The Causal Effect of the Fed's Corporate Credit Facilities on Eligible Issuer Bonds[1]

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Abstract. We study the effects of the Federal Reserve's Corporate Credit Facilities (CCFs) that were launched in early 2020 amid significant volatility in the U.S. corporate bond market. We find that the initial announcement of the CCFs on March 23, 2020 benefited issuers eligible for direct primary and secondary support from the CCFs more than ineligible issuers. In contrast, we find that ineligible issuer bond spreads tightened more in the subsequent announcement of the CCF expansion on April 9, 2020. Inconsistent with the CCF eligibility criteria, most research has used issue ratings, rather than issuer ratings, to identify eligible bonds; we document that this results in a sizeable bias when estimating the April 9 effect and trace the source of this bias. We also provide an estimate of the potential (counterfactual) improvement in bond spreads ineligible issuers would have experienced, had they been eligible for the CCFs. Analysis of the channels through which the CCFs operated suggests that the liquidity channel was more important than the default risk channel. We also find that the start of the CCF's purchases of ETFs on May 12, 2020 and bonds on June 16, 2020 had a smaller effect on bond spreads, though the latter was more impactful. Additionally, a causal machine learning approach that estimates these effects using high-dimensional controls, while allowing for rich, nonlinear interactions, produces similar results and recovers the distribution of conditional average treatment effects. We show that this distribution can be used to identify counterfactual policy targeting schemes that would have resulted in an even more significant reduction in the average treatment effect on the treated. We also discuss how this distribution can be used to decompose the channels through which the Fed CCFs may have operated.

Keywords: Corporate bonds, COVID-19, Federal Reserve, Monetary Policy, PMCCF, SMCCF, Quantitative Easing, Liquidity, Bond Markets, Financial Crisis.

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1 Introduction

In response to market and economic stress caused by the COVID-19 pandemic, the Federal Reserve expanded its monetary policy toolkit to include corporate bond purchases for the first time in its history. On March 23, 2020, with equity capital provided by the U.S. Treasury, the Fed established two emergency lending facilities: the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF) to purchase primary market debt of up to four years in maturity and secondary market bonds of up to five years in maturity for non-financial investment grade (IG) issuers with significant U.S. operations. Additionally, the facilities gave the Fed the ability to purchase corporate bond exchange-traded funds (ETFs) with broad exposure to IG issuers. On April 9, 2020, the Fed expanded the size of the PMCCF and the SMCCF, as well as its scope to include high-yield (HY) corporate bond ETFs and extended eligibility to issuers who were rated as IG as of March 22, 2020, as long as on the day of purchase they are rated BB- or above. The Fed began purchasing IG and HY ETFs on May 12, 2020, and concluded purchases on July 23, 2020, after the start of secondary market corporate bond purchases. On June 15, 2020, the Fed announced the formation of the SMCCF Broad Market Index to guide secondary market purchases of bonds from eligible issuers, departing from the need for individual issuers to certify eligibility with the Fed in order to participate in the CCFs. Secondary market corporate bond purchases began on June 16, 2020 and continued until the close of the facility on December 29, 2020.

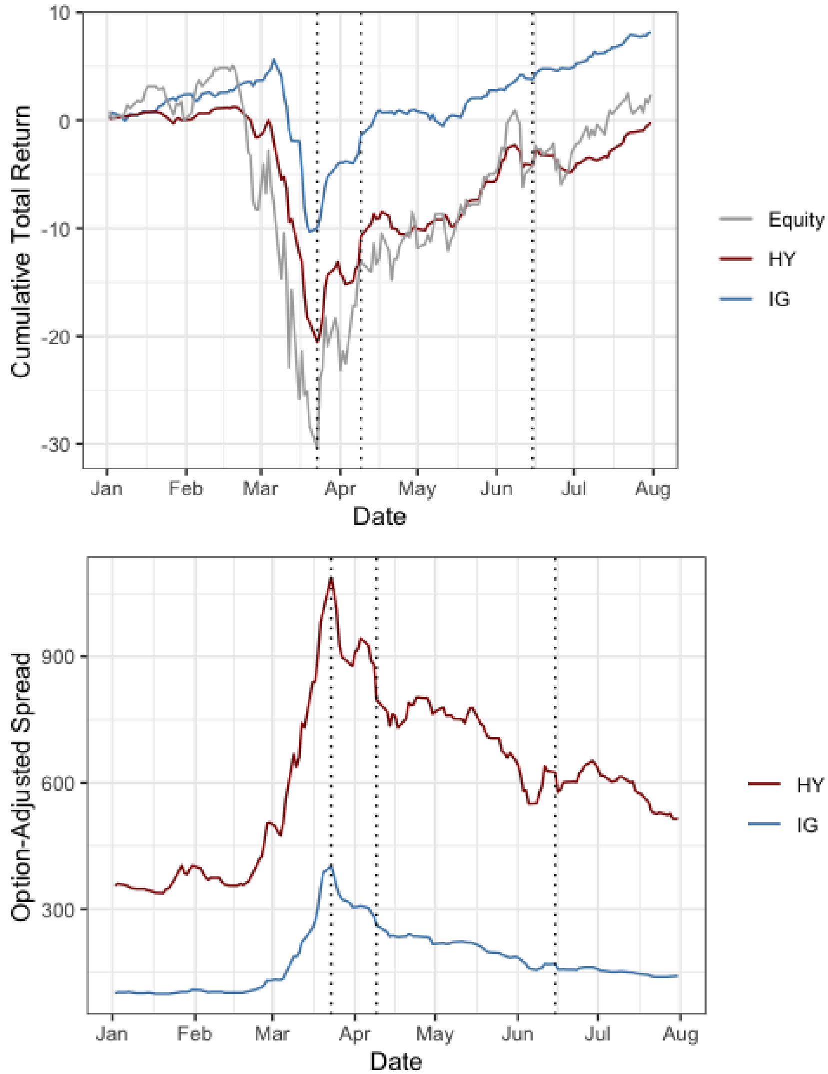
The bottom panel of Figure 1 shows the deterioration in IG and HY spreads in the run up to the Fed's CCF announcements, as well as their subsequent improvement. A similar dynamic is seen when viewing the cumulative total return of the S&P 500 Index and ICE BAML US IG and HY indices. In the top panel, the relative outperformance of IG debt compared to HY debt and equity is striking, while in the bottom panel, the spread between HY and IG debt actually peaks on the date of the initial CCF announcement on March 23, 2020, and remains elevated through future event dates. This is consistent with the construction of the facilities to predominantly provide support to IG issuers, as described above.

Indeed, Section 13(3) of the Federal Reserve Act constrains the Fed's ability to design and deploy emergency facilities to nonbank entities. In addition to requiring Treasury participation to establish the CCFs, the Fed was limited to lending to solvent entities and was required to protect taxpayers from loss.[2] These conditions directly informed the eligibility requirements for the facilities and the choice of issuer ratings over issue ratings.[3] Specifi-

[2] https://www.federalreserve.gov/aboutthefed/section13.htm

[3] See Section 2.4 of Boyarchenko et al. (2021) for a discussion.

Fig 1 Total Returns of S&P 500 Index, ICE BAML US Corporate Index and ICE BAML US High Yield Index



The top panel plots the cumulative total returns of the S&P 500 Index (Equity), the ICE BAML US High Yield Index (HY) and the ICE BAML US Corporate Index (IG) between Jan 2, 2020 and July 31, 2020. The ICE BAML US High Yield Index consists of U.S. corporate bond securities rated below investment-grade. The ICE BAML US Corporate Index consists of U.S. corporate bonds rated investment-grade. The bottom panel plots the option-adjusted credit spreads of the ICE BAML US High Yield Index (HY) and the ICE BAML US Corporate Index (IG) for the same period. The three dotted vertical lines correspond to March 23, 2020 when the Fed announced the creation of the PMCCF and the SMCCF, April 9, 2020 when the Fed expanded the size and scope of the facilities, and June 15, 2020 when the Fed announced the creation of the SMCCF Broad Market Index and the launch of the SMCCF.

cally, an issue is eligible if the associated issuer is rated IG by at least two ratings agencies, if the issuer has multiple ratings.[4] In contrast, the European Central Bank (ECB)'s eligibility criteria for its corporate credit facility, the Corporate Sector Purchase Program (CSPP), is more permissive, deeming an issue eligible if its highest issue rating is rated IG.[5] While its easy to see that the ECB's criteria is more permissive along the ratings dimension, it is in fact also more permissive through a greater reliance on issue versus issuer ratings. This is because an issuer can attain a higher rating on its issue than at the entity level depending on the issue's seniority and collateral security. As a result, HY issuers are potentially in scope for direct bond purchases via the ECB's CSPP but not the Fed's CCFs.

This leads to the natural question of what was the relative performance of IG firms (hence, eligible issuers) compared to HY firms (ineligible issuers). Surprisingly, existing papers do not answer this particular question, since they identify eligible versus ineligible issues at the issue-level by using issue ratings, rather than at the issuer-level by using issuer ratings.[6] Since HY firms have heterogeneous capital structures, which include IG debt, identification at the issue level potentially biases estimates of the relative treatment effects of the CCFs.

1.1 Overview of Results

Our first result is to compute the effect of the Fed CCFs on the relative change of eligible issuer corporate bond spreads compared to ineligible issuer spreads using issuer-level identification of treatment and control groups, and to quantify the bias in the relative treatment effect generated from using issue-level identification of treated versus untreated bonds. Consistent with the literature, we focus on the most significant policy announcement dates, March 23, 2020 and April 9, 2020, since bond spreads reacted most strongly on these dates, compared to the start of actual purchases by facilities. Controlling for issue ratings and remaining issue maturity, on the initial program announcement date of March 23, 2020, we find that the relative treatment effect was -96 bps and -136 bps for eligible issuer bonds relative to ineligible issuer bonds for all bonds and bonds with less than 5 years maturity, respectively. Similarly, on the program expansion date of April 9, 2020, we find that the relative treatment effect was 65 bps and 87 bps for all bonds and bonds with less

[4] https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20200728a1.pdf

[5] https://www.ecb.europa.eu/mopo/implement/app/html/cspp-qa.en.html

[6] These include papers studying prices/spread reactions, as well as liquidity impacts: Boyarchenko et al. (2020), D'Amico et al. (2020), Haddad et al. (2021), Kargar et al. (2021), O'Hara and Zhou (2021), and Nozawa and Qiu (2021). Notable exceptions are Flanagan and Purnanandam (2020) and Gilchrist et al. (2021), both of which limit their analyses to IG issuers.

than 5 years maturity, respectively. All estimates are significant at the one percent level. This shows that eligible issuer spreads reacted more strongly on March 23, 2020, while ineligible issuer spreads reacted more strongly on April 9, 2020.

Repeating this exercise using issue-level ratings to identify the treated and untreated groups, as is done by other papers in the literature, we find that the relative treatment effect estimates for March 23, 2020 are similar to what we computed using the issuer-level identification strategy: -100 bps and -135 bps for all bonds and bonds with less than 5 years maturity, respectively. However, the estimates for April 9, 2020 show considerable upward bias, overestimating the effect for ineligible issuer bond spreads relative to eligible issuer bond spreads. Specifically, we obtain relative treatment effect estimates of 91 bps and 107 bps for all bonds and bonds with less than 5 years maturity, respectively. Again, all estimates are significant at the one percent level. Digging deeper, we find that excluding Fallen Angels (i.e. those issuers who were rated IG as of March 22, 2020, but are subsequently downgraded to HY before April 9, 2020 and so become ineligible before the program expansion grandfathered these issuers back-in) does not explain the difference. Indeed, both the issue-level and issuer-level identification strategy would correctly classify Fallen Angels as treated on March 23 and April 9. Instead, we find evidence that the bias arises due to the IG debt of HY issuers being classified as treated by the issue-level identification strategy.

Our second result is to compute a counterfactual treatment effect for how ineligible issuer bonds would have reacted had they been in scope for direct bond support by the Fed CCFs. As a baseline, we compare the response of Fallen Angel bond spreads to ineligible issuer bond spreads. In our specification with issue ratings and remaining time to maturity fixed effects, we find that the relative movement of eligible non-FA issuer spreads to ineligible issuer spreads was -97 bps and -138 bps on March 23, 2020, for all bonds and bonds with less than five years maturity, respectively. These estimates are significant at the one percent level and nearly identical to the effects computed without separating out the effect on Fallen Angel issuer bonds. However, on April 9, 2020, the relative treatment effect of eligible non-FA issuer spreads rose to 78 bps and 104 bps for all bonds and bonds with less than five years maturity, respectively. The estimates are significant at the one percent level. Examining the relative movement in Fallen Angel issuer spreads, we find that on March 23, 2020, there was actually a positive effect of 55 bps and 84 bps for all bonds and bonds with less than five years maturity, respectively. The former estimate is significant at the five percent level, while the latter is significant at the one percent level. This seems to indicate that the market priced in a smaller decrease in Fallen Angel issuer spreads on March 23, 2020, perhaps anticipating these issuers to be downgraded out of facility eligibility. On the other, on April 9, 2020, Fallen Angel issuer spreads experienced a tightening of -229 bps and -272 bps relative to other eligible issuer spreads on all bonds and bonds with less than five years maturity, respectively. These estimates are significant at the one percent level. This sharp reaction by Fallen Angel issuer bonds after regaining eligibility on April 9, 2020 helps to explain why the estimated movement on eligible non-FA issuer spreads is higher relative to ineligible issuer spreads than when the whole sample of eligible issuer spreads including Fallen Angel issuers are considered.

Relative to ineligible bond spreads, Fallen Angel issuer bond spreads tightened 42 bps and 54 bps on March 23, 2020, and 151 bps and 168 bps on April 9, 2020, for all bonds and bonds with less than five years maturity, respectively. However, to better obtain a causal estimate, we construct a control group consisting of issuers with at least one IG rating but who were ineligible for CCFs. These issuers were ineligible due to not having at least two IG ratings when they had more than one IG rating (e.g. were rated IG by one rating agency but HY by least one other). We show that the treatment (Fallen Angel issuers) and control (IG but ineligible issuers) groups have similar capital structures in terms of issue ratings and similar CDS spreads entering into the announcement date. On April 9, 2020, using issue ratings and remaining maturity fixed effects, we find that the treated group tightened spreads relative to the control group at a magnitude of 126 bps and 86 bps for all maturities and with less than five years maturity, respectively. These estimates are significant at the one percent level and provide an estimate of a counterfactual treatment effect: the potential response in ineligible issuer bonds had they been eligible for the CCFs. Here, we exploit the fact that Fallen Angel issuers lost eligibility to the CCFs between March 23, 2020 and April 9, 2020. While it is surprising that the magnitude of the coefficient for the sample of all bonds is higher than that of the coefficient for only bonds with less than five years maturity, we note that the estimates are comparable to the relative treatment effect computed for March 23, 2020 using the broader sample of eligible and ineligible issuers.

Our third result is to provide evidence on the channels (i.e., liquidity and default risk) through which the CCFs operated and to analyze the effects from the start of ETF purchases and later corporate bond purchases. We find that default risk, as measured using CDS spreads, declined more for eligible issuers on March 23, 2020, but then declined more for ineligible issuers on April 9, 2020. We see the same pattern for liquidity improvements, as measured through changes in the bond-CDS basis, but note that the magnitude of the effect is larger than what is seen through CDS spreads. Another measure of liquidity, the ETF-NAV basis, shows considerable narrowing for March 23, 2020, across all ETFs, but with a greater effect seen for IG ETFs than HY ETFs. On April 9, 2020, we actually observe a widening of the ETF-NAV basis, but this could be due to ETF prices trading at a premium relative to NAV. In fact, at the start of ETF purchases on May 12, 2020, we also find a widening of the ETF-NAV basis. Interestingly, the start of ETF purchases resulted in a relatively greater movement in eligible issuer bond spreads compared to ineligible issuer bonds spreads. While at the start of the direct eligible issuer bond purchases on June 16, 2020, ineligible issuer bond spreads experienced a relatively greater tightening.

Our fourth result is to estimate the treatment effects of the CCF interventions using a causal machine learning (ML) approach, i.e. the two-step semi-parameteric difference-in-differences (DiD) estimator of Momin (b), which is based on Farrell et al. (2021) and Farrell et al. (2020). The structural equation specifying the potential outcomes model for spread changes is a linear combination of a non-parameteric intercept term and the product of a non-parametric slope term and treatment indicator. The intercept term corresponds to the potential outcome of spread changes absent intervention, while the slope term is the conditional average treatment effect (CATE). The non-parameteric terms used in the estimator are estimated using deep neural networks and utilizes a high-dimensional set of controls. In addition to better potentially controlling for omitted variable variables, the high-dimensional features allow for the estimation of heterogeneous treatment effects. The results from the causal ML approach are largely consistent with the panel DiD regressions. Additionally, exploiting the distribution of CATEs to construct counterfactual policy targeting schemes shows that the average treatment effect of the treated (ATET) can be improved by different targeting. This result can be used to uncover which firms and bonds were most sensitive to the CCF interventions. Similarly, we discuss how the distribution of CATEs can be used to decompose the channels through which the CCF interventions operated.

As additional robustness exercises, we 1. recompute the relative treatment effect of the facilities on eligible issuer bonds using bond returns (e.g. change in log bond prices) and 2. replace issuer ratings with inclusion in the Fed's SMCCF Broad Market Index, published on June 15, 2020, to proxy facility eligibility. Using issue ratings and maturity fixed effects, we find that eligible issuer bonds, compared to ineligible issuer bonds, experienced a 3.72 percent and 2.70 percent higher return on March 23, 2020, and 1.47 percent and 1.93 percent lower return on April 9, 2020 for all bonds and bonds with less than five years maturity, respectively. All coefficient estimates are significant at the one percent level. This is consistent with the direction of the relative treatment effects we estimated using spreads. Perhaps more interestingly, we find that proxying eligibility using the SMCCF Index leads to smaller estimates for the relative treatment effects in the bond spread space. Note that the use of this proxy results in a subset of potential eligible issuers computed using ratings. For SMCCF Index eligible issuers, relative to ineligible issuers, bond spreads declined 47 bps and 69 bps on March 23, 2020, and widened 32 bps and 35 bps on April 9, 2020 for all bonds and bonds with less than five years maturity, respectively. These estimates are significant at the one percent level.

1.2 Contribution to Literature

This paper primarily contributes to the large literature studying the effects of the Fed CCFs on corporate bond pricing, spreads, and liquidity, that were written contemporaneously with ours. It does so on three dimensions. First, it points out a potential identification concern that affects most of these papers, which determine eligibility by issue rather than issuer ratings (Boyarchenko et al., 2020; D'Amico et al., 2020; Haddad et al., 2021; Kargar et al., 2021; Nozawa and Qiu, 2021; O'Hara and Zhou, 2021).[7] The novel identification strategy approached here exploits the heterogeneity of the U.S. corporate capital structure, and the fact that differentially rated issuers have similarly rated bonds to measure the differential impact of the CCFs for bonds with similar ratings and maturity. Second, armed with this, we study the potential identification bias that may have arisen from using issue rather than issuer ratings to determine eligibility.

Third, noting that the expansion of the CCFs on April 9, 2020 also brought into inclusion HY ETFs for purchases, we observe the difficulty of measuring the effect of the April 9, 2020 on eligible issuers. To better identify this effect, we exploit quasi-experimental variation between the March 23, 2020 and April 9, 2020 announcement dates. There were several firms that were initally eligible for the CCFs but were subsequently downgraded out of eligibility before having their eligibility reinstated (the so-called Fallen Angels). We track the relative movements of the spreads of this group of firms with a control group of firms that just missed the ratings cutoff for eligibility to determine the treatment effect of the April 9, 2020 announcement. Alternatively, we can view this as the counterfactual effect on spreads of granting eligibility to ineligible firms.

Fourth, we utilize another novel identification strategy: the two-step semi-parametric DiD estimator of Momin (b), which is based on Farrell et al. (2021) and Farrell et al. (2020). The causal ML approach allows for correct inference while using high-dimensional controls and ML-driven model selection. It also allows for the estimation of average treatment effects (ATEs) accounting for heterogeneity. Other papers using double-debiased ML (DML) methods[8] in the empirical asset pricing literature include Borri et al. (2024), Feng et al. (2020), Gomez-Gonzalez et al. (2024), Hansen and Siggaard (2024), and Maasoumi et al. (2024). To the best of our knowledge, this paper is the first to provide an application of policy counterfactuals on asset price movements in the finance literature, using DML and related methods.

The remainder of the paper is organized as follows. Section 2 discusses the related

[7] Notable exceptions are Flanagan and Purnanandam (2020) and Gilchrist et al. (2021), both of which limit their analyses to IG issuers.

[8] See the cannonical references of Belloni et al. (2014) and Chernozhukov et al. (2018).

literature. Section 3 provides a general description of the data and sample construction, as well as descriptive statistics on issuers. Section 4 provides a simple decomposition of credit spreads that we use to motivate our empirical design. Section 5 reports our main empirical specification and results. Section 6 provides additional robustness checks to support our results. Section 7 concludes.

2 Related Literature

There are several papers that study the effect of the CCFs on prices/spreads, as well as liquidity. Haddad et al. (2021) identify that the safest securities, including IG corporate bonds, experienced relatively greater selling pressure at the start of the COVID-19 financial crisis due to investor liquidity demands. O'Hara and Zhou (2021) and Kargar et al. (2021) corroborate this narrative by showing that liquidity deteriorated as corporate bond dealers shed inventory. O'Hara and Zhou (2021) further show that customer trades migrated to centralized client-to-client exchanges, though at higher costs. Kargar et al. (2021) show that costs of principal trades rose markedly, leading to an increase of lower-quality, slower agency trades. These papers all find that the Fed's interventions worked to drastically improve liquidity in corporate bond markets, which our results also support. However, Nozawa and Qiu (2021) use a variance decomposition approach to identify a greater reduction in bond spreads due to the reduction of default risk, rather than improvements in liquidity, due to the announcement of the Fed CCFs.

Among all papers, there is tentative consensus that the March 23, 2020 event was more beneficial for eligible issuer bonds, but Boyarchenko et al. (2020) and Haddad et al. (2021) present some evidence that April 9, 2020 may have been more beneficial for eligible issuer bonds. In contrast, this paper, D'Amico et al. (2020) and Nozawa and Qiu (2021) find that April 9, 2020 may have benefited ineligible issuer bonds to a greater extent. Additionally, D'Amico et al. (2020) and Boyarchenko et al. (2020) find that issuance, particularly for IG issuers, quickly picked up pace following the introduction of the CCFs. Similar to our focus on Fallen Angel issuers to estimate a counterfactual treatment, Nozawa and Qiu (2021) perform a similar, albeit descriptive, exercise and compare the change in spreads averaged across bonds for both the treated Fallen Angels and a matched control group. They compute an average two-day change in spreads of 340 bps for Fallen Angels versus 120 bps for the control group around the facility announcement dates. The implied treatment effect of 220 bps far exceeds our estimate of 126 bps.

Unlike this paper and those above, Flanagan and Purnanandam (2020) and Gilchrist et al. (2021) restrict their samples to only IG issuers Consequently, they do not bias their results by identifying eligible issuers by the use of issuer rather than issue ratings. Flanagan and Purnanandam (2020) find that the bonds that the Fed ultimately ended up purchasing were those that had become more 'informationally sensitive,' in the sense that these bonds were used as collateral in repo transactions and were sold by mutual funds meeting redemption demand. In contrast, the extent of bond price depreciation and the issuer's payroll size seems to have matter less for SMCCF Index inclusion. Among eligible issuers, Gilchrist et al. (2021) find that issues below the five year maturity cutoff experienced a greater decrease in spreads than those issues above the cutoff. The authors find that the impact of the facilities on spreads seem to come from a reduction in credit risk premia, though this effect disappears when controlling for a correction in the credit term structure induced by the facility announcements. Consistent with our results and those of other papers, they find that the facility announcements induced a greater reduction in spreads than actual purchases of bonds.

This paper also relates to the literature on the ECB's corporate bond purchase facility, the CSPP, which predates the Fed CCFs. A key difference between the Fed CCFs and the CSPP relates to eligibility criteria, as the CCFs' ratings eligibility is determined at the issuer level whereas the CSPP is determined at the issue level. Several papers study the impact of the CSPP on European corporate bonds. Using pooled regression, Zaghini (2019) focus on the primary market issuances and find that the CSPP improved yield spreads for both eligible and ineligible bonds, upholding the re-balance channel. Abidi and Miquel-Flores (2018) exploit a slight difference between the CSPP and market IG/HY cutoff and propose a regression discontinuity design. They document both an improvement in bond spreads and an increase in primary market issuance, and find that the announcement impact was most noticeable in the sample of CSPP-eligible bonds that were perceived as HY by the market, highlighting both the portfolio re-balance channel and the liquidity channel. Similarly, Todorov (2020) finds a sizeable impact on the spreads of eligible bonds from the introduction of the CSPP.

3 Data

3.1 Sample Construction

Corporate bond transaction data are obtained from the Enhanced TRACE database. The enhanced version of TRACE is made available on Wharton Research Data Services (WRDS) and updated quarterly. The Enhanced TRACE contains trade-level information on U.S. corporate bond transactions, including bond CUSIP, trade-level price, uncapped trade volume, execution time-stamp, buy/sell indicator, counterparty code, and other related metrics. We follow the literature and apply a standard filtering procedure (e.g., Dick-Nielsen (2014)) to clean the Enhanced TRACE. We remove all primary transactions from the data.

Table 1 Ratings Scales

Moody's	S&P	Fitch	Value
Aaa	AAA	AAA	10
Aa1	AA+	AA+	9
Aa2	AA	AA	8
Aa3	AA-	AA-	7
A1	A+	A+	6
A2	A	A	5
A3	A-	A-	4
Baa1	BBB+	BBB+	3
Baa2	BBB	BBB	2
Baa3	BBB-	BBB-	1
Ba1	BB+	BB+	0
Ba2	BB	BB	-1
Ba3	BB-	BB-	-2
B1	B+	B+	-3
B2	B	B	-4
B3	B-	B-	-5
Caa1	CCC+		-6
Caa2	CCC	CCC	-7
Caa3	CCC-		-8
Ca	CC	CC	-9
C	C	C	-10
	D	D	-11

Credit ratings scales and corresponding numeric values for Moody's, S&P, and Fitch.

We obtain bond characteristics from Mergent FISD Bond Issues dataset via WRDS. These characteristics inlcude issuer CUSIP, coupon, coupon type, maturity, offering date, maturity date, total par amount outstanding, industry, currency, country domicile, etc. The dataset also includes indicators for whether the bonds are perpetual, convertible, pay-in-kind etc. Bond characteristics are merged with the TRACE dataset, and thus only TRACE-reportable bonds that have traded between January 1, 2020 and June 30, 2020 are included in our sample. We also filter out any variable-coupon, convertible, perpetual or pay-in-kind securities as well as any security that appears in TRACE but is not included in the Mergent FISD dataset. We further only keep issuers domiciled in the U.S. since CCF eligibility was restricted to issuers with material U.S. operations.

We obtain bond ratings from Mergent FISD Bond Ratings dataset. This dataset contains issue ratings from Moody's, S&P and Fitch, which are mapped by us to their corresponding numeric values according to Table 1. We compute issuer ratings from issue ratings by selecting the minimal issue rating on senior unsecured debt per issuer.[9] After obtaining issuer ratings, we determine eligibility for the Fed CCFs by using ratings as of March 22, 2020, and classify issuers as eligible if they were rated as IG or had at least two IG ratings if the issuer had more than one issuer rating. To compute issue fixed effects, we aggregate issue ratings by using its maximal issue rating and assign it to its respective rating bucket (eg. AAA, AA, A, BBB, BB, B). The results are robust to other definitions aggregating issue ratings.

Thus, our sample is constructed using corporate bond transaction data from cleaned Enhanced TRACE for the period between January 1, 2020 and June 30, 2020 merged with the Mergent FISD Bond Issues and Bond Ratings information and filters. Daily volume-weighted price and yield data is computed using trades of institutional size (i.e., greater than or equal to $100,000). While this is a standard cleaning procedure, our results are robust to using the entire sample of trades.

We compute G-spreads for bonds by differencing the yields on corporate bonds and the corresponding zero coupon bond spread of the same duration. The zero coupon bond spreads are generated using the Nelson-Siegel-Svensson yield curve parametrization of Gürkaynak et al. (2007). Data is available through the Federal Reserve.[10] Since TRACE reports 'clean' bond prices without accrued interest, we compute the accrued interest between a bond's last coupon date and the settlement date and add this to the 'clean' price

[9] Moody's explicitly equates the two in its ratings definition: "Long-Term Issuer Ratings are opinions of the ability of entities to honor long-term senior unsecured financial obligations and contracts." See: https://www.moodysanalytics.com/-/media/products/Moodys-Rating-Symbols-and-Definitions.pdf.

[10] https://www.federalreserve.gov/data/nominal-yield-curve.htm

to get the final 'dirty' bond price faced by an investor at settlement. Spreads and bond prices are trimmed at the 1 percent and 99 percent levels to limit the influence of outliers. Results are robust to using untrimmed data. Spread changes and change in log bond prices are computed as one-day changes, and hence, are conditional on the availability of trade-weighted data in the current and previous trading days.

We obtain CDS spread data from Markit through WRDS. CDS-bond basis are constructed as the difference between the spreads of five-year CDS contracts on senior unsecured bonds and averaged bond spreads for senior unsecured bonds with remaining time to maturity of four to six years, per issuer. The ETF-NAV basis is constructed from the sample of ETFs purchased by the SMCCF, as of June 28, 2020. We take the difference in the ETF price and the ETF's NAV to obtain the basis. For both the CDS-bond basis and the ETF-NAV basis, we take absolute values and compute one-day changes to measure narrowing (negative change) or widening (positive change), where the former represents improving liquidity and the latter deteriorating liquidity.

As a robustness check, we proxy CCF eligibility by using the constituents of the Fed's SMCCF Broad Market Index at inception.[11] While the creation of the SMCCF Broad Market Index was announced on June 15, 2020, the initial index constituent list dates from June 5, 2020. If this list of eligible issuers was both the same set of eligible issuers as of the facility launch date on March 23, 2020 and could have also been inferred by the markets using issuer ratings information, then it would be a perfect proxy for eligible issuers. However, Flanagan and Purnanandam (2020) and Gilchrist et al. (2021) show that the SMCCF Broad Market Index constituents are a subset of all eligible issuers and that certain characteristics can predict index inclusion. Consequently, this proxy is a subset of the set of eligible issuers constructed using issuer ratings, as we do in our main results.

The causal ML approach used in Section 5.2 uses firm fundamental characteristics obtained from the Financial Ratios Suites on WRDS.

3.2 Descriptive Statistics

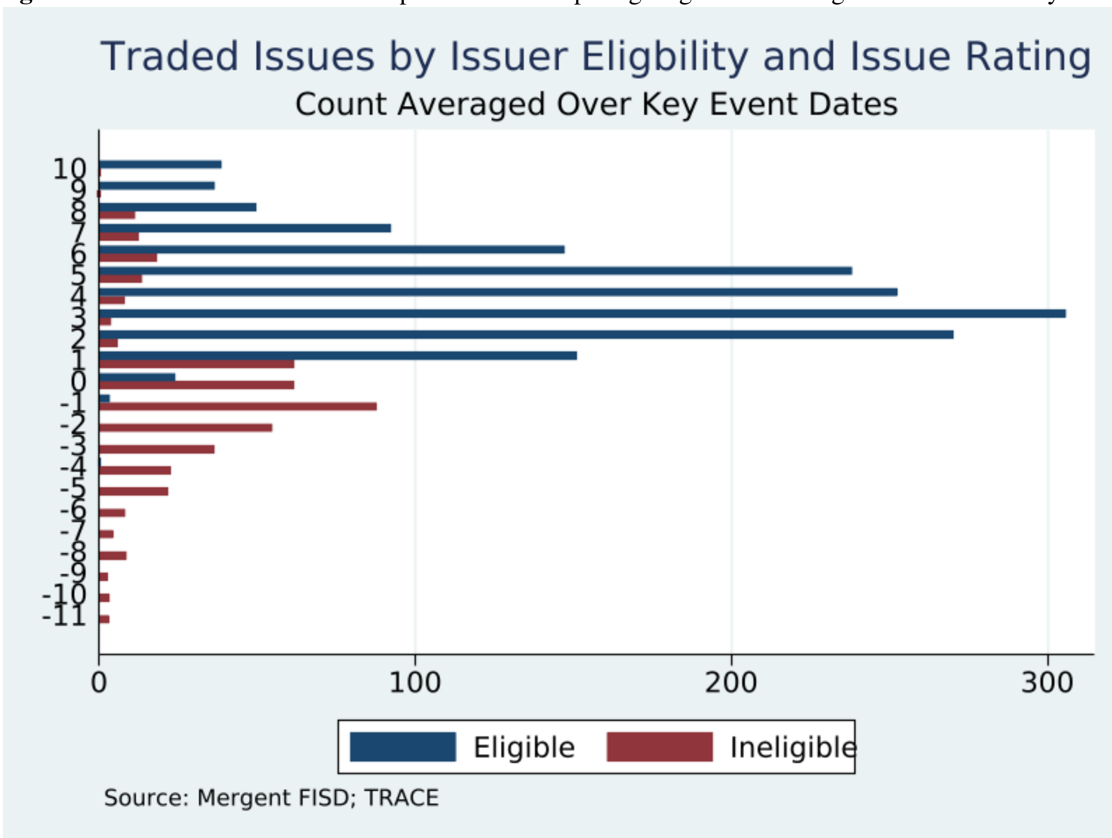
3.2.1 Issuer Characteristics

Momin (b) examines the differences in firm fundamentals and CDS spreads across publicly traded eligible and ineligible firms. Although there is substantial overlap and in real and financial variables, eligible firms are larger, more liquid, and more solvent than ineligible firms.

[11] `https://www.newyorkfed.org/markets/secondary-market-corporate-credit-facility/secondary-market-corporate-credit-facility-broad-market-index`

3.2.2 *Issuer Capital Structure*

Fig 2 Relative Treatment Effects Computed from Comparing Eligible and Ineligible Issuer Bonds by Rating



The figure shows the relative count of issues by eligible and ineligible issuers over their numerical issue ratings (see Table 1 for the mapping between the letter and numerical ratings). We average issue ratings for issues which traded on March 23, 2020 and April 9, 2020. As expected, eligible issuers almost entirely issue IG debt (debt rated above 0). While ineligible issuers mainly issue HY debt (debt rated 0 or below). However, ineligible issuers also issue a notable amount of IG debt. The overlap of eligible and ineligible issuers within IG rated debt performs the basis of our empirical identification.

Despite ineligible issuers having worse risk characteristics on average, this does not imply that individual issues for ineligible issuers are uniformly worse than eligible issuer issues. Figure 2 shows the ratings distribution across eligible and ineligible traded issuers for issuer-issue observations average over key event dates. While the vast majority of eligible traded issuers have IG rated issues, ineligible traded issuers have issues spanning the HY and IG rated spectrum. The reason is principally due to some HY issuers issuing IG-rated debt.

Figure 2 reinforces our concern about potential measurement issues when attempting to infer the reaction of eligible and ineligible issuer bonds by using issue ratings to classify said bonds, or using ETFs with issue ratings criteria for their IG and HY indices. On the other hand, the overlap in HY and IG rated issues across eligible and ineligible issuers suggests a natural identification strategy from comparing similarly rated issues across differentially eligible issuers on key Fed event dates.

4 Spread Decomposition

We specify the issue default risk component in a way to make the object comparable to bond ratings and CDS spreads. Namely, we scale issuer default probability by that particular issue's loss given default. Consequently, let T equal remaining time to maturity, then:

$$y^T_{ijt} = r^T_t + \phi^T_{it}\gamma_{jt} + \psi^T_{jt} \tag{1}$$

where y^T_{ijt} is the yield of bond j for issuer i at time t, r^T_t is the reference risk-free rate, ϕ^T_{it} is the default probability for issuer i over the remaining time to maturity, γ_{jt} is the loss given default, and ψ^T_{jt} is the liquidity risk over the remaining time to maturity.

As mentioned, issue ratings are approximately captured by $\phi_{it}\gamma_{jt}$. Hence, for a given issuer with fixed ϕ_{it} across issues, issue ratings may vary due to recovery values, which may be driven by issue seniority in the capital structure, the security of collateral supporting the issue, etc.. Naturally, this specification corresponds to the definition of issue ratings utilized by the rating agencies, as seen in the excerpt from S&P's definition below:

> An S&P Global Ratings issue credit rating is a forward-looking opinion about the creditworthiness of an obligor with respect to a specific financial obligation . . . reflects S&P Global Ratings' view of the obligor's capacity and willingness to meet its financial commitments as they come due, and this opinion may assess terms, such as collateral security and subordination, which could affect ultimate payment in the event of default.[12]

Additionally, observe that CDS spreads are analogous to issue ratings: $CDS_{ijt} \approx \phi_{it}\gamma_{jt}$. Issuer ratings capture issuer default probability and so, map to ϕ_{it}. Market implied issuer ratings (i.e. issuer probability of default) can be obtained by dividing CDS spreads by the contractually specified loss given default, γ_{jt}. Hence, $\phi_{it} \approx CDS_{ijt}/\gamma_{jt}$.

[12] https://www.spglobal.com/ratings/en/products-benefits/products/issue-credit-ratings

In this framework, we have the typical result that the liquidity spread can be proxied by the bond-CDS basis:

$$\underbrace{(y_{ijt}^T - r_t^T)}_{\text{Bond Spread}} - CDS_{ijt} \approx \psi_{jt}^T \tag{2}$$

We exploit this decomposition to study changes in bond spreads attributable to improving or deteriorating liquidity, but the downside is that this measure is generally only viable for a narrow class of an issuer's securities (i.e. five year senior unsecured debt).

Using (1), we can get a sense of relative spread differences between eligible and ineligible bond yields, at any time t. That is, $y_{ijt}^{T,Elg}$ and $y_{ijt}^{T,Inelg}$, respectively:

$$\Delta y_{ijt}^{T,Elg} - \Delta y_{ijt}^{T,Inelg} = \Delta(\gamma_{jt}^{T,Elg}\phi_{it}^{T,Elg}) - \Delta(\gamma_{jt}^{T,Inelg}\phi_{it}^{T,Inelg}) + \Delta\psi_{jt}^{T,Elg} - \Delta\psi_{jt}^{T,Inelg} \tag{3}$$

where Δr_t^T nets out. Note also that differencing in such a fashion also nets out other common (e.g. macroeconomic) sources of variation. Thus, differences in spread changes are driven by relative changes in default risk and liquidity across differentially eligible issuers on same-rated, same-maturity issues.

5 Empirical Strategy and Results

5.1 Difference-in-Differences

In the spirit of our yield decomposition, our DiD specifications are variations of the following functional form:

$$\Delta O_{ijt} = \alpha + \beta_1 \text{Group}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Group}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt} \tag{4}$$

where ΔO_{ijt} is the first-difference of an outcome variable of interest (e.g. a bond's G-spread), Group_i is an indicator variable equal to one if issuer i is a member of a particular set (e.g., the set of issuers eligible for the Fed facilities), Events_t is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. We use bond rating and time-to-maturity by date fixed effects due to the stationarity of our outcome variables, which tend toward zero as we increase the time horizon of its average to the full time-series. We compute fixed effects at the weekly instead of daily frequency to avoid issues of multicollinearity arising between the fixed effects and indicator variables. Additionally, note that the parallel trends assumptions for our DiD regressions are satisfied as a result of our using first-differenced, and hence, stationary, outcome variables for all of our analyses.[13]

5.1.1 Relative Treatment Effect

As a baseline, we compute the relative treatment effect of the CCF announcements on eligible issuer bond G-spreads versus ineligible issuer bond G-spreads. The corresponding regression equation is:

$$\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt} \tag{5}$$

where ΔS_{ijt} is the change in the G-spread of bond j at time t and Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020. The results are reported in Table 2.

Columns (1) and (2) correspond to specifications where fixed effects are omitted, while columns (3) and (4) report the coefficient estimates with fixed effects included. Columns (1) and (3) are estimates over the full sample of bonds, while columns (2) and (4) are estimates for the sample bonds with less than five years maturity. We note that the coefficient estimates decrease with the inclusion of fixed effects, consistent with our expectations that these fixed effects absorb variation common across issue ratings or bond maturities.

Our main estimates of interest correspond to the interacted variables, "March 23 X Eligible" and "April 9 X Eligible," which map to β_3 in Equation (5). We focus on our full specification with fixed effects: columns (3) and (4). We find that the coefficient estimates for "March 23 X Eligible" are negative for the full sample and restricted sample with bonds with less than five years maturity and significant at the one percent level. These values result indicate that eligible issuer bonds decreased -96 bps and -135 bps, respectively, for the full sample and restricted sample. The greater decline in the restricted sample is consistent with bonds in direct purview of potential purchase by the CCFs experiencing a greater decline in spreads. Note that on this date the Fed only indicated that it would support eligible issuer bonds, either directly through primary or secondary market purchases, or through purchases of IG ETFs. Hence, the estimates for March 23, 2020 provide an unambiguous measurement of the treatment effect on bond spreads induced by the Fed announcing its facilities.

In contrast, the Fed's announcement on April 9, 2020, while expanding the size of the facilities, featured two other innovations: 1. the intention to purchase HY ETFs and 2. the

[13] We perform panel data unit root tests of our key outcome variables (e.g. change in G-spreads) and find evidence consistent with this data being stationary (unreported).

Table 2 Change in G-Spreads (Issuer Ratings as Proxy)

	(1)	(2)	(3)	(4)
		<5yrs Maturity		<5yrs Maturity
Eligible	-2.0307	-2.2468	-0.6726	-0.8641
	(2.3932)	(3.1463)	(0.6668)	(1.2100)
March 23	62.3515***	90.6787***	16.2943	37.0732
	(3.3844)	(7.0570)	(36.3108)	(47.9197)
April 9	-138.4193***	-172.0778***	-104.2630***	-130.8509***
	(3.5355)	(7.5417)	(9.8927)	(12.9011)
March 23 X Eligible	-106.4632***	-145.9185***	-95.9738***	-135.5091***
	(3.0282)	(6.6175)	(17.8893)	(28.4905)
April 9 X Eligible	90.2442***	116.6548***	65.0596***	87.0349***
	(3.1742)	(7.0753)	(12.4963)	(16.3173)
Constant	2.4722	2.4600	1.5160	1.5448
	(2.9531)	(3.7777)	(0.9777)	(1.3948)
Issue Ratings by Week F.E.	N	N	Y	Y
Remaining Maturity by Week F.E.	N	N	Y	Y
Observations	4.304e+05	2.100e+05	4.303e+05	2.100e+05
R2	0.0030	0.0030	0.1206	0.1242

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, Eligible$_i$ is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. < 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. From the table, we see that eligible issuer bonds tightened more than ineligible issuer bonds on March 23, 2020, as indicated by the coefficient estimate for “March 23 X Eligible.” On April 9, 2020, we uncover the opposite relationship, as indicated by the positive coefficient estimate for “April 9 X Eligible.”

continued support for 'Fallen Angels,' issuers eligible as of March 22, 2020, but who were downgraded out of eligibility between March 22, 2020 and April 9, 2020. The former directly benefits from HY ETFs since most, but not all, of ineligible issuer securities are rated HY. The latter benefits ineligible issuer bonds indirectly. While re-including Fallen Angel issuers may induce some spillover benefits to ineligible issuers, since these issuers are also rated HY, the direct impact will be seen for the eligible group in the coefficient estimates, since on both March 23, 2020, and April 9, 2020, Fallen Angel issuers are classified as eligible. We analyze the Fallen Angel issuers separately later.

In Table 2, the coefficient estimates on "April 9 X Eligible" measure the relative impact of the program expansion, which proportionally results in more stimulus directed to eligible issuers, and the reinstatement of Fallen Angel issuers as eligible for the facilities, versus the impact on ineligible issuers of having HY ETFs include for purchase by the CCFs. The positive coefficients indicate that the latter force dominates. In the full specification, columns (3) and (4), on April 9, 2020, we find that ineligible issuer spreads experienced 65 bps and 87 bps additional tightening, compared to eligible issuer spreads, in the full sample and restricted sample, respectively. Given that the Fed indicated that it would purchase HY ETFs in much smaller quantities than other securities, a fact validated by ex post purchases, these results imply that ineligible issuer securities were far more responsive to announced monetary stimulus.

In Table 3, we re-run the specification given by Equation (5), but instead proxy issue eligibility by issue-level ratings, as of March 22, 2020, instead of using issuer-level ratings as the Fed criteria stipulates. We do this to quantify the bias that results from using an improper proxy for issue eligibility. This is an important questions since we find that the literature uses such proxies when analyzing the effects of the facilities across IG and HY issuers.[14] Consequently, our specification becomes:

$$\Delta S_{ijt} = \alpha + \beta_1 \text{IG Issue}_{ij} + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{IG Issue}_{ij} + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt} \tag{6}$$

where the subscript on the variable IG Issue$_{ij}$ suggests that its possible for issuers i to have some issues j classified as eligible for the CCFs and others ineligible, depending on the issue rating. Figure 2 shows that a nontrivial of HY issuers have both IG and HY bonds, which give rise to the preceding dynamic.

Comparing columns (3) and (4) of Table 3 with columns (3) and (4) of Table 2, we

[14]These include papers studying prices/spread reactions, as well as liquidity impacts: Boyarchenko et al. (2020), D'Amico et al. (2020), Haddad et al. (2021), Kargar et al. (2021), O'Hara and Zhou (2021), and Nozawa and Qiu (2021). Notable exceptions are Flanagan and Purnanandam (2020) and Gilchrist et al. (2021), both of which limit their analyses to IG issuers.

Table 3 Change in G-Spreads (Issue Ratings as Proxy)

	(1)	(2) <5yrs Maturity	(3)	(4) <5yrs Maturity
IG Issue	-1.8840	-1.8512		
	(3.2672)	(3.8830)		
March 23	71.7128***	94.5870***	25.6632	43.0376
	(5.2138)	(9.8448)	(42.9512)	(54.3325)
April 9	-158.6382***	-186.6985***	-129.0811***	-150.5372***
	(5.5242)	(10.6646)	(4.4110)	(10.1600)
March 23 X IG Issue	-109.9258***	-142.3483***	-100.2265***	-135.0450***
	(5.5746)	(10.1711)	(26.2299)	(38.2180)
April 9 X IG Issue	109.5167***	129.2813***	91.0465***	107.0200***
	(5.2386)	(10.5055)	(7.5892)	(13.8572)
Constant	2.4427	2.2147	0.9900	0.8904
	(3.7445)	(4.3929)	(0.7378)	(0.9631)
Issue Ratings by Week F.E.	N	N	Y	Y
Remaining Maturity by Week F.E.	N	N	Y	Y
Observations	4.304e+05	2.100e+05	4.303e+05	2.100e+05
R2	0.0029	0.0028	0.1206	0.1241

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{IG Issue}_{ij} + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{IG Issue}_{ij} + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, IG Issue$_{ij}$ is an indicator variable equal to one if issue j is eligible for the Fed CCFs based on its issue ratings as of March 22, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. In contrast to Table 2, treated bonds are determined by issue ratings, as opposed to issuer ratings. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. Similar to Table 2, we see that eligible issuer bonds tightened more than ineligible issuer bonds on March 23, 2020, as indicated by the coefficient estimate for "March 23 X Eligible." Similarly, on April 9, 2020, we find the opposite relationship, as indicated by the positive coefficient estimate for "April 9 X Eligible." However, in contrast to Table 2, we find a larger estimate for "April 9 X Eligible," which we attribute to the bias induced by incorrectly using issue ratings, as opposed to issuer ratings, to identify treated bonds.

find that the coefficient estimates for the interacted event and eligibility proxy variable for March 23, 2020 are roughly the same, suggesting that using issue ratings does not significantly bias the results. The values are -96 bps and -136 bps for "March 23 X Eligible" in Table 2 versus -100 bps and -135 bps for "March 23 X IG Issue" in Table 3 for all bonds and bonds with less than five years maturity, respectively. All estimates are significant at the one percent level. In contrast, we find that there is significant distortion of the treatment effect estimates for April 9, 2020. We compute coefficient estimates of 65 bps and 87 bps for "April 9 X Eligible" in Table 2 versus 91 bps and 107 bps for "April 9 X IG Issue" in Table 3 for all bonds and bonds with less than five years maturity, respectively. All estimates are significant at the one percent level. Moreover, the common effect on all bonds on April 9, 2020 is denoted by the "April 9" variable in Tables 2 and 3 and is estimated to be roughly the same. Consequently, the issue ratings identification leads one to conclude that ineligible issuer bonds tightened 26 bps and 20 bps more on April 9, for all bonds and bond with less than five years maturity, respectively, than the more accurate specification proxying issuer eligibility using issuer ratings.

We explore two potential explanations for why the issue-level identification strategy overstates the impact on ineligible issuer bonds on April 9, 2020: 1. Fallen Angel issuers are classified as ineligible issuers by the issue-level identification strategy, and 2. HY issuers with both IG and HY debt leads to a biasing of the estimates. Given that issuer ratings often serves as a lower bound on issue ratings, the first explanation should not explain the resulting bias in the estimates, since both the issue-level and issuer-level identification strategies would have classified Fallen Angel issuers, as well as their individual securities, as eligible, as of March 22, 2020. Table 4 supports this claim by presenting the resulting coefficient estimates from both identification strategies over the sample excluding Fallen Angel issuer securities. Again, we find that the coefficient estimates for "March 23 X Eligible" and "March 23 X IG Issue" to be similar, while those of "April 9 X Eligible" and "April 9 X IG Issue" differ by similar margins as before. If it was the case that Fallen Angels somehow induced a bias in the coefficient estimates, we would have expected the margins to disappear or close once we excluded their securities from the sample, in contrast to what we find instead.

To explore the second explanation for the biased induced by issue-level versus issuer-level identification, we run supplementary regressions and show the results in Table 5. In columns (1) and (2), we run the regression given by Equation (6) over the sample of only ineligible issuer securities (where eligibility is determined by issuer ratings). By implicitly shutting off the comparison with eligible issuer securities, by restricting our sample to only ineligible issuer securities, we find that coefficient estimate for "April 9 X IG Issue" drops to 80 bps and 77 bps versus 91 bps and 107 bps in columns (3) and (4) of Table 3 for

Table 4 Change in G-Spreads (Excluding Fallen Angels)

	(1)	(2) <5yrs Maturity	(3)	(4) <5yrs Maturity
Eligible	-0.4597	-0.3374		
	(0.7033)	(1.5109)		
March 23	17.4688	39.0503	25.6057	42.9729
	(35.7056)	(46.8250)	(42.9706)	(54.3660)
April 9	-106.1417***	-132.8231***	-129.9957***	-152.0360***
	(7.2388)	(10.7186)	(4.7329)	(10.2248)
March 23 X Eligible	-96.6549***	-137.0712***		
	(17.6330)	(28.2168)		
April 9 X Eligible	76.3711***	102.9581***		
	(9.3067)	(13.5590)		
March 23 X IG Issue			-99.2787***	-133.8459***
			(26.0463)	(37.9482)
April 9 X IG Issue			100.1804***	121.4783***
			(7.0857)	(12.7432)
Constant	1.3521	1.1394	0.9949	0.8862
	(1.0342)	(1.6180)	(0.7211)	(0.9326)
Issue Ratings by Week F.E.	Y	Y	Y	Y
Remaining Maturity by Week F.E.	Y	Y	Y	Y
Observations	4.205e+05	2.038e+05	4.205e+05	2.038e+05
R2	0.1200	0.1239	0.1199	0.1237

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In columns (1) and (2), we report the regression estimates and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events_t is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. In columns (3) and (4), we report the regression estimates and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{IG Issue}_{ij} + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{IG Issue}_{ij} + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. The main difference here is the replacement of Eligible_i with IG Issue_{ij}, which is an indicator variable equal to one if issue j is eligible for the Fed CCFs based on its issue ratings as of March 22, 2020. All regressions are run over a sample where bonds of Fallen Angel issuers are excluded. Columns (1) and (3) include bonds of all maturity, while columns (2) and (4) sample to bonds with less than five years of maturity. Notably, we find that the difference on the coefficient estimates for "April 9 X Eligible" and "April 9 X IG Issue" persists even after excluding Fallen Angel issuers.

Table 5 Change in G-Spreads (April 9 Comparison)

	(1) Ineligible	(2) Ineligible + <5yrs Maturity	(3) IG Issues ex. FA	(4) IG Issues ex. FA + <5yrs Maturity
April 9	-130.2434***	-152.0626***	-106.2246***	-132.9275***
	(4.8662)	(10.9130)	(7.2298)	(10.7044)
April 9 X IG Issue	79.5392***	77.1819***		
	(9.0520)	(15.8635)		
Eligible			-0.8165	-0.9174
			(0.7821)	(1.6564)
April 9 X Eligible			76.4771***	103.0967***
			(9.2933)	(13.5408)
Constant	2.6221*	2.6736	1.3823	1.2583
	(1.5416)	(1.9591)	(0.9673)	(1.5755)
Issue Ratings by Week F.E.	Y	Y	Y	Y
Remaining Maturity by Week F.E.	Y	Y	Y	Y
Observations	93748.0000	50866.0000	4.205e+05	2.038e+05
R2	0.1356	0.1455	0.1183	0.1221

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In columns (1) and (2), we report the regression estimates and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{IG Issue}_{ij} + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{IG Issue}_{ij} + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, IG Issue$_{ij}$ is an indicator variable equal to one if issue j is eligible for the Fed CCFs based on its issue ratings as of March 22, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. In columns (3) and (4), we report the regression estimates and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. The main difference in the regression specification is the replacement of IG Issue$_{ij}$ with Eligible$_i$, which is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020. Additionally, the regressions in columns (1) and (2) are run over a sample of only ineligible issuer bonds, while those in columns (3) and (4) are run over a sample of IG bonds, excluding Fallen Angel bonds. Columns (1) and (3) include bonds of all maturity, while columns (2) and (4) sample to bonds with less than five years of maturity. We find that, on April 9, 2020, the IG bonds of ineligible issuers saw a smaller reduction in spreads compared to HY bonds of these issuers. We also find that IG bonds of eligible issuers saw a smaller reduction in spreads compared to IG bonds of ineligible issuers.

all bonds and bonds with less than five years maturity, respectively. The fact that we still find that HY bonds respond more strongly than IG bonds on April 9, 2020, even for HY issuers, stems from the inclusion of HY ETFs into the purview of the Fed's purchases. We find that HY ETFs primarily use issue-level ratings eligibility for ETF inclusion so this corresponds precisely with the set of HY bonds of HY issuers.

Spillovers of a reduction in HY bond yields for HY issuers to IG bonds issued by these same issuers can also explain why the relative movements between across HY-IG bonds is narrower for just the subset of HY issuers than in a broader comparison of HY bond movements with both eligible and ineligible issuer IG bonds. To emphasize this point, we run the regression given by Equation (5) over the sample of IG issues, excluding Fallen Angel securities, and report the results in columns (3) and (4) of Table 5. As expected, we find that on April 9, 2020 ineligible issuer IG bonds experience an additional narrowing of 76 bps and 103 bps compared to eligible issuer IG bonds, for all bonds and bonds with less than five years maturity, respectively. These estimates are significant at the one percent level. Incidentally, these coefficient estimates are quite close to that estimated in columns (1) and (2) of Table 4, suggesting that our fixed effects soak up extraneous variation (perhaps induced by HY bonds) that could impact our treatment effect estimation.

5.1.2 Causal Treatment Effect

A key question concerns what the treatment effect would have been for ineligible issuers who never received direct primary or secondary bond support from the CCFs. As mentioned, the coefficient on the variable "March 23 X Eligible" in Table 2 in columns (3) and (4) may provide one estimate of this effect, since on March 23, 2020 the Fed's announcements primarily targeted eligible issuers. However, to the extent that ineligible HY issuers have IG bonds, as Figure 2 indicates, this estimate is downwardly biased, since the Fed also included IG ETFs in the purview of the CCFs on March 23, 2020. The coefficient estimate for the effect on April 9, 2020 would be inappropriate to use because on this date, the Fed announced its intention to provide both eligible and ineligible issuers with varied amounts of support. Apart from these concerns, one may imagine that ineligible issuer spreads may behave differently than eligible issuer spreads for the same sized bond program announcement.

Another strategy to estimate this counterfactual causal treatment effect for ineligible issuers would be to exploit the behavior of Fallen Angel issuer spreads. Namely, Fallen Angel issuers were eligible at the initial program announcement date on March 23, 2020, but then fell out of eligibility as they were downgraded between March 23, 2020 and April 9, 2020. To get a baseline sense of the movement in Fallen Angel issuers, we modify Equation (5) to add an additional interaction term:

$$\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Fallen Angel}_i + \beta_3 \text{Events}_t$$
$$+ \beta_4 \text{Events}_t \times \text{Eligible}_i + \beta_5 \text{Events}_t \times \text{Eligible}_i \times \text{Fallen Angel}_i + \theta_{jt}^{Rating} \quad (7)$$
$$+ \theta_{jt}^{Maturity} + \epsilon_{jt}$$

where Fallen Angel_i indicates if issuer i is a Fallen Angel as defined above. Since Fallen $\text{Angel}_i = \text{Eligible}_i \times$ Fallen Angel_i, we drop the latter term from the saturated regression.

The results of the regression of Equation (7) is shown in Table 6. We first check to see how the coefficients on "March 23 X Eligible" and "April 9 X Eligible" change with the effect from the Fallen Angel issuers separated out. Compared to Table 2, in columns (3) and (4), we find that the coefficient estimates are roughly unchanged for the "March 23 X Eligible" estimate. However, we find that the coefficient on "April 9 X Eligible" now increases to 78 bps from 65 bps for all bonds and to 104 bps from 87 bps for bonds with less than five years maturity. These estimates are significant at the one percent level. There are two forces at play: 1. the number of Fallen Angel issues is orders of magnitudes lower than the overall number of eligible issues, 2. Fallen Angel issues can be more sensitive to the facility announcements. On balance, the latter force dominated the former in increasing the coefficient estimate for "April 9 X Eligible." That is, the sharp narrowing of Fallen Angel issuer spreads decreased the overall average effect estimated for eligible issuer spreads in Table 2. With this effect partialed out, we find instead that non-Fallen Angel eligible issuer bonds widened more compared to ineligible issuer bonds than previously estimated.

The additional spread narrowing or widening of Fallen Angel issuer spreads are given by the coefficients "March 23 X Eligible X Fallen Angel' and "April 9 X Eligible X Fallen Angel" in Table 6. Interestingly, we estimate a positive effect on March 23, 2020 but a negative effect on April 9, 2020. The former suggests that Fallen Angel issuers spreads did not narrow as much as other eligible issuer spreads. However, by summing the coefficients on "Eligible", "Fallen Angel", "March 23", "March 23 X Eligible", and "March 23 X Eligible X Fallen Angel", we do see that Fallen Angel issuers spreads did decline on average on this date. This suggests that the markets factored in the possibility that Fallen Angel issuers would, in fact, be downgraded out of eligibility, thus losing CCF support.

In contrast, when Fallen Angel issuer eligibility was restored on April 9, 2020, we find that their spreads narrowed 229 bps and 272 bps more compared to eligible issuer spreads for all bonds and bonds with less than five years maturity, respectively. This may be one potential estimate of the counterfactual treatment effect on ineligible issuer spreads we are after, since Fallen Angel issuers were technically ineligible for CCF support entering April 9, 2020. However, other eligible issuers may not be the most appropriate control group for the Fallen Angel issuers. First, these issuers have a better risk profile than

Table 6 Change in G-Spreads (with Fallen Angel Interaction)

	(1)	(2)	(3)	(4)
		<5yrs Maturity		<5yrs Maturity
Eligible	-2.0283	-2.2572	-0.7865	-1.1253
	(2.4711)	(3.2700)	(0.6733)	(1.3835)
Fallen Angel	-0.0828	0.2670	1.1462	1.3553
	(2.8414)	(3.5955)	(1.8098)	(2.4170)
March 23	62.3515***	90.6787***	16.5548	37.6210
	(3.3819)	(6.9953)	(36.3555)	(48.0478)
April 9	-138.4193***	-172.0778***	-108.1523***	-134.8096***
	(3.5358)	(7.4739)	(6.1970)	(9.9283)
March 23 X Eligible	-108.0201***	-148.7916***	-97.4222***	-138.4093***
	(2.9902)	(6.7883)	(17.9364)	(28.7550)
April 9 X Eligible	99.0936***	129.9784***	78.1181***	104.4044***
	(3.1483)	(7.2762)	(8.1861)	(12.8580)
March 23 X Eligible X Fallen Angel	76.4135***	108.7288***	55.3663**	84.0850***
	(21.6537)	(27.9802)	(22.1747)	(28.3553)
April 9 X Eligible X Fallen Angel	-244.7509***	-289.0271***	-229.2277***	-271.9726***
	(14.3982)	(7.1994)	(14.7137)	(16.9799)
Constant	2.4722	2.4600	1.5791	1.7033
	(2.9533)	(3.7782)	(1.0371)	(1.5822)
Issue Ratings by Week F.E.	N	N	Y	Y
Maturity Bucket by Week F.E.	N	N	Y	Y
Observations	4.304e+05	2.100e+05	4.303e+05	2.100e+05
R2	0.0036	0.0037	0.1211	0.1247

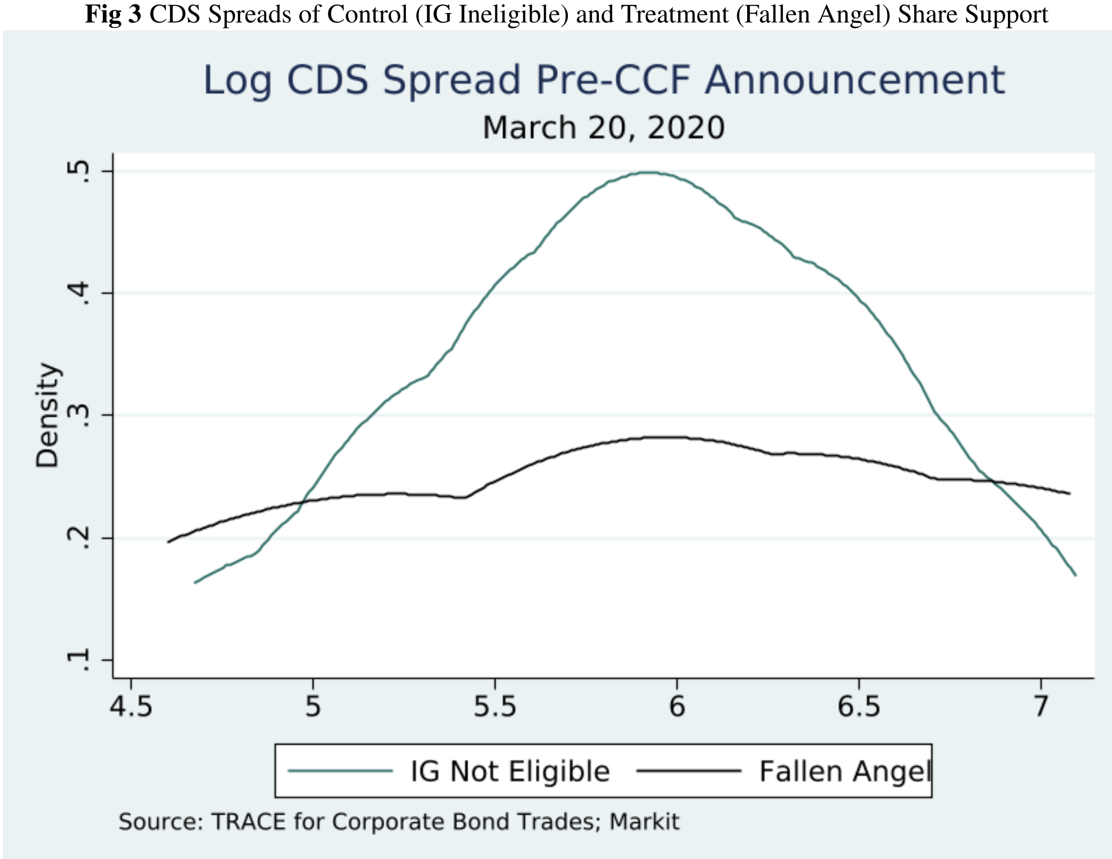
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Fallen Angel}_i + \beta_3 \text{Events}_t + \beta_4 \text{Events}_t \times \text{Eligible}_i + \beta_5 \text{Events}_t \times \text{Eligible}_i \times \text{Fallen Angel}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. As in Table 2, ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events_t is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. The new variable, Fallen Angel_i, indicates if issuer i was eligible for the Fed CCFs on March 23, 2020 but lost eligibility between March 23, 2020 and April 9, 2020 due to being downgraded. On April 9, 2020, the Fed restored the eligibility of these issuers. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. We find that Fallen Angel issuer bonds tighten less than eligible issuer bonds on March 23, 2020 and tighten significantly more than eligible issuer bonds on April 9, 2020.

the Fallen Angel issuers, and second, the effect of additional stimulus on spreads may generally not be as strong as initial announcement effects pledging stimulus for the bonds of certain issuers. Consequently, both of these reasons may lead to an overstatement of the counterfactual treatment effect we see to estimate. Instead, we will seek to refine this estimate by choosing a more suitable control group that may better share the risk profile of the Fallen Angel issuers than other eligible issuers do.

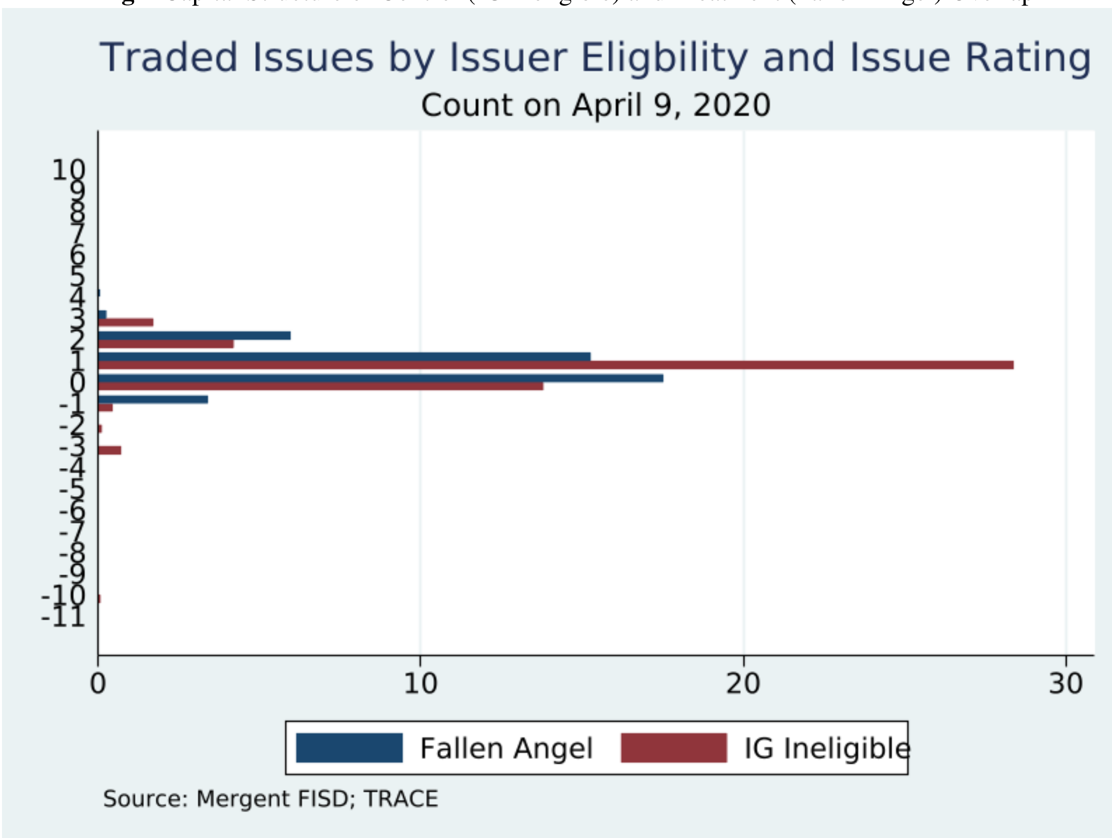
Fig 3 CDS Spreads of Control (IG Ineligible) and Treatment (Fallen Angel) Share Support



The figure plots the log CDS spread distributions of IG ineligible (i.e. those issuers with multiple ratings where exactly one is IG so are not eligible for the Fed CCFs) and Fallen Angel issuers on March 20, 2020. We find that IG ineligible and Fallen Angel issuers share the same support.

Specifically, we compare Fallen Angel issuers to issuers 'just below' the Fed's eligibility cutoff: issuers with multiple ratings and exactly one IG rating. By the CCF criteria, these issuers are ineligible since they lack at least two IG ratings when they have more than one rating. Figure 3 compares the distribution of log CDS spreads for IG but never eligible issuers with Fallen Angel issuers. We see that the support of the two groups coincides,

Fig 4 Capital Structure of Control (IG Ineligible) and Treatment (Fallen Angel) Overlap



The figure shows the count of issue ratings for IG ineligible and Fallen Angel bonds which traded on April 9, 2020. We find considerably less heterogeneity between IG ineligible and Fallen Angel issuer capital structures along the bond risk dimension than we see for the broader sample of eligible and ineligible issuer capital structures, as seen in Figure 2. On this note, we find relatively similar proportions of IG and HY debt by IG ineligible and Fallen Angel issuers. While our identification strategy compares same-rated, same-maturity but differentially eligible bonds, the similar exposure to IG and HY ETFs across IG ineligible and Fallen Angel issuers is an advantage compared to comparing the broader sample of eligible and ineligible issuer bonds with each other, since the broader samples are differentially exposed to IG and HY ETFs.

suggesting that the market-based risk assessment of the two groups are similar. Figure 4 shows the capital structure of Fallen Angel and IG ineligible issuers. While there is a higher count of IG ineligible issues, we see that the number of issues is roughly comparable across the two groups and that the relative risk distribution of their capital structures, as of April 9, 2020, is aligned around the IG/HY cutoff. Besides reinforcing the argument that the relative risk in Fallen Angel and IG ineligible bonds is similar, it also suggests that both groups are similarly exposed to the Fed's ETF purchases, either through IG or HY ETFs.

The resulting regression specification to recover a counterfactural treatment effect from comparing these two groups is given by:

$$\begin{aligned}\Delta S_{ijt} = \beta_0 &+ \beta_1 \text{IG (Max Rating)}_i + \beta_2 \text{Eligible}_i + \beta_3 \text{Fallen Angel}_i \\ &+ \beta_4 \text{Events}_t + \beta_5 \text{Events X IG (Max Rating)}_{it} \\ &+ \beta_6 \text{Events}_t \times \text{IG (Max Rating) X Eligible}_{it} \\ &+ \beta_7 \text{Events}_t \times \text{IG (Max Rating) X FA}_{it} \\ &+ \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}\end{aligned} \tag{8}$$

where IG (Max Rating)$_i$ is the sample of issuers which have a maximum issuer rating that is IG, as of March 22, 2020. Since Fallen Angel $\subset$ Eligible $\subset$ IG (Max Rating), the above is a saturated regression with collinear terms omitted. To obtain our estimate for the counterfactual treatment effect, we subtract the effect on IG but ineligible issuers from the effect on Fallen Angel issuers:

- Effect on IG but ineligible issuers given by: $\beta_0 + \beta_1 + \beta_4 + \beta_5$
- Effect on Fallen Angel issuers given by: $\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7$
- Estimate of additional effect of Fed CCF eligibility given by difference: $\beta_2 + \beta_3 + \beta_6 + \beta_7$.

After estimating Equation (8), we compute the effects on the control (IG ineligible) and treatment (Fallen Angel) groups by summing coefficients as detailed above. We also compute the variance-covariance matrix for the coefficients by double-clustering on issuer and time. The difference between the treatment and control group gives our estimate of the counterfactual treatment effect of HY CCF eligibility. Standard errors for the summed estimates are obtained using the delta method. These results are reported in Table 7.

We can interpret the March 23, 2020 treatment effect as an alternative estimate of the effect the facilities had on eligible issuers, with the caveat that Table 6 suggests that the

Table 7 Change in G-Spreads (Causal Treatment Effect)

	All	5yrs Maturity
March 23, 2020		
	All	5yrs Maturity
Effect on IG Ineligible Issuers:	43.1 bps	81.9 bps
	(35.8 bps)	(54.2 bps)
Effect on Fallen Angels:	-22.8 bps	-13.5 bps
	(33.3 bps)	(43.6 bps)
Treatment Effect:	-65.9 bps	-95.4 bps
	(46.0 bps)	(61.3 bps)
April 9, 2020		
	All	5yrs Maturity
Effect on IG Ineligible Issuers:	-132.8 bps***	-217.4 bps***
	(18.1 bps)	(30.4 bps)
Effect on Fallen Angels:	-258.4 bps***	-303.0 bps***
	(18.5 bps)	(19.4 bps)
Treatment Effect:	-125.6 bps***	-85.6 bps***
	(24.5 bps)	(35.1 bps)

Standard errors in parentheses. Standard errors are double-clustered by issuer and time.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table shows particular linear combinations of coefficient estimates corresponding to the regression $\Delta S_{ijt} = \beta_0 + \beta_1 \text{IG (Max Rating)}_i + \beta_2 \text{Eligible}_i + \beta_3 \text{Fallen Angel}_i + \beta_4 \text{Events}_t + \beta_5 \text{Events X IG (Max Rating)}_{it} + \beta_6 \text{Events}_t \times \text{IG (Max Rating) X Eligible}_{it} + \beta_7 \text{Events}_t \times \text{IG (Max Rating) X FA}_{it} + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, IG (Max Rating)$_i$ indicates if the maximum issuer rating of issuer i is IG on March 22, 2020, Fallen Angel$_i$ indicates if issuer i is a Fallen Angel (see text for definition), Eligible$_i$ is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. The effect of the CCF announcements on IG ineligible issuers (see text for definition) are given by $\beta_0 + \beta_1 + \beta_4 + \beta_5$. The effect on Fallen Angel issuers are given by $\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \beta_7$. Hence, our estimates of the counterfactual treatment effect on HY issuers if they had been eligible for the Fed CCFs are given by the difference, specifically for April 9, 2020 (see text for explanation). This is given by $\beta_2 + \beta_3 + \beta_6 + \beta_7$. Standard errors are computed using the delta method on the variance-covariance matrix for the coefficients, which are double-clustered by issuer and time.

market priced in the possibility that Fallen Angels would fall out of eligibility. This may explain why the resulting treatment effect estimate is smaller than what we compute on the 'March 23 X Eligible' coefficients in Table 2. In fact, Table 7 presents evidence supporting a null effect for both issuers, as well as their difference, on March 23, 2020.

In our view, the more interesting treatment estimate is that for April 9, 2020, which are also more precisely estimated as indicated by the standard errors and are significant at the one percent level. We estimate that Fallen Angel spreads declined 126 bps points more than the control group for all bonds and 86 bps more for bonds with less than five years maturity. Contrary to expectations and other estimates, the treatment effect is larger when computed over all bonds than for bonds with less than five years maturity. This reversal seems to be driven by a proportionally greater decline from the control group's spreads versus that of Fallen Angels for bonds with less than five years maturity, though both groups show greater declines for shorter maturity bonds, as expected. Moreover, these estimates are of similar magnitude as the relative treatment effect estimates given by the 'March 23 X Eligible' coefficients in Table 2.

5.1.3 Channels

The announcement and subsequent expansion of the CCFs may have led to changes in corporate bond spreads by affecting default risk or trading liquidity. By backstopping borrowing by eligible firms in the primary market, and by boosting trading prices through commitment to direct purchases in the secondary market, the announcement of the CCFs improves firms' ability to roll over maturing debt and decreases default risks. On the other hand, the SMCCF signals the central bank's commitment to act as the market-maker of last resort, improving liquidity and asset prices. Both the default risk channel and the liquidity channel would lead to a decrease in credit spreads. It is thus worthwhile to disentangle these two potential channels.

From Section 4, we see that the CDS-bond basis serves as a good proxy for liquidity. In the absence of liquidity risk, a bond's spread and CDS spread should coincide, as suggested by (2) with $\psi_{jt}^{T} = 0$. Otherwise, arbitrage opportunities would arise. The existence of a CDS-bond basis presumes the presence of liquidity risk which makes such arbitrage infeasible. Similarly, we also use the ETF-NAV basis as an alternative measure for liquidity. Absent market frictions, differences in ETF price and the underlying NAV should not exist, due to the arbitrage incentives it creates for APs. We acknowledge that these measures are imperfect proxies for liquidity, as other factors such as funding cost, dealer constraint, counterparty risk, and collateral quality could also contribute to a higher basis. However, given that the banking sector remained relatively healthy during our estimation period, and the post-GFC reform imposes stringent risk management requirements on banks, the large bases observed during March and April 2020 were most likely attributable to liquidity risk.

We estimate the DiD specification (4), using change in CDS spreads and change in absolute value of bond-CDS basis as outcome variables, respectively. The treatment group consists of eligible issuers while the control group consists of ineligible issuers. The key event dates are March 23, 2020 and April 9, 2020. Table 8 reports the results. Column (1) shows that on March 23, 2020, CDS spreads of eligible issuers decreased by 11.6 bps more than those of ineligible issuers. In contrast, CDS spreads for ineligible issuers decreased by 24.9 bps more on April 9, 2020. Both estimates are statistically significant at the one percent level. These results suggest that default risk declined more for eligible issuers on March 23, but then declined more for ineligible issurs on April 9. However, compared to the coefficient estimates in Table 2, the relative changes in CDS spreads between eligible and ineligible issuers account for a small portion of the large relative responses in G-spreads, suggesting that the observed responses in relative credit spread changes were not only driven by the default risk channel. Column (2) of Table 8 estimates the effect of the liquidity channel. On March 23, 2020, the bond-CDS bases for the eligible issuers decreased by 83.9 bps more than those for the ineligible issuers, suggesting that the initial announcement of the CCFs decreased credit spreads mainly through the liquidity channel. The estimated coefficient is statistically significant at the five percent level. In contrast, on April 9, 2020, the bond-CDS bases for the ineligible issuers decreased by 61.0 bps more than those for the eligible issuers. The coefficient estimate is statistically at the 10 percent level. In Table 11, we show similar patterns using the absolute value of the ETF-NAV bases to proxy liquidity.

In sum, although default risk for eligible issuer bonds decreased following the initial announcement of the CCFs, the liquidity channel appears to be the main channel at work on March 23, 2020. The Fed's commitment to purchase bonds in the secondary market through its SMCCF improved liquidity of eligible issuer bonds, reducing bond spreads and narrowing bond-CDS bases. On the other hand, following the April 9, 2020 expansion of the facilities, both default risk and liquidity seem to have improved, and these improvements were more pronounced for ineligible issuer bonds. Again, liquidity seems to have improved more than default risk. Given that our specifications control for rating-by-week and maturity-by-week fixed effects, the larger responses of ineligible issuer bonds are unlikely associated with differential loadings on risk premia. Instead, the results are consistent with market segmentation between IG and HY issuers.

Table 8 Default and Liquidity Indicators

	(1)	(2)
	Chg. CDS Spreads	Chg. Abs. Bond-CDS Basis
Eligible	-2.6817**	-21.1371
	(1.0725)	(35.1333)
March 23	14.3539***	52.0287
	(2.4077)	(32.4652)
April 9	-41.0606***	-97.1676***
	(3.5419)	(34.0362)
March 23 X Eligible	-11.6183***	-83.8620**
	(3.5131)	(32.4922)
April 9 X Eligible	24.8556***	61.0156*
	(4.4763)	(34.0670)
Constant	2.9232**	21.9060
	(1.3179)	(35.1114)
Observations	16199.0000	9409.0000
R2	0.0180	0.0002

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The reports the regression coefficients and robust standard errors for $\Delta O_{it} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \epsilon_{it}$. ΔO_{it} is the change in a particular outcome variable at time t for issuer i, Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, and Events_t is an indicator variable equal to one if day t is an event day. In column (1), the outcome variable is the change in five-year senior unsecured CDS spreads, which is a proxy for changes in default risk. In column (2), the outcome variable is the change in the absolute value of the bond-CDS basis (measured as the average difference between the spreads of bonds with four- to six-years remaining maturity and the five-year CDS spread). An increase in the bond-CDS basis indicates a deterioration in liquidity, as suggested by Equation (2). Conversely, a decrease indicates an improvement in liquidity. We find that both default risk and liquidity risk improved more for eligible issuers than ineligible issuers on March 23, 2020, while the opposite was true on April 9, 2020. Moreover, we see sharper movements in the liquidity indicator than default risk indicator, suggesting that the Fed CCF announcements primarily operated through the liquidity channel.

5.1.4 Subsequent Purchase Events

The above analyses focus on the announcement effects of the Fed's CCFs. In this section, we repeat our analyses for three subsequent purchase events, in order to evaluate whether the actual purchases of targeted securities had any impact on bond spreads. The three event dates are May 12, 2020, June 15, 2020 and June 16, 2020, respectively. May 12, 2020 corresponds to the actual purchase of IG and HY ETFs by the SMCCF. On June 15, 2020, the Fed announced the formation of the SMCCF Broad Market Index. One June 16, 2020, the SMCCF commenced its bond purchases.

Table 9 reports the results from estimating the difference-in-differences specification (4) for the purchase events. On May 12, 2020, the credit spreads of eligible issuer bonds decreased by 8.7 bps more than those of the ineligible issuer bonds, when controlling for rating and maturity fixed effects. When restricting our attention to bonds maturing in less than five years, the magnitude of the differential response in credit spreads is slightly larger at 10.1 bps. Both estimates are statistically significant at the one percent level. On June 15, 2020, the announcement of the SMCCF Broad Market Index did not seem to result in differential responses between eligible and ineligible issuer bonds, as none of the coefficient estimates is statistically distinguishable from zero. On the other hand, on June 16, 2020, the credit spreads of ineligible issuer bonds decreased by 27.4 bps more than those of eligible issuer bonds, when controlling for rating and maturity fixed effects. When focusing on bonds with less than five years to maturity, the credit spreads of ineligible issuer bonds decreased by 34.4 bps more than those of eligible issuer bonds.

We then replace the outcome variable with change in CDS spreads to evaluate whether the responses of credit spreads on these purchase event dates were due to changes in default risk. On May 12, 2020 and June 15, 2020, the estimated coefficients on the interaction terms are both statistically insignificant and small in magnitudes. Thus, neither the start of ETF purchases nor the announcement of the SMCCF Broad Market Index differentially affected default risk for eligible issuer bonds versus ineligible issuer bonds. On June 16, 2020, the CDS spreads of ineligible issuer bonds decreased by 9.2 bps more than those of eligible issuer bonds, suggesting that ineligible bonds experienced greater reduction in default risk following the start of SMCCF bond purchases. Interestingly, the coefficient estimate of 9.2 bps accounts for only a small fraction of the differential changes in G-spreads presented in Table 9, suggesting that ineligible issuer bonds experienced far greater improvements to liquidity from the direct bond purchases, even when it was only eligible issuer bonds that were purchased, perhaps due to the portfolio re-balance channel.

In Table 11, we report the changes in the absolute value of the ETF-NAV bases across ETF scope and event date, with standard errors clustered by ETF. We restrict our sample

Table 9 Change in G-Spreads on Purchase Event Dates

	(1)	(2)	(3)	(4)
		<5yrs Maturity		<5yrs Maturity
Eligible	-2.30	-2.66	-0.93	-1.28
	(2.45)	(3.23)	(0.71)	(1.29)
May 12	-7.57**	-8.11**	3.61	7.47**
	(3.11)	(4.05)	(2.47)	(3.36)
June 15	-2.48	-4.42	-8.61	-10.57
	(3.27)	(4.23)	(14.70)	(17.32)
June 16	-36.59***	-44.78***	-42.68***	-51.29***
	(3.26)	(4.18)	(14.25)	(16.94)
May 12 X Eligible	3.21	4.42	-8.73***	-10.10***
	(2.59)	(3.52)	(3.00)	(3.65)
June 15 X Eligible	1.83	3.84	5.77	7.72
	(2.76)	(3.68)	(11.22)	(13.29)
June 16 X Eligible	23.53***	30.31***	27.42**	34.43***
	(2.77)	(3.67)	(10.80)	(13.12)
Constant	2.44	2.46	1.38	1.41
	(3.00)	(3.84)	(0.91)	(1.33)
Issue Ratings by Week F.E.	N	N	Y	Y
Remaining Maturity by Week F.E.	N	N	Y	Y
Observations	4.3e+05	2.1e+05	4.3e+05	2.1e+05
R2	0.00	0.00	0.12	0.12

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Extending Table 2, this table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, Eligible$_i$ is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. < 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. Focusing on columns (3) and (4), we find that eligible issuer spreads declined more than ineligible issuer spreads at the start of ETF purchases on May 12, 2020, as seen by the negative coefficient on “May 12 X Eligible.” Conversely, ineligible issuer spreads declined more than eligible issuer spreads at the start of bond purchases on June 16, 2020, as seen by the positive coefficient on “June 16 X Eligible.”

Table 10 Change in CDS Spreads on Purchase Event Dates

	(1)
Eligible	-2.93**
	(1.13)
May 12	-1.56
	(0.96)
June 15	-3.98**
	(1.87)
June 16	-14.13***
	(2.34)
May 12 X Eligible	-0.12
	(0.68)
June 15 X Eligible	1.46
	(1.75)
June 16 X Eligible	9.21***
	(2.24)
Constant	3.09**
	(1.40)
Observations	16254.00
R2	0.01

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Extending column (1) of Table 8, this table reports the regression coefficients and robust standard errors for $\Delta CDS_{it} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \epsilon_{it}$. ΔCDS_{it} is the change in the five-year senior unsecured CDS spreads at time t for issuer i, Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, and Events_t is an indicator variable equal to one if day t is an event day. Comparing eligible and ineligible issuer CDS spreads, we find no differential effect for ineligible issuer CDS spreads at the start of ETF purchases on May 12, 2020 or the announcement of bond purchases (to begin the next day) on June 15, 2020. However, we do find that ineligible issuer CDS spreads declined more than eligible issuer CDS spreads at the start of bond purchases on June 16, 2020.

to the IG and HY ETFs the SMCCF purchased as of June 18, 2020. We also note that there is not a one-to-one mapping of the constituents of IG ETFs to eligible issuers and that of HY ETFs to ineligible issuers. For example, as of June 18, 2020, the SMCCF held its largest ETF position in LQD, by market value. However, bonds rated IG by an average of Moody's, S&P, and Fitch ratings are eligible for inclusion in LQD. Thus, a large portion of ineligible issuer bonds may potentially satisfy this criterion. But this effect is asymmetric since eligible issuer bonds appear to be mostly rated IG. Hence, in general, IG ETFs may include eligible and ineligible issuer bonds, while HY ETFs include some but

Table 11 Change in the Absolute Value of ETF-NAV Basis

	(1) All	(2) HY	(3) IG
March 23 Event	-95.47***	-34.08***	-143.21***
	(9.60)	(5.74)	(12.90)
April 9 Event	95.49***	145.12***	56.90***
	(11.58)	(14.90)	(14.26)
May 12 Event	8.18**	8.79	7.70*
	(2.98)	(6.89)	(3.98)
June 15 Event	52.32***	42.18***	60.20***
	(7.03)	(10.84)	(14.25)
June 16 Event	-41.58***	-41.45***	-41.69**
	(7.81)	(10.50)	(12.99)
Constant	0.43	-0.16	0.88
	(1.35)	(1.25)	(1.98)
Observations	2560.00	1120.00	1440.00
R2	0.11	0.19	0.12

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The table reports the regression coefficients and double-clustered standard errors (by ETF and date) for $\Delta Basis_{it} = \alpha + \beta_1 \text{Events}_t + \epsilon_{it}$. $\Delta Basis_{it}$ is the change in absolute value of the difference between the price of ETF i and its underlying NAV and Events$_t$ is an indicator variable equal to one if day t is an event day. $Basis_{it}$ is a measure for liquidity, since deviations of the ETF price from its underlying basket of security may suggest that either have deviated from fundamentals. Column (1) runs the panel regression for the sample of all ETFs, column (2) runs it for only HY ETFs, and column (3) for only IG ETFs. We find significant reductions in the basis at the initial facility announcement date on March 23, 2020 and the start of the bond purchases on June 16, 2020. Interestingly, we see the basis widening on the date of the facility expansion announcement on April 9, 2020, but note that ETFs were trading at a premium by this date. Moreover, we find that the start of ETF purchases on May 12, 2020 lead to a widening of the basis for all samples, though the estimate is not statistically significant for the HY ETF sample.

not all ineligible issuer bonds.

Additionally, because we restrict our analysis to the day-on-day change in the ETF-NAV basis, our results may be particularly unfavorable to assessing the SMCCF's ETF purchases. We acknowledge that ETF prices may initially overshoot or may react faster to information than their underlying less liquid corporate bond counterparts, thus creating or widening a basis. This then signals a deterioration of liquidity. While this suggests that the spread between ETF prices and the underlying NAV, possibly induced by the Fed, is not immediately closed by the arbitrage activity of APs, it is possible that the basis narrows over a wider window of observation.

With that in mind, we find that the ETF-NAV bases narrowed on March 23, 2020 for all ETFs, as well as for the subsamples of HY and IG ETFs. The tightening was more pronounced for IG ETFs than HY ETFs. On April 9, 2020, the ETF-NAV basis widened for each sample, led by HY ETFs. Similarly, the basis widened at the start of ETF purchases on May 12, 2020 for the overall sample of bonds, and the subsample of IG ETFs. Tentatively, recalling the previous caveats, we view this result as suggesting that ETF purchases have an impaired transmission to its underlying corporate bond holdings, seeing as the basis increases. Juxtaposing the results for June 15, 2020 and June 16, 2020 provides an interesting insight: the ETF-NAV basis widened for all samples at the announcement of the creation of the SMCCF Broad Market Index on June 15, 2020 but then narrowed on June 16, 2020 after corporate bond purchases began. The tentative interpretation of these results is that policy announcements may be immediately incorporated into ETF prices but actual facility bond purchases may reduce the ETF-NAV basis by raising the value of underlying securities. Alternatively, direct ETF purchases may fail to close the basis due to incomplete transmission from ETF demand to prices of underlying corporate bonds.

5.2 *Causal Machine Learning Approach with High-Dimensional Controls*

In this section, we present another identification method based on the two-step semi-parametric DiD estimator presented in Momin (b), which is based on Farrell et al. (2021) and Farrell et al. (2020). The identification strategy exploits the use of high-dimensional controls and the estimator accounts for possible heterogeneous treatment effects, which could be important as several papers identified the heterogeneous dynamics of firms during the pandemic.[15]

The structural equation representing the potential outcomes model is given by:

$$\Delta S_{ijt} = \alpha(X_i) + \beta(X_i)\text{Eligible}_i + \epsilon_{ijt} \tag{9}$$

[15] See Darmouni and Siani (2025); Greenwald et al. (2020); Haque and Varghese (2021); Hassan et al. (2023); Pagano and Zechner (2022).

where ΔS_{ijt} is the change in the G-spread for bond j for issuer i at time t from the previous market close, X_i are a collection of pre-treatment covariates (data realized on or before 2019Q4), and Eligible_i is an indicator if issuer i is eligible for cash bond purchases under the CCFs. The $\alpha(X_i)$ and $\beta(X_i)$ terms are non-parametric functions of the pre-treatment covariates and are computed using deep neural networks. In addition, the estimators for $\alpha(X_i)$ and $\beta(X_i)$ require the estimation of a non-parametric propensity score, $p(X_i)$, which takes values between 0 and 1 and represents the probability of a firm being treated, given its pre-treatment covariates. This is also done using deep nets.

The distribution of the CATEs is given by the vector $\beta(X_i)$. The average treatment effect is given by $\mathbb{E}[\beta(X_i)]$ and so, incorporates potential heterogeneous responses. The object $\mathbb{E}[\alpha(x)]$ is referred to as the base effect and also incorporates in potential heterogeneity.[16] This quantity can be interpreted as the potential outcome for spread changes absent treatment. The ATE is identified if the assumptions of unconfoundedness and the overlap condition holds. Unconfoundedness is justified on the basis of a high-dimensional feature set and estimation using deep nets which permit rich, nonlinear interactions between features. Overlap is argued to hold because ratings are slow-moving and far more stable than firm characteristics, allowing for significant overlap in these distributions.[17]

The architectures for the deep nets are described in Tables 20 and 21 in Appendix 8.2. These vary based on the amount of pre-treatment data used (i.e. quarterly data going back 1 year, 5 years, or 10 years) and missingness tolerance in the pre-treatment data. Features with less than 1% and 10% missing data are listed in Tables 18 and 19, respectively, in Appendix 8.1. Missing data are replaced by quarter-industry medians, and an indicator variable is used to track missing data. Additionally, two-digit NAICS industry codes are used as features.

Table 12 reports the results for the base effects across key event dates. These results correspond to the Events_t coefficients reported in Tables 2 and 9. The results are generally robust across different model specifications, with the preferred model using 10 years of feature history with 1% missingness tolerance. The reported base effects are far more positive for March 23 and slightly less negative for April 9, compared with the results in Column (3) of Table 2. This suggests that bond spreads widened significantly on March 23, while narrowing significantly on April 9, absent treatment. Compared with Column (3) of Table 9, the causal ML approach picks up a widening of spreads on June 15 and far less narrowing of spreads on June 16, while results are null for May 12 in both cases.

Table 13 reports the treatment effects for the change G-spreads over different event

[16] $\alpha(X)$ is called the nuisance parameter in the DML literature (Chernozhukov et al., 2018).

[17] See Momin (b) for further discussion on these assumptions, as well as explicit expressions for the estimators.

Table 12 Change in G-Spreads: Base Effects

Change in G-Spreads						
Base Effect Accounting for Heterogeneity						
	Model (Feature History, Missingness Tolerance)					
Year	(1,1)	(1,10)	(5,1)	(5,10)	(10,1)	(10,10)
mar23	93.24	180.40**	90.34***	95.51***	94.29***	98.33***
	(96.68)	(84.60)	(21.56)	(21.72)	(20.27)	(20.09)
apr09	-165.80*	-77.88*	-81.13***	-91.92***	-92.84***	-106.31***
	(92.28)	(43.78)	(13.04)	(11.72)	(10.84)	(11.33)
may12	34.32	14.71	4.79	2.28	2.60	1.42
	(49.43)	(19.25)	(5.61)	(5.49)	(4.67)	(4.83)
jun15	-4.75	0.81	7.38*	4.54	6.03*	4.74
	(10.05)	(6.35)	(3.85)	(3.70)	(3.41)	(3.35)
jun16	-23.58	-20.68*	-19.03***	-24.98***	-23.46***	-24.53***
	(22.21)	(12.17)	(4.34)	(3.62)	(3.64)	(3.60)

Standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports the base effects for the change G-spreads over different event dates. The results correspond to the two-step semi-parametric DiD estimator for the $\mathbb{E}[\alpha(X_i)]$ term in Equation 9. Results for all model specifications are reported here; the corresponding architectures are reported in Tables 20 and 21 in the Appendix. These results are the counterparts to the Events$_t$ coefficients reported in Tables 2 and 9 for the panel regressions. The reported base effects are far more positive for March 23 and slightly less negative for April 9, compared with the results in Column (3) of Table 2. This suggests that bond spreads widened significantly on March 23, while narrowing significantly on April 9, absent treatment. Compared with Column (3) of Table 9, the causal ML approach picks up a widening of spreads on June 15 and far less narrowing of spreads on June 16, while results are null for May 12 in both cases.

Table 13 Change in G-Spreads: Treatment Effects

	Change in G-Spreads					
	Average Treatment Effect Accounting for Heterogeneity					
	Model (Feature History, Missingness Tolerance)					
Date	(1,1)	(1,10)	(5,1)	(5,10)	(10,1)	(10,10)
mar23	-155.38	-212.62**	-126.47***	-128.09***	-133.79***	-134.85***
	(127.48)	(100.44)	(22.07)	(21.99)	(20.98)	(21.33)
apr09	162.27	24.87	12.29	33.25***	31.42***	42.13***
	(126.79)	(42.18)	(14.33)	(12.22)	(11.21)	(11.81)
may12	-40.68	-16.49	-10.02*	-7.43	-7.14	-5.59
	(58.14)	(16.88)	(5.46)	(5.22)	(4.72)	(4.72)
jun15	9.35	0.70	-7.46*	-5.20	-5.64	-4.87
	(45.25)	(8.93)	(4.11)	(3.72)	(3.48)	(3.37)
jun16	40.24	9.47	2.44	8.53**	9.49**	10.12***
	(27.26)	(10.09)	(5.40)	(3.90)	(3.89)	(3.76)

Standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table reports the treatment effects for the change G-spreads over different event dates. The results correspond to the two-step semi-parametric DiD estimator for the $\mathbb{E}[\beta(X_i)]$ term in Equation 9. Results for all model specifications are reported here; the corresponding architectures are reported in Tables 20 and 21 in the Appendix. These results are the counterparts to the $\text{Events}_t \times \text{Eligible}_i$ coefficients reported in Tables 2 and 9 for the panel regressions. Compared with Column (3) of Table 2, the ATE estimated here is more negative for March 23 and less positive for April 9. Incorporating in heterogeneity and high dimensional controls suggests that eligible issuer spreads were more responsive (in terms of narrowing further) to the CCF announcements than what was suggested by the panel regressions. Compared with Column (3) of Table 9, the two-step semi-parametric DiD estimator produces a null effect for May 12, versus a slightly negative negative effect in the panel DiD regressions, and a smaller effect for June 16. Overall, in contrast to the announcement date effects, the actual start start of ETF and cash bond purchases show more muted reactions after incorporating heterogeneity and high-dimensional controls.

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In summary, while there are some nuanced differences, the causal ML estimates for the base and treatment effects presented in Tables 12 and 13 are comparable to the panel DiD regressions reported in Tables 2 and 9.

Table 14 Change in G-Spreads: CATE Targeting

Change in G-Spreads						
Uplift Accounting for Heterogeneity, CATE < 25 Targeting						
	Model (Feature History, Missingness Tolerance)					
Year	(1,1)	(1,10)	(5,1)	(5,10)	(10,1)	(10,10)
mar23	-2.82	-89.08	-76.68***	-87.56***	-73.18***	-69.37***
	(105.43)	(85.85)	(22.80)	(20.71)	(19.86)	(20.48)

Standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The table shows the estimates of the change in the average treatment effect on the treated that is obtained from a counterfactual policy targeting bonds with CATEs of less than 25 bps. This corresponds to the expression given by Equation 10. Results for only March 23 are shown since the announcement of the CCFs on that date targeted only IG issuers for potential cash bond purchases and IG ETFs. The estimator is a non-linear combination of various terms, including $\alpha(x)$, $\beta(x)$, and $p(x)$ and is not necessarily monotonically decreasing as the threshold for the CATE used for the construction of the counterfactual policy is lowered. We find that treating this group of more sensitive bonds would result in an additional narrowing of spreads for treated bonds by over 70 bps.

The causal ML framework presented here allows for the estimation of counterfactual policies, which equivalently can be used to determine which subsets of bonds and firms were the most sensitive to the CCF interventions. This can be done by estimating the change in ATET for some counterfactual policy, Counter, which is a vector of indicator variables denoting if bond j is treated or not. Formally, we estimate:

$$\mathbb{E}[\beta(X)(\text{Counter} - \text{Eligible})] \tag{10}$$

We focus on March 23, since that was the cleanest intervention of just IG issuer securities, either through potential cash bond or ETF purchases. Table 14 reports the results of the estimates of Equation 10, corresponding to a counterfactual targeting policy that only treated bonds with a CATE of less than 25 bps. The estimator is a non-linear combination of various terms, including $\alpha(x)$, $\beta(x)$, and $p(x)$ and is not necessarily monotonically decreasing as the threshold for the CATE used in the construction of the counterfactual policy is lowered. We find that treating this group of more sensitive bonds would result in an additional narrowing of spreads for treated bonds by over 70 bps.

The characteristics of the issuers and bonds of the counterfactual target group can be unpacked by a logistic or probit regression of the vector Counter and firm- and bond-level characteristics. This would uncover the types of firms and bonds particularly sensitive to the Fed CCFs. Additionally, this framework can be used to decompose the channels through which the CCF announcements may operate, in the same spirit as Krishnamurthy and Vissing-Jorgensen (2011). Let Channel be a vector of indicator variables denoting if bond j is affected by a particular channel (e.g. default risk). Then, we seek to estimate:

$$\mathbb{E}[\beta(X)\text{Channel}] \tag{11}$$

As an example, both the definition and construction of the Channel variable can be determined by the sign of particular factors that explain the cross-section of corporate bond returns. These investigations are left to future work.

6 Robustness

6.1 Return Space

As a further check on results, we update the outcome variable in our regression specifications in Section 5 to change in log bond prices, from change in bond spreads. The appeal of using the change in log bond prices as the regressand is that transaction prices are directly reported by TRACE and it is an intuitive measure as it approximates returns.

Table 15 reports the relative changes in log bond prices for eligible issuer bonds and ineligible issuer bonds on the two main event dates including March 23, 2020 and April

Table 15 Change in Log Prices

	(1)	(2) <5yrs Maturity	(3)	(4) <5yrs Maturity
Eligible	0.0561	0.0396	0.0227	0.0107
	(0.0784)	(0.0891)	(0.0302)	(0.0275)
March 23	-2.0193***	-2.1996***	-0.5026	-0.9625
	(0.1605)	(0.1040)	(1.1060)	(0.8812)
April 9	4.3257***	3.7855***	3.2744***	2.8066***
	(0.1755)	(0.1106)	(0.2142)	(0.2135)
March 23 X Eligible	3.9629***	3.2772***	3.7199***	2.7132***
	(0.1492)	(0.0981)	(0.2551)	(0.5640)
April 9 X Eligible	-2.1414***	-2.6724***	-1.4698***	-1.9348***
	(0.1655)	(0.1039)	(0.3053)	(0.2897)
Constant	-0.0565	-0.0421	-0.0340	-0.0221
	(0.1019)	(0.0942)	(0.0359)	(0.0308)
Issue Ratings by Week F.E.	N	N	Y	Y
Remaining Maturity by Week F.E.	N	N	Y	Y
Observations	4.317e+05	2.163e+05	4.317e+05	2.163e+05
R2	0.0039	0.0024	0.1732	0.1864

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Similar to Table 2, this table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $R_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. R_{ijt} is the change in log bond prices of bond j at time t for issuer i, Eligible_i is an indicator variable equal to one if issuer i is eligible for the Fed CCFs based on its issuer ratings as of March 22, 2020, Events_t is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. The results here in 'return-space' corroborate our core results in 'spread-space' (Table 2): eligible issuer bonds experience higher returns on the initial facility announcement date on March 23, 2020, and ineligible issuer bonds experience higher returns on the facility expansion announcement date on April 9, 2020.

9, 2020. Columns (1) and (2) of Table 15 present the regression results for the full sample and the sub-sample of bonds maturing in less five years, without fixed effects. Columns (3) and (4) repeat the regressions in columns (1) and (2) respectively, but including rating-week and maturity-week fixed effects. The coefficients of interest are the interaction terms between the event date and the eligibility dummy. As before, we find that eligible issuer bonds experienced relatively greater increase in log bond prices on March 23, 2020, in both the full sample and the sample containing bonds with maturities less than five years. Using issue ratings and maturity fixed effects, eligible issuer bonds experienced a higher return of 3.72 percent on March 23, 2020, relative to ineligible issuer bonds. For bonds with less than five years maturity, eligible issuer bonds experienced 2.71 percent higher returns compared to ineligible issuer bonds on the same day. In fact, while eligible issuer bonds increase in log prices on March 23, 2020 ineligible issuer bonds continued to decrease in prices and reached their trough on March 23. In contrast, ineligible issuer bonds enjoyed relatively greater increase in log bond prices on April 9. Using issue ratings and maturity fixed effects, ineligible issuer bonds experienced a higher return of 1.47 percent, relative to ineligible issuer bonds. For bonds with less than five years maturity, ineligible issuer bonds experienced 1.93 percent higher returns compared to eligible issuer bonds on that day. All estimated coefficients of interest are statistically significant at the one percent level.

6.2 SMCCF Index Constituents as Proxy

For robustness, we also carry out our previous analyses while using the published SMCCF Broad Market Index constituents to define the population of eligible and ineligible issuers. While the creation of the SMCCF Broad Market Index was announced on June 15, 2020, the initial index constituent list dates from June 5, 2020. This method to identify issuer eligibility relies on the assumptions that this list of eligible issuers was the same set of eligible issuers as of the facility launch date on March 23, 2020 and that these eligible issuers could have been correctly inferred by the market using publicly-available information. As discussed in Section 3, proxying eligible issuers this why likely identifies a subset of the true set of eligible issuers on the event dates. Nonetheless, the SMCCF Broad Market Index constituents published by the Fed bypasses the many issues involved in attempting to accurately identify the set of eligible issuers. Thus, it is important to see if our previous results are robust to this alternative method of identifying eligible issuers.

Table 16 presents the rating distributions of the SMCCF Broad Market Index published on June 15, 2020, as well as the actual holdings of the SMCCF at the end of June 2020. Overall, the actual holdings of the SMCCF match the published index quite well. The actual bonds holdings of the SMCCF tend to be slightly higher in credit quality and longer

Table 16 Ratings Distribution of SMCCF Holdings and Index

Rating	SMCCF Holding	SMCCF Broad Market Index
AAA/AA/A	48.07%	42.43%
BBB	48.31%	54.77%
BB	3.62%	2.80%
Weighted Average Maturity	3.3	2.8

Source: https://www.federalreserve.gov/publications/files/smccf-transition-specific-disclosures-6-28-20.xlsx

in maturity, compared to the index.

In Table 17, we repeat our regressions in Table 2 but instead identify eligible issuers using the published SMCCF Broad Market Index constituents. Again, we compare the relative spread changes for eligible and ineligible issuer bonds on the key event dates of March 23, 2020 and April 9, 2020. The results are similar as before, albeit smaller in magnitude. Using issue ratings and remaining maturity fixed effects, the credit spreads of eligible issuer bonds decreased 47 bps more than the credit spreads of ineligible issuer bonds, on March 23, 2020. For bonds with less than five years maturity, on the other hand, the credit spreads of eligible issuer bonds decreased 69 bps more than the credit spreads of ineligible issuer bonds on the same day. In contrast, on April 9, 2020, the credit spreads of ineligible issuer bonds decreased 32 bps more than those of eligible issuer bonds for the full sample, and 35 bps for bonds maturing in less than five years. All estimated coefficients of interest are statistically significant at the one percent level. The lower magnitudes are consistent with the findings by Flanagan and Purnanandam (2020) that the Fed did not select bonds that experienced the greatest decline in prices (increase in spreads), leading up to the facility announcements, for inclusion in the SMCCF Broad Market Index. Additionally, this proxy results in comparing SMCCF constituents, which are a subset of eligible issuers, to a broader set of both eligible and ineligible issuers. Hence, using the SMCCF Broad Market Index constituents to identify eligible issuers likely yields a conservative estimate of the program effect.

7 Conclusion

In this paper, we study the effect of the Fed's CCFs on the credit spreads of eligible and ineligible issuer bonds. A key feature of the Fed CCF's is that it directed primary and secondary bond support to issuers rated IG, not individual IG-rated bonds. Nonetheless, we point out that existing studies identify treated versus untreated bonds at the issue-level and not at the issuer-level, as the Fed criteria indicates. We note that issuers have heterogeneous capital structures, where HY issuers have substantial amounts of IG debt. We

Table 17 Change in G-Spreads (SMCCF Index Proxy for Eligibility)

	(1)	(2) <5yrs Maturity	(3)	(4) <5yrs Maturity
Eligible (SMCCF Index)	-1.22	-1.38	-0.47	-0.52
	(1.50)	(1.81)	(0.29)	(0.46)
March 23	12.85***	18.66***	-30.55	-30.34
	(4.41)	(5.00)	(29.90)	(36.07)
April 9	-97.06***	-111.39***	-71.95***	-82.43***
	(4.89)	(5.60)	(7.03)	(8.08)
March 23 X Eligible (SMCCF Index)	-56.25***	-75.05***	-47.01***	-68.61***
	(4.21)	(4.76)	(10.35)	(15.02)
April 9 X Eligible (SMCCF Index)	49.17***	54.03***	31.57***	35.03***
	(4.67)	(5.30)	(9.64)	(11.94)
Constant	1.64	1.53	1.28	1.18
	(2.05)	(2.44)	(0.79)	(1.00)
Issue Ratings by Week F.E.	N	N	Y	Y
Remaining Maturity by Week F.E.	N	N	Y	Y
Observations	4.3e+05	2.1e+05	4.3e+05	2.1e+05
R2	0.00	0.00	0.12	0.12

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Similar to Table 2, this table reports the regression coefficients and standard errors (double-clustered by issuer and time) for $\Delta S_{ijt} = \alpha + \beta_1 \text{Eligible}_i + \beta_2 \text{Events}_t + \beta_3 \text{Events}_t \times \text{Eligible (SMCCF Index)}_i + \theta_{jt}^{Rating} + \theta_{jt}^{Maturity} + \epsilon_{jt}$. ΔS_{ijt} is the change in G-spread of bond j at time t for issuer i, Eligible (SMCCF Index)$_i$ is an indicator variable equal to one if issuer i was a member of the initial constituent list for the SMCCF Broad Market Index, published on June 15, 2020, Events$_t$ is an indicator variable equal to one if day t is an event day, θ_{jt}^{Rating} are fixed effects for bond j rating (i.e. Aaa, Aa1, etc.) by week, and $\theta_{jt}^{Maturity}$ are fixed effects for bond remaining time-to-maturity (i.e. $<$ 1 year, 1-2 years, 2-3 years, 3-4 years, 4-5 years, and 5+ years) by week. Columns (1) and (2) report the regression estimates without fixed effects. Columns (3) and (4) report the estimates with fixed effects. Columns (1) and (3) show the results for the regression run over the full sample of bonds, while columns (2) and (4) show the results for the sample of bonds with less than five years maturity. The coefficient results broadly align with those reported in Table 2. However, we do find that the magnitude of the coefficient estimates here are smaller than those in Table 2. This is consistent with Flanagan and Purnanandam (2020), who find that that the Fed did not select eligible issuer bonds which experienced the greatest decline (leading up to the facility announcements) for the SMCCF Broad Market Index.

exploit this to estimate a relative treatment effect by conceptually comparing same-rated, same-maturity but differentially eligible bonds. Over the entire same of bonds, we estimate that eligible issuer spreads tightened 96 bps compared to ineligible issuer spreads when the facilities were initially announced on March 23, 2020. On the subsequent expansion of the facilities on April 9, 2020, eligible issuer spreads tightened 65 bps compared to ineligible issuer spreads.

We also compare the size of the estimates we get if we incorrectly identify eligible issuer bonds by using issue ratings, instead of issuer ratings. We find that such a mis-classification does not materially impact the estimate of the March 23, 2020 effect, but does materially change the estimate of the April 9, 2020 effect. Using the issue-level classification, we obtain a coefficient estimate of 91 bps, instead of 65 bps, over all bonds on April 9, 2020. The upwardly biased estimate would lead one to conclude that HY issuer bonds were more sensitive to the Fed's expansion of the CCFs on April 9, 2020 than they actually were. We quantitatively explore the potential sources of this upward bias. While Fallen Angel issuers were eligible on March 23, 2020, they lost eligibility between March 23, 2020 and April 9, 2020, as the result of being downgraded. The April 9, 2020 expansion of CCF reinstated their eligibility for the facilities, but we do not find this to be the source of the upward bias. Indeed, both an issuer-level and an issue-level classification of bonds as eligible or ineligible would have largely correctly classified Fallen Angel bonds as eligible on both dates, since either classification makes use of ratings as of March 22, 2020, prior to any downgrades. Instead, we provide evidence that the bias is induced by mis-classifying IG bonds issued by HY issuers as eligible, rather than ineligible.

Given their migration out of eligible and then back in, Fallen Angel issuers are of particular interest. We first show that Fallen Angel issuer spreads actually increase compared to other eligible issuer spreads on March 23, 2020. While both show sharp declines on this date, the relatively smaller effect on Fallen Angel issuer spreads may suggest that the market priced in the possibility that these issuers would be downgraded out of eligibility. In contrast, we find a much stronger decline in Fallen Angel issuer spreads than other eligible issuer spreads, as well as ineligible issuer spreads. We argue that neither the relative movement of Fallen Angel issuer spreads to eligible or ineligible issuers satisfactorily provides an estimate of a key counterfactual treatment effect: the potential response of HY issuers had they been eligible for direct primary or secondary bond support by the Fed.

To refine our estimate, we construct a more robust control group. We show that ineligible issuers with more than one rating where one is IG, as of March 22, 2020, are a natural control group. The distribution of Fallen Angel and IG ineligible issuers share the same support, indicating that market-based risk assessments of these two groups coincided. Moreover, we show that their capital structures correspond in terms of the underlying distributions of IG and HY debt issued by each group. That also suggests that both groups would have been similarly impacted by the Fed's ETF purchase declarations, since ETF inclusion is generally determined at the issue-level. Our main focus is in the relative movement of spreads across these issuers on April 9, 2020, since entering that date, both groups were ineligible. We find that Fallen Angel issuers spreads tighten 126 bps more than IG ineligible spreads, on this date, providing an estimate of a counterfactual treatment effect for HY issuer CCF eligibility.

We also explore the impact of the default risk and liquidity risk channels in explaining the relative movement of eligible versus ineligible spreads on the facility announcement dates. We find that default risk, measured by CDS spreads, decreased more for eligible issuers than ineligible issuers on March 23, 2020, while the opposite held true for April 9, 2020. We see similar patterns in the reduction of liquidity risk, as measured by the bond-CDS spreads, but find that these movements are of a far larger magnitude than the changes in default risk. We also find a large reduction in the ETF-NAV basis, another proxy for liquidity, on March 23, 2020, but actually find that this basis widened on April 9, 2020, though as result of ETFs trading at a premium relative to its respective basket. Nonetheless, we note that our findings are broadly consistent with several other papers in the literature which have identified the liquidity risk channel as the primary channel through which the Fed CCFs impacted bond spreads.

We identify other dates of potential interest: the start of ETF purchases on May 12, 2020, the announcement of the start of bond purchases on June 15, 2020, and the actual start of these purchases of these purchases on June 16, 2020. We find that the start of ETF purchases benefited eligible issuer spreads more than ineligible issuer spreads, consistent with IG ETFs being purchased in far greater quantifies. We do not find any effect from the June 15, 2020 announcement, but we do see both eligible and ineligible issuer spreads narrowing at the start of bond purchases on June 16, 2020. Interestingly, ineligible issuer spreads tighten more than eligible issuer spreads at the start of bond purchases. We find a similar pattern in CDS spread movement on June 16, 2020, with all spreads declining, but ineligible issuer spreads falling by a larger amount. Another interesting pattern is the tightening of the ETF-NAV basis on June 16, 2020, but not on May 12, 2020. Taken together, these patterns suggest that bond purchases have a greater effect on markets than ETF purchases.

We also present another identification strategy based on two-step semi-parametric DiD estimators of the treatment effect and the potential effect on spreads absent intervention. These results largely align with the results obtained from the panel DiD regressions for the key event dates. We further show how the CATEs obtained from the causal ML approach can be used to study the effects of counterfactual policy targeting schemes and outline ways the causal ML approach can be used to decompose the channels through which the Fed CCFs influenced spreads, which is left to future work.

As robustness checks, we rerun our analysis in return-space and proxy eligible issuers by ex-post SMCCF index inclusion. Both analyses corroborates our previous results. However, while we match the direction of relative effects of the Fed CCF announcements on eligible and ineligible issuer bonds, we recover smaller, though still sizeable, coefficient estimates when proxying eligible issuers by ex-post SMCCF index inclusion. We note that this is consistent with other research showing that the Fed did not choose eligible issuer bonds which experienced the greatest decline in spreads (leading up to the facility announcements) for inclusion in the SMCCF index. Additionally, this proxy results in comparing SMCCF constituents, which are a subset of eligible issuers, to a broader set of both eligible and ineligible issuers.

While several papers have studied the financial effects of the Fed CCFs, including ours, far fewer papers have studied the potential real effects of the Fed CCFs and its design. Momin (b) and Momin (a) aim to fill these gaps.

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8 Appendix

8.1 Features

Variable	Description
accrual	Accruals/Average Assets
adv_sale	Advertising Expenses/Sales
aftret_eq	After-tax Return on Average Common Equity
aftret_equity	After-tax Return on Total Stockholders Equity
aftret_invcapx	After-tax Return on Invested Capital
at_turn	Asset Turnover
capital_ratio	Capitalization Ratio
cash_debt	Cash Flow/Total Debt
cash_lt	Cash Balance/Total Liabilities
cfm	Cash Flow Margin
de_ratio	Total Debt/Equity
debt_assets	Total Debt (ltq)/Total Assets
debt_at	Total Debt (dlcq+dlttq)/Total Assets
debt_capital	Total Debt/Capital
debt_ebitda	Total Debt/EBITDA
debt_invcap	Long-term Debt/Invested Capital
equity_invcap	Common Equity/Invested Capital
evm	Enterprise Value Multiple
gpm	Gross Profit Margin
gprof	Gross Profit/Total Assets
lt_debt	Long-term Debt/Total Liabilities
lt_ppent	Total Liabilities/Total Tangible Assets
npm	Net Profit Margin
opmad	Operating Profit Margin After Depreciation
opmbd	Operating Profit Margin Before Depreciation
pcf	Price/Cash flow
pe_exi	P/E (Diluted, Excl. EI)
pe_inc	P/E (Diluted, Incl. EI)
pe_op_basic	Price/Operating Earnings (Basic, Excl. EI)
pe_op_dil	Price/Operating Earnings (Diluted, Excl. EI)
ps	Price/Sales
ptpm	Pre-tax Profit Margin
rd_sale	Research and Development/Sales
roa	Return on Assets
roce	Return on Capital Employed
staff_sale	Labor Expenses/Sales
totdebt_invcap	Total Debt/Invested Capital

Table 18 Features with Less than One Percent Missing Observations

Variable	Description
bm	Book/Market
capei	Shillers Cyclically Adjusted P/E Ratio
cash_ratio	Cash Ratio
curr_debt	Current Liabilities/Total Liabilities
curr_ratio	Current Ratio
dltt_be	Long-term Debt/Book Equity
int_debt	Interest/Average Long-term Debt
intcov	After-tax Interest Coverage
intcov_ratio	Interest Coverage Ratio
ocf_lct	Operating CF/Current Liabilities
pay_turn	Payables Turnover
peg_1yrforward	Forward P/E to 1-year Growth (PEG) ratio
pretret_earnat	Pre-tax Return on Total Earning Assets
pretret_noa	Pre-tax return on Net Operating Assets
profit_lct	Profit Before Depreciation/Current Liabilities
ptb	Price/Book
quick_ratio	Quick Ratio (Acid Test)
rect_act	Receivables/Current Assets
rect_turn	Receivables Turnover
roe	Return on Equity
sale_equity	Sales/Stockholders Equity
sale_invcap	Sales/Invested Capital
short_debt	Short-Term Debt/Total Debt

Table 19 Additional Features with Less than Ten Percent Missing Observations

8.2 Deep Net Architectures

Feature History (Years)			
	1	5	10
Number of Features	333	1342	3204
Hidden Layer Architecture	[300, 150, 75, 35, 15]	[1500, 750, 375, 150, 75, 35, 15]	[2700, 1350, 675, 300, 150, 75, 35, 15]
Dropout Rate	20%		

Table 20 Architecture for Deep Nets with 1% Tolerance for Missing Observations

Feature History (Years)			
	1	5	10
Number of Features	517	2502	5314
Hidden Layer Architecture	[500, 300, 150, 75, 35, 15]	[3000, 1500, 750, 375, 150, 75, 35, 15]	[5000, 2700, 1350, 675, 300, 150, 75, 35, 15]
Dropout Rate	20%		

Table 21 Architecture for Deep Nets with 10% Tolerance for Missing Observations