Index, and Bond Illiquidity Measures: December 2019 to June 2020. The top panel plots the ICE BoA option-adjusted credit spreads on corporate bonds and the S&P 500 index. The Wuhan lockdown is on January 23, 2020; the 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.
credit spreads or their medium-term reaction to the news. These movements need to be attributed to various channels through which monetary policy affects financial markets. While the signalling effect by which the Fed commits to keeping short-term rates low is important for many assets, we focus on changing default risk and liquidity because we study difference in yields between bonds with the same maturity. 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 investors' 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 changed little. 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. 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 QE, on the financial market. Krishnamurthy and Vissing-Jorgensen (2011) document the reaction of the financial markets to QE 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). Another strand of research presents evidence for QE's impact on prices of a variety of financial assets, including Treasuries (e.g. Guidolin et al., 2017), MBS (e.g. Rodnyansky and Darmouni, 2017; Krishnamurthy et al., 2013), European sovereign bonds (Krishnamurthy et al., 2018), equity (Barbon and Gianinazzi, 2019) as well as European corporate bonds (Abidi and Miquel-Flores, 2018; Todorov, 2020a; Kojien et al., 2021; Zaghini, 2019). Furthermore, Guo et al. (2020) study the effect of monetary policy shocks on the U.S. corporate bond indices, though their paper does not study changing default risks as drivers of credit spread reactions. Our paper contributes to this strand of literature by studying the corporate QE in the U.S. and presenting consistent evidence that QE indeed affects bond prices, and that its effect is more pronounced for bonds that are the target of the purchase. Furthermore, we study transmission channels of QE on corporate bonds explicitly.

There is a growing literature that investigates the effect of COVID-19 on the bond market. D'Amico et al. (2020) examine the reactions of bond ETFs to the QE announcement, while Haddad et al. (2020) study the discrepancy between corporate bonds and related markets during the market turmoil. Kargar et al. (2020), Gilchrist et al. (2020), and O'Hara and Zhou (2020) study the impact of the corporate bond purchase program and find that changing liquidity is a key driver for credit spreads. He et al. (2020) build a term structure model with preferred habitat investors to explain the Treasury yield reactions to the pandemic. Aramonte and Avalos (2020) document the reaction of the ETF discounts to the Fed’s corporate QE announcement. Finally, Brunnermeier and Krishnamurthy (2020) discuss the debt overhang problem amid the COVID-19 recession and the potential improvements of the Fed’s QE program. Our work contributes to the nascent literature by exploiting the cross-sectional heterogeneity of corporate bond market responses and by dissecting channels through which QE provides support to the asset market.

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 Kojien (2020) use dividend futures to measure the impact of the pandemic on investors' expectations for dividend growth. Barro et al. (2020) examine how past pandemics affected economic activities and stock prices.

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2 The signalling channel, when interpreted broadly, may have an impact on credit spreads. We discuss this issue in Section 2.2.
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 of 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. Among the 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. 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, and 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.

The ETF purchase includes, for example, iShares ETF, which tracks Markit iBoxx USD Liquid Investment Grade Index, 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 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 at the time of index rebalancing, 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 have affected 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 2019. The announced limit on the corporate QE is $750 billion, which is slightly less than 10% of the outstanding bond market.

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3 In addition to expanding asset classes, the Fed removed the limit on the purchase amount of Treasury securities and MBS on March 23.

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 had plowed $7.97 billion 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.
amount, and more than half of new issues in a year. Thus, the Fed’s purchase program is large enough to potentially impact corporate bond prices. However, the actual implementation of the purchase program was rather gradual. As of December 31, 2020, the SPV had purchased only $8.8 billion of ETFs and $5.5 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 habit 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. Empirically, 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 effect of the QE announcement and its implementation can be somewhat different. Upon announcement, the need to “fire-sell” corporate bonds may be attenuated, but dealers’ inventory absorption capacity does not improve. When the Fed actually purchases bonds, then those bonds are removed from dealers’ inventory, increasing the slack for the capacity constraint. 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 was 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 or not a specific corporate bond in question is actually purchased 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, we study credit spreads, which is the difference in yields between corporate bonds and Treasury securities with the same maturity, and thus these channels are less relevant.6 One could argue that the signaling channel affects corporate credit spreads because the commitment to keep federal funds rate low in the future could change default risks and liquidity of corporate bonds. Because these indirect effects are difficult to isolate from default risk and liquidity channels, we adopt the relatively narrow view on the signaling channel proposed by Krishnamurthy and Vissing-Jorgensen (2011), who measure the signaling channel using the federal funds futures contract with differ-

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

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 et al. (2001), this component is small relative to other determinants of credit spreads.
ent maturity. In this admittedly narrow definition, the direct effect from the signaling channel is likely to be small.\footnote{We thank the anonymous referee for raising the issue in isolating the signaling channel from other channels.}

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 announcements do 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.\footnote{Unlike enhanced TRACE, standard TRACE masks transaction volume above certain threshold values. However, the price reported in standard TRACE is the same as that in enhanced TRACE.} 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.

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

\[
BAS_{i,d} = \frac{Sell_{i,d} - Buy_{i,d}}{0.5(Sell_{i,d} + Buy_{i,d})}
\]

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.\footnote{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.}

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 Reuters’ 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.\footnote{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, Jotkasthira et al. (2012) and Fratzscher et al. (2018). We only focus on U.S. bond funds in the first half of 2020 in this study.}

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 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 LJD and HYG from March 20 to March 24. The Fed’s announcement occurred at 8:00 a.m. EST on March 23, which falls in after hours. Because there is no futures contract on LJD and HYG, we do not observe the price reaction at 8:00 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 Fig. 2 shows prices for LJD, 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 LJD and HYG’s reactions shows that the Fed’s announcement was the primary driver for the jump over the weekend. If another announcement over the weekend, such as fiscal policy, was 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 LJD after the announcement. Overall, Figs. 2 and 3 support our claim that the Fed’s announcement was 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. Specifically, we run a panel regression of two-day credit spread changes on an event dummy which equals one if day \( d \) is the event date, and zero otherwise:

\[
\Delta S_{i,d} = b_0 + b_1 \text{Event}_{i,d} + b_2 \text{Event}_{i,d} \text{Frac}_{i,d} + \gamma \text{Ctrl}_{i,d} + \epsilon_{i,d},
\]
Fig. 2. Intraday Prices for Corporate Bond ETFs Around March 23 Announcement. The figure plots intraday movements in price for the iShares IBoxx $ Investment 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.

where $D^n_{i,t}$ is a vector of dummy variables, each of which corresponds to categories of bonds, including credit rating, maturity, size of the issue, size of the issuing firm, and industry. The unit of the analysis is bond-day. We include in the regression control variables used in Todorov (2020b), such as credit rating, age, and par amount of the bonds. Standard errors are double-clustered by day and firm.

Table 3 shows coefficients $b_1$ and $b_2$ separately for each event date. 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. As a result, estimated coefficients are generally small and less than 10 bps in absolute values. 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: for example, the spreads for the bonds in the omitted category (short-term IG bonds issued by a large issuer operating in consumer goods industry with face value less than $750 million) increased 73 bps. The credit spreads for short-term HY bonds increased even more. 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 bonds in the omitted category by 58 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
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.

European corporate credit spreads. 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.

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11 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 EUR5 trillion reported in Çelik et al. (2020).

12 Koijen et al. (2021) show that a portfolio rebalancing channel also plays a role in transmitting monetary policies.

Even though it is difficult to draw a general conclusion from two data points, market segmentation seems to prevent 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. The changes in credit spreads for most categories are less than 10 bps on May 12, while those for the omitted category on June 15 are −19 bps. These findings suggest that the beginning of the purchase was anticipated by dealers and bond investors, and thus the potential improvement in liquidity due to the purchase had already been reflected in asset prices before the event dates. As a result, it is difficult to detect the impact of the policy using our event-study setup. Therefore, in the next section, we focus on...
because between In purchase is all fore maturity, of bond’s value, we indicate the reaction 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 the economic significance of the changes in credit spreads on March 23 and April 9 across different sectors of bonds, we examine the breakdown of bonds by credit rating, maturity, the bond’s face value, issuer 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 decreased from 533 bps to 486 bps. However, IG and HY bonds behave differently; credit spreads on IG bonds decreased from 424 bps to 365 bps, while credit spreads on HY bonds increased slightly from 1095 to 112 bps. Table 3 shows that the difference between IG and HY bonds is statistically significant (t=15.02). This 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. In Table A2 of the Appendix, we use finer credit rating categories and show that there are discreet jumps in credit spread reactions between bonds rated BBB or above and those rated BB or below.

The point estimates for the difference in Tables 3 and 4 do not agree exactly because the high-yield dummy in Table 3 compares HY bonds with those in the omitted category, while in Table 4 we compare all HY bonds with all IG bonds.

The small change in HY credit spreads is consistent with intra-day price changes for HV ETF in Fig. 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 et al. (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 to be expected. 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 12.48%, which is higher than those for IG issuers (6.7%). 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 were 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

| EvtDate   | Mar_03 | Mar_15 | Mar_23 | Apr_9 | May_12 | Jun_15 |
|-----------|--------|--------|--------|-------|--------|--------|
| EvtDate   | -6.5** | -7.5** | -7.5** | -6.5  | -6.5   | -6.5   |
| EvtDate   | (−2.24)−(3.37)−(3.66)−(3.20)−(0.52)−(0.81) | (−1.89)−(2.64)−(2.67)−(1.05)−(1.0)−(1.94) | (−1.48)−(2.90)−(2.93)−(2.30)−(1.92)−(1.68) | (−0.5)−(0.89)−(1.94)−(2.87)−(2.97)−(0.47) | (−1.1)−(3.3)−(3.2)−(10.3)−(6.2)−(14.8) | (−1.01)−(0.79)−(1.23)−(1.47)−(4.21)−(0.48) |

This table presents the estimates of event dummies and their interaction terms in the panel regressions over the sample period from Jan 2020 to Jun 2020. The dependent variable is the two-day credit spread changes around event days (Mar 3, Mar 15, Mar 23, Apr 9, May 12, and Jun 15) and non-event days. The bond category dummies are based on bond characteristics, i.e., credit rating, maturity, face value, issuer size, and industry. The omitted category is IG bonds, issued by a large issuer operating in consumer goods industry, with maturity between 6 months and 1 year, and face value less than $750 million on the non-event days. Control variables include credit ratings, size, and the logarithm of par amount. Standard errors are double-clustered by firm and time. t-statistics are shown in parentheses.

***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.
year declined 107 bps, while those for bonds with maturities of 5 to 10 years declined 36 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 Sections 4.5 and 5.1.

For the breakdown by the size of bonds and issuers, the QE announcement benefits large issuers and large issuers more than smaller issuers. Credit spreads for bonds with face value less than $750 million fell 36 bps after the announcement, while they decreased 53 bps for larger bonds. Large bond issuers who are above the 70th percentile in terms of total issue size of bonds saw their credit spreads fall 55 bps, while the decrease was only 1 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 “other” into finance and other, non-finance industries. The breakdown by industry reveals that the high-tech, healthcare, and finance industries enjoyed a greater decrease in credit spreads around the Fed’s announcement than did 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 were much higher than other industries. The corporate QE lowered their credit spreads, but only as much as other industries. Thus, the unprecedented policy action still did not stimulate enough demand for the energy sector to recover. Panel B of Table 4 reports the event study for the April 9 announcement. The reaction to the announcement is similar to that to 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 fell 146 bps. This reaction again highlights the role of market segmentation across credit ratings.

14 On the other hand, commercial banks (a part of the finance industry) saw their credit spreads fall 66 bps, which is greater than other industries (except HiTec). 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 fell after the announcement.
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 reveals that the credit spreads of corporate bonds that are the direct target of the purchase program declined more than those that are not. 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 were downgraded from IG 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 were newly downgraded to a HY rating between March 22 and April 9 and firms that were already rated as HY as of March 22. 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 were 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 the 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 were mostly rated IG as of March 22.

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 decreased 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 fell about 340 bps over the two-day window. In contrast, the credit spreads averaged within the control group declined about 120 bps. Thus, the analysis on this small sample suggests that credit spreads for the treatment group firms fell more than for other firms that share a similar default risk but that did 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.

As an alternative strategy to identify the policy impact, we run difference-in-differences regressions following Gilchrist et al. (2020). Specifically, we regress difference in credit spreads between the issuer-paired bonds with time to maturity of five years or less (treatment group) and those with longer maturity (control group) on a post-event dummy:

$$ s_{t}^{treated} - s_{t}^{control} = \beta \times 1[t > t^*] + \eta_{t} + e_{t}, $$

where $$ s_{t}^{treated} $$ (or $$ s_{t}^{control} $$) is the credit spread on issuer i’s bond in the treatment (control) group, and $$ 1[t > t^*] $$ is a dummy variable which equals one if the date t is greater than the announcement date t*, which is either March 23 or April 9. The main identification assumption is that the Fed would mainly purchase individual bonds rather than ETFs and thus bonds with a maturity of at least five years will have lower credit spreads after the announcement.

Table 7 reports that the estimated coefficient on $\beta$ is significantly negative, showing that credit spreads for the bonds with a shorter maturity decreased significantly more than those on longer-term bonds of the same issuer.

We see that there are pros and cons for different identification strategies. The first identification scheme involves less ambiguity (as the effect of the April 9 announcement on fallen angel firms was widely reported in the media) but leads to a small sample. The second approach enables us to use a larger sample size, but the validity of the identification assumption is debatable, as ETFs are not downgraded from IG to HY. (including)

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

| Perumno | Name               | Rating after downgrade | SIC  | Control group |
|---------|--------------------|------------------------|------|---------------|
| 39490   | Apache Corp        | BB+                    | 1311 | 79915         |
| 91983   | Continental Resources | BB+                  | 1311 | 87137         |
| 91926   | Delta Airlines     | BB                     | 4512 | 91103         |
| 81917   | Hospitality Properties | BB+                | 6798 | 85234         |
| 77462   | Macy’s Retail Holdings | BB+              | 5311 | n.a.          |
| 25785   | Ford Motor Co      | BB                     | 3711 | n.a.          |

The treatment group is six bond issuers that were downgraded from IG to HY (must still be rated at least BB-/Ba3) between March 23 and April 8 in our sample. 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 23 and April 8. Following the Fed’s SMCCF term sheet, we require the issuer to have been rated at least BBB-/Ba3 as of Mar 22, 2020. If rated by multiple major credit rating agencies, the issuer must be rated at least BBB-/Ba3 by two or more agencies.
Table 6
Changes in Credit Spreads and Bid-Ask Spreads on April 9 Announcement.

| Credit Spreads (bps) | Liquidity | \( \Delta AS \) (bps) \( \Delta VOL \) (oil) |
|----------------------|-----------|----------------------------------|
| Apache Corp          | 1,604     | 1,117                            | 488 |
| Control              | 775       | 654                              | -121 |
| Continental Resources| 1,295     | 951                              | -344 | 29 | -6 |
| Control              | 775       | 654                              | -121 | 197 | 0 |
| Delta Airlines       | 1,002     | 721                              | -281 | 36 | -3 |
| Control              | 1,181     | 990                              | -191 | 24 | 1 |
| Hospitality Properties| 1,440    | 1,188                            | -252 | 210 | -2 |
| Control              | 539       | 477                              | -62  | -17 | -1 |
| Macy’s Retail Holdings| 1,774    | 1,226                            | -548 | -34 | -1 |
| Ford Motor Co        | 809       | 511                              | -298 | -20 | 3 |

For each firm, we take the average of credit spreads, bid-ask spreads and transaction volume for bonds issued by the firm to compute the firm-level values on April 8 and April 13. \( \Delta AS \) is the change in firm-level credit spreads over the period. \( \Delta AS \) and \( \Delta VOL \) are the changes in firm-level bid-ask spreads and trading volume, respectively. Control is the average of the firm-level credit spreads, bid-ask spreads and transaction volume in the control group, which is defined in Table 5. We only include bonds with remaining maturity of five years or less for the treatment group.

Table 7
Difference-in-Differences Regressions of Credit Spreads on QE Announcement Dummies and Maturity Cutoff Dummies.

| DepVar: Credit Spreads (%) | 1-day | 5-day | 10-day |
|---------------------------|-------|-------|--------|
| A. \( t^* = \text{March 23} \) \( 1[t^* < t^*] \) | -0.219* | -0.207** | -0.077** |
| (2.47)                    | (4.70) | (2.21) |
| Obs                       | 667    | 2,559 | 4,912  |
| R²                        | 0.606  | 0.391 | 0.284  |

| B. \( t^* = \text{April 9} \) \( 1[t^* < t^*] \) | -0.014 | -0.109*** | -0.168*** |
| (3.33)                    | (4.23) | (6.88) |
| Obs                       | 624    | 2,588 | 4,952  |
| R²                        | 0.641  | 0.503 | 0.472  |

The table reports the coefficients of the regression, \( s_{t^*}^{\text{control}} = \beta \times 1[t^* > t^*] + \eta_1 + \xi_1 \), where \( s_{t^*}^{\text{control}} \) is the credit spread on issuer’s bond in the treatment (control) group. The treatment/control group are issuer-paired bonds (IG as of March 22) with time-to-maturity closest to five years (treated bonds less than or equal to five years, control bonds greater than five years but cannot exceed 10 years). The dummy variable \( 1[t^* > t^*] \) equals one if the date \( t^* \) is greater than the specified announcement date \( t^* \), either March 23 or April 9. All specifications include firm fixed effects. Standard errors are clustered by firm. \( t \)-statistics are shown in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

are unlikely to purchase short-term bonds. Thus, it is important to ensure that we obtain a consistent assessment of the policy impact using both approaches. Furthermore, 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.10

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. However, examining the changes over a wider event window, such as two weeks, 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 8 reports the credit spread changes for various types of bonds.

We find that credit spread reactions to the March 23 announcement are more pronounced over the two-week horizon than over the two-day horizon. The average credit spread fell 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 declined 97 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 76 bps over the two-day window, but it shrinks to 41 bps over the two-week window. To investigate the transition, Fig. 4 plots the regression coefficients of n-day credit spread changes on the March 23 announcement dummy separately for IG bonds and HY bonds. Both IG and HY spreads peaked April 31, and then IG spreads stabilized while HY spreads somewhat mean-reverted. Thus, we do not see evidence for subsequent events (such as the passing of fiscal stimulus bills on March 25) leading to a discrete jump in credit spreads.

The narrowing gap between IG and HY credit spreads 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. Because there are multiple policy announcements after March 23, it is difficult to draw strong conclusions from credit spread changes over the two-week window. However, this convergence between IG and HY spreads provides some support to 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 ann-

10 The Bloomberg article “Fed’s Power To Buy Corporate Debt Market Curbed by Bailout Law” dated April 28, 2020, points out this ambiguity about the eligibility for purchase.
Table 8
Changes in Credit Spreads Around March 23 QE Announcement: Two-Week Window.

| Credit Spreads | Stock Returns | Bond Liquidity |
|----------------|--------------|----------------|
| Pre | Post | Δs | r | ΔΔ | Δρ | ΔΔVOL | Δψ |
| (bps) | (bps) | (bps) | (%) | (bps) | (bps) | (mil) | (bps) |
| All | 565 | 428 | -137 | 8.48 | -10 | -100 | -0.99 | -4 |
| By rating IG | 414 | 275 | -138 | 9.34 | -10 | -118 | -1.12 | -4 |
| HY | 1,200 | 1,102 | -97 | 4.31 | -8 | -26 | -0.37 | -2 |
| By maturity 6m-1y | 657 | 375 | -283 | 7.06 | -19 | -78 | -1.77 | -11 |
| 1-2y | 697 | 545 | -152 | 7.62 | -13 | -107 | -0.86 | -6 |
| 2-3y | 567 | 402 | -165 | 7.04 | -10 | -159 | -0.01 | -8 |
| 3-5y | 667 | 491 | -175 | 6.96 | -7 | -71 | -0.69 | -3 |
| 5y-10y | 582 | 462 | -121 | 8.62 | -9 | -80 | -0.86 | -3 |
| 10y- | 400 | 314 | -86 | 10.55 | -9 | -134 | -1.68 | 0 |
| By face value | 750 mil | 479 | 329 | -150 | 8.52 | -10 | -115 | -1.80 | -4 |
| Stock | 476 | 557 | -120 | 8.42 | -9 | -72 | 0.06 | -4 |
| By issuer size | 70% tile | 472 | 317 | -155 | 9.07 | -10 | -117 | -1.34 | -4 |
| 30%-70% | 708 | 597 | -111 | 7.22 | -7 | -65 | -0.02 | -4 |
| −30%-tile | 1,158 | 1,151 | -7 | 5.96 | -9 | -3 | -0.29 | 0 |
| By industry | Cons | 533 | 423 | -110 | 6.84 | -11 | -99 | -0.76 | -3 |
| Manuf | 1,576 | 1,486 | -90 | 13.20 | -5 | -81 | -0.02 | 2 |
| HiTec | 441 | 290 | -151 | 7.48 | -7 | -90 | -2.23 | -5 |
| HiTech | 402 | 270 | -132 | 9.91 | -8 | -114 | -1.25 | -2 |
| Finance | 547 | 355 | -193 | 6.61 | -8 | -121 | -0.89 | -6 |
| Other | 660 | 513 | -146 | 8.08 | -14 | -133 | -1.15 | -6 |
| Within | Banks | 412 | 237 | -175 | 2.26 | -3 | -162 | -1.62 | -7 |
| Finance | 576 | 380 | -196 | 7.54 | -9 | -110 | -0.73 | -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 (r) 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.

Fig. 4. Credit Spread Changes from March 20. The figures show coefficient b1 from the regression, Δs,b1,t = b0 + b1EntDate,t + yCTRL,t + εt,b1. run separately for IG and HY bonds with 2-standard error bars. b is from 2 (corresponding to March 24) to 12 (April 3). Standard errors are clustered by time and firm.

Announcement 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’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,

\[ X_t = \begin{pmatrix} r_t \cr s_t \cr \tau_t \cr DD_t \end{pmatrix} \]  

where \( r_t \) 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; \( \tau_t \) 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

\[ X_{t+52} = A_0 + AX_t + U_t + s_t \]  

where \( A \) is assumed to be constant.

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

\[ s_t \approx \frac{1}{E_t} \sum_{j=0}^{\infty} \rho^j r_{t+52}(j+1) + \sum_{j=0}^{\infty} \rho^j l_{t+52}(j+1) \]  

where \( l_{t+j} \) is credit loss, and \( \rho \) is 0.992.\(^{19}\)

\(^{19}\) Nozawa (2017) uses \( \rho = 0.992 \) for monthly returns.
The first term and the second term on the right-hand side of (5) are the risk premium and expected credit loss component of credit spreads, respectively, which can be written as

\[ s_t^r = \frac{1}{T_t} \sum_{j=0}^{\infty} \rho^j t_{t+52(j+1)} = \frac{1}{T_t} e_t \sigma_t G X_t \]

\[ s_t^l = \frac{1}{T_t} \sum_{j=0}^{\infty} \rho^j l_{t+52(j+1)} = \frac{1}{T_t} e_t \sigma_t G X_t \]

(6)

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 (4) 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 log-linear identity, we decompose changes in credit spreads into two components,

\[ \Delta s_t = \Delta s_t^r + \Delta s_t^l \]

(7)

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 A5 in the Appendix.

Table 9 reports changes in credit spreads, state variables in (3), 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 –22 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 9, 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 (3), and re-estimate a VAR. This procedure allows long-run predictive coefficients in (6) to depend on the characteristics of bonds.

Table 9 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 –55 bps out of a total change of –59 bps. This result is expected because IG bonds have relatively small default risk, and the result is consistent with the historical credit spread variation for IG bonds reported in Nozawa (2017). On the other hand, given that much of the credit spread reactions to March 23 announcement comes from IG bonds, the large contribution of the risk premium component (which may reflect default risk and liquidity risk as in Lin et al. (2011)) poses a challenge in quantifying the default risk channel. Thus, we estimate the contribution of liquidity in risk premium variation and isolate default risk premiums in the next section. 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 accounted for credit spread changes for HY bonds, while it explained slightly more than half 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 decreased 77 bps for bonds with maturities of less than a year, while it decreased 11 bps for bonds with maturities of 10 years or longer. In contrast, changes in risk pre-
mum components did not vary significantly across maturity. As shown in Table 8, 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 72 bps for IG bonds but increased 25 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 bonds. This 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 a 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, 
\[
\Delta S_{i,j, d} = b_0 D_{i,j, d} + b_1 D_{i,j, d} \Delta B A S_{i,j, d} + b_2 D_{i,j, d} \Delta V O L_{i,j, d} + u_{i,j, d}, \tag{8}
\]
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 \(\Delta B A S_{i,j, d}\) and \(\Delta V O L_{i,j, d}\) 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 (8). 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 et al., 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.20 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 pa-

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20 For the exact start and end dates of the crisis, we use the definition in Bao et al. (2018).
rameter vectors $b$ on the bond’s characteristics, such as default risk and maturity of bonds.

Summary statistics for the variables in (8) are reported in Table A1 in the Appendix. Not surprisingly, both credit spreads and the illiquidity measures are volatile during the crisis period. The standard deviation for changes in credit spreads and bid-ask spreads is 45 bps and 199 bps, respectively.

The estimated coefficients are reported in Table A3 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 is more nuanced. For short-term bonds, changes in volume and credit spreads are positively related. Though this is somewhat counter-intuitive, 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 (8), 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 small in magnitude. For example, on March 23, liquidity-implied credit spread changes were $−3$ bps for IG bonds and $0$ bps for HY bonds. Even though bid-ask spreads for IG bonds fell $72$ 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 were $−2$ 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 from Feldhutter (2012), and confirm that our results are not driven by the particular choice of liquidity proxies. In the last column of Table 9, we repeated the regression in (8), replacing credit spreads with the risk premium component, and calculate the liquidity-driven risk premiums. We confirm the similar pattern in risk premiums in the sense that the risk premium reaction to the QE announcement is not associated with changes in liquidity measures.

To evaluate the importance of illiquidity from another perspective, we examine how credit default swap (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 11, 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. The limited role of the liquidity channel may be due to the fact 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 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, Schafer 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, because 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,

$$
\Delta s_{i,j,d} = b_0D_{i,j,d} + b_1D_{i,j,d}F_{j,d} + u_{i,j,d}.
$$

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

### Table 11

| 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 | $−125$ |
| 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                              | 760 | 782 | 22 | 708 | 612 | $−96$ |
| 3 year                              | 866 | 723 | $−143$ | 625 | 555 | $−70$ |
| 5 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).
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 A3 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 constructed predicted changes in credit spreads during the event window,

$$\Delta s_{i,j,d} = b_0 D_{i,j,d} + b_1 D_{i,j,d} r_{j,d}. \quad (10)$$

Table 4 presents predicted changes for the average bonds using the full sample as well as subsamples. For the average bond issuer, stock returns upon the March 23 announcement 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 (10) are more negative for HY bonds than for IG bonds. Based on this analysis, the changes in HY credit spreads have a “wrong” sign, 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 13.3%, which leads to predicted credit spread changes of $-28$ 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 fall 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 multiple factors to determine credit spreads, as we did in Section 5.1.

6. Conclusion

This paper examines 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. In contrast, both IG and HY credit spreads fell after the April 9 announcement. The market segmentation between IG and HY likely explains such differences in initial reactions to the March 23 announcement, 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 corporate bonds segments. In particular, the results from variance decomposition suggest that reduced default risk over the short term well explains the 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 affected the prospects for the real economy and then spread 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.

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

To assess the effect of the QE announcement on corporate bonds, we compare the U.S. issuers with non-U.S. issuers that are not the target for purchase. In the March 23 announcement, the Fed defines issuers eligible for purchase as “U.S. businesses with material operations in the United States.” In the April 9 announcement, the definition of U.S. firms is more clearly specified to be “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 A4 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

| Table A1 Summary Statistics for the Panel Regressions of Daily Credit Spread Changes. |
|-----------------------------------------------|
| Variables | Obs | Mean | Std | P1 | P25 | Median | P75 | P99 |
| Full Sample | 194,846 | 0.20 | 44.62 | -152.75 | -10.98 | -0.39 | 10.14 | 167.33 |
| $\Delta s$ | 194,747 | -0.03 | 4.18 | -13.04 | -1.80 | -0.06 | 1.62 | 14.17 |
| $\Delta AB$ | 36,255 | -1.30 | 198.79 | -692.51 | -67.51 | -0.03 | 65.95 | 689.66 |
| $\Delta AVOL$ | 194,846 | -0.08 | 8.03 | -28.68 | -2.11 | 0.00 | 2.00 | 27.89 |
| Stock Return Regression | 194,747 | 0.23 | 44.38 | -150.07 | -10.97 | -0.38 | 10.13 | 165.93 |
| $\Delta s$ | 194,747 | -0.03 | 4.18 | -13.04 | -1.80 | -0.06 | 1.62 | 14.17 |
| $\Delta AB$ | 36,255 | -1.45 | 54.96 | -232.85 | -15.84 | -2.12 | 11.31 | 253.84 |
| $\Delta AVOL$ | 36,255 | -1.30 | 198.79 | -692.51 | -67.51 | -0.03 | 65.95 | 689.66 |

This table reports the summary statistics for daily credit spread changes (in bps) during the Global Financial Crisis period. Following Zhao et al. (2018), we define the crisis period as from July 1, 2007, to April 30, 2009. To calculate credit spread changes, we require at least two consecutive daily observations for bond prices. $r$ is stock returns adjusted for delisting. $\Delta AB$ is changes in bid-ask spreads, and $\Delta AVOL$ is changes in trading volume. We winsorize all continuous variables at the 1% and 99% levels to exclude outliers.
Table A2
Regression of Two-Day Changes in Credit Spreads on Calendar Day Dummies and Rating Categories.

| EvtDate | Mar_03 | Mar_15 | Mar_23 | Apr_9 | May_12 | Jun_15 |
|---------|--------|--------|--------|-------|--------|--------|
| Intercept | 17.0*** | 127.0*** | 7.3 | −131.0*** | 13.7 | −29.9*** |
| (2.64) | (9.30) | (0.49) | (−15.31) | (1.41) | (−2.58) |
| EvtDate * D_{AA} | −21.6*** | −99.7*** | −58.0*** | 106.4*** | −15.3 | 18.0 |
| (−3.83) | (−7.42) | (−3.92) | (12.80) | (−1.63) | (1.60) |
| EvtDate * D_{A} | −20.7*** | −91.9*** | −66.5*** | 90.4*** | −13.4 | 17.4 |
| (−3.78) | (−6.85) | (−4.52) | (10.92) | (−1.44) | (1.55) |
| EvtDate * D_{BBB} | −21.3*** | −79.9*** | −61.5*** | 70.9*** | −15.0 | 11.4 |
| (−4.11) | (−5.97) | (−4.22) | (8.53) | (−1.63) | (1.02) |
| EvtDate * D_{BB} | −33.7*** | −28.7*** | −3.1 | 7.5 | −3.6 | −14.0 |
| (−7.54) | (−6.08) | (−0.21) | (1.85) | (−0.40) | (1.27) |
| EvtDate * D_{B} | −40.7*** | 17.5 | 11.7 | −1.5 | −8.4 | −25.3*** |
| (−6.64) | (1.34) | (0.65) | (−0.16) | (−0.77) | (−2.04) |

This table presents the estimates of event dummies and their interaction terms with rating categories in the panel regressions over the sample period from Jan 2020 to Jun 2020. The dependent variable is the two-day credit spread changes around event days (Mar 3, Mar 15, Mar 23, Apr 9, May 12, and Jun 15) and non-event days. The credit rating categories are AA+, A, BBB, BB, and B. The omitted category is CCC and below. Control variables include age and the logarithm of par amount. Standard errors are double-clustered by firm and time. r-statistics are shown in parentheses. ‘***’, ‘**’, and ‘*’ indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table A3
Panel Regressions of Daily Credit Spread Changes.

| Stock Return Regressions | Liquidity Regressions |
|--------------------------|------------------------|
|                          | Const. | r     | Const. | ΔBAS | ΔVOL |
| Intercept                | −4.861*** | −2.681*** | −4.062 | 0.047 | 1.554*** |
| (−2.86)                  | (−4.92) | (−0.95) | (0.86) | (2.98) |
| D_{(HV)}                | 2.759*** | 1.681*** | 0.207 | 0.003 | 0.057 |
| (2.93)                   | (−7.72) | (0.06) | (−0.45) | (−0.28) |
| D_{(1-2y)}               | 3.108*  | 0.587  | 3.885 | 0.002 | 0.381 |
| (1.81)                   | (1.01)  | (0.92) | (0.04) | (−0.69) |
| D_{(2-3y)}               | 3.871** | 0.860  | 1.234 | −0.015 | 0.723 |
| (2.40)                   | (1.62)  | (0.31) | (−0.25) | (−1.36) |
| D_{(3-5y)}               | 4.321*** | 1.259*** | 1.535 | −0.051 | 0.905* |
| (2.69)                   | (2.61)  | (0.38) | (−0.94) | (−1.71) |
| D_{(5-10y)}             | 4.304*** | 1.287** | 1.576 | −0.038 | 1.217** |
| (2.61)                   | (2.59)  | (0.39) | (−0.67) | (−2.31) |
| D_{(>10y)}               | 4.198** | 1.294** | 2.896 | −0.051 | 1.327** |
| (2.58)                   | (2.54)  | (0.73) | (−0.91) | (−2.55) |
| D_{(>750 m)}            | 1.211*** | −0.238 | 1.677* | 0.002 | 0.099 |
| (3.80)                   | (−1.38) | (1.94) | (−0.26) | (−1.00) |
| D_{(Medium)}            | −0.503 | 0.270  | −1.215 | 0.009 | −0.011 |
| (−1.32)                  | (1.52)  | (−0.84) | (1.06) | (−0.10) |
| D_{(Low)}               | −1.053* | 0.255 | 1.184 | 0.016 | −0.022 |
| (−1.81)                 | (1.11)  | (0.46) | (1.13) | (−0.07) |
| D_{(Energy)}            | −0.848* | 1.356*** | 1.310 | −0.009 | 0.133* |
| (−1.84)                 | (6.50)  | (0.96) | (−0.93) | (−1.67) |
| D_{(Manuf)}             | −0.404 | 0.802*** | 1.040 | 0.004 | 0.283*** |
| (−1.00)                 | (3.92)  | (0.98) | (0.40) | (3.09) |
| D_{(HiTech)}            | −0.628 | 0.928*** | −1.398 | 0.009 | −0.182* |
| (−1.30)                 | (3.65)  | (−1.12) | (0.80) | (−2.25) |
| D_{(Eth)}               | −1.126*** | 1.040*** | 1.0660 | −0.010 | −0.108 |
| (−2.53)                 | (4.56)  | (−0.89) | (−0.96) | (−1.30) |
| D_{(Fin)}               | −0.241 | 0.374 | −0.813 | 0.015 | 0.201** |
| (−0.46)                 | (1.59)  | (−0.65) | (1.55) | (−2.53) |
| D_{(NonFin)}            | −0.041 | 0.620** | 1.118 | 0.006 | 0.660*** |
| (−0.06)                 | (2.20)  | (0.42) | (0.35) | (2.36) |

This table reports the estimated coefficients and r-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:

\[\Delta s_{j,d} = b_0 + b_1 D_{j,d} + b_2 D_{j,d} r_{j,d} + u_{i,j,d}.\]

\[\Delta s_{j,d} = b_3 + b_4 D_{j,d} \Delta B A S_{j,d} + b_5 D_{j,d} \Delta V O L_{j,d} + u_{i,j,d}.\]

Following Bao et al. (2018), we define the crisis period as from July 1, 2007, to April 30, 2009. To calculate credit spread changes, we require at least two consecutive daily observations for bond prices. The stock returns are adjusted for delisting. D_{j,d} is a vector of dummy variables each of which corresponds to categories of bonds, including credit rating, maturity, face value, issuer size, and industry. We cluster standard errors by calendar date and report r-statistics in parentheses. ‘***’, ‘**’, and ‘*’ correspond to statistical significance at the 1%, 5%, and 10% levels, respectively.
average credit spread for U.S. bonds decreased 47 bps after the announcement, while the average for non-U.S. bonds decreased 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 had a -51 bps change in credit spreads, which is lower than HY bonds by U.S. firms. This difference likely reflects the high estimation uncertainty for the average due to the small sample. 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 can be interpreted in two ways. First, it suggests that the decline in credit spreads in response to the corporate QE is not a simple reflection of the 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 contribute to the decline in credit spreads. Second, the distinction between U.S. and non-U.S. firms may not be obvious to investors at the time of announcement, and thus there is no difference in market price reactions to the news between these two groups.

### Appendix B. Variance Decomposition of Credit Spreads

Table A5 reports the estimated long-run predictive regression coefficients for different subsamples of corporate bonds.

### Table A4
Comparison Between U.S. and Non-U.S. Issuers.

|                  | U.S. Issuers | Non-U.S. Issuers |
|------------------|--------------|------------------|
|                  | Pre (bps)    | Post (bps)       | Δs (bps) | Pre (bps) | Post (bps) | Δs (bps) |
| All              | 533         | 486             | -47      | 808       | 763        | -45      |
| By rating        |             |                 |          |           |            |          |
| IG               | 424         | 365             | -59      | 525       | 480        | -45      |
| HY               | 1,095       | 1,112           | 17       | 1,452     | 1,401      | -51      |
| By maturity      |             |                 |          |           |            |          |
| 6m-1y            | 679         | 572             | -107     | 1,019     | 789        | -230     |
| 1-2y             | 551         | 472             | -80      | 619       | 583        | -35      |
| 2-3y             | 551         | 491             | -59      | 1,552     | 1,493      | -59      |
| 3-5y             | 642         | 596             | -46      | 982       | 904        | -78      |
| 5y-10y           | 549         | 518             | -31      | 524       | 495        | -30      |
| 10y-              | 394         | 357             | -36      | 625       | 621        | -4       |
| By face value    |             |                 |          |           |            |          |
| 750 mil          | 621         | 585             | -36      | 1,508     | 1,466      | -42      |
| 750 mil-        | 479         | 426             | -53      | 644       | 598        | -46      |
| By issuer size   |             |                 |          |           |            |          |
| 70%-tile        | 457         | 403             | -55      | 547       | 507        | -40      |
| 30%-70%-tile    | 705         | 681             | -25      | 918       | 863        | -55      |
| -30%-tile       | 1,100       | 1,099           | 1        | 2,799     | 2,741      | -58      |
| By industry     |             |                 |          |           |            |          |
| Cnsmr           | 546         | 501             | -45      | 409       | 358        | -51      |
| Energy          | 1,212       | 1,174           | 37       | 1,178     | 1,141      | -37      |
| Manuf           | 467         | 442             | -25      | 814       | 817        | -4       |
| HiTec           | 432         | 364             | -68      | 697       | 633        | -64      |
| HiTh            | 386         | 335             | 51       | 513       | 450        | -63      |
| Finance         | 480         | 426             | -54      | 829       | 775        | -55      |
| Other           | 689         | 646             | -42      | 783       | 799        | 16       |
| Within          |             |                 |          |           |            |          |
| Banks           | 427         | 360             | -66      | 1,056     | 1,000      | -56      |
| Finance         | 492         | 441             | -51      | 533       | 480        | -53      |

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. Δs is stock-implied credit spread changes computed as β0 + β1r, where β0, β1 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), HiTh (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 A5
Estimated Long-Run VAR Coefficients.

|                  | All | IG | HY |
|------------------|-----|----|----|
|                  | r1  | s1 | d1 |
|                  | r1  | s1 | d1 |
| 6m - 1y          | erG | 0.02 | 0.50 | 0.00 |
|                  | eLG | 0.02 | 0.50 | 0.00 |
| 1 - 2y           | erG | 0.01 | 0.08 | 0.00 |
|                  | eLG | 0.03 | 0.53 | 0.02 |
| 3 - 5y           | erG | 0.03 | 0.53 | 0.02 |
|                  | eLG | 0.04 | 0.53 | 0.02 |
| 5 - 10y          | erG | 0.03 | 0.53 | 0.02 |
|                  | eLG | 0.04 | 0.53 | 0.02 |

This table reports the VAR-implied long-run coefficients for long-run excess returns, ɛ, G and long-run credit losses, ɛ, G, where G = (I − ρA)^−1A. The three state variables are average bond excess returns (r^*_t), the product of the average credit spreads and average duration (s, r_t), and the average distance to default (DD_t). The sample period is weekly from July 2003 to Sep 2020.

### CRediT authorship contribution statement

**Yoshio Nozawa**: Methodology, Writing - original draft, Writing - review & editing. **Yancheng Qiu**: Methodology, Writing - original draft, Writing - review & editing, Formal analysis.
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