Unexpected Corporate Bond Demand and the Impact on Firm Acquisition Activity

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Abstract

This paper analyzes the interaction between firms' corporate bond issuance and their acquisition decisions. Using a novel dataset of firm level financials, credit ratings, bond issuance and acquisition activity, we first establish that firms with credit ratings are more likely to engage in acquisitions than those without and the timing between bond issuance and acquisition announcements. We then use the Federal Reserve's first ever intervention in the corporate bond markets (the Corporate Credit Facilities (CCFs)) as a natural experiment to measure how an unexpected demand shock for corporate bonds influences decisions around firm's bond issuance and acquisitions. Using heterogeneity in program requirements set by the Fed, we find no effect of the intervention on the likelihood of acquisition, but that the timing between issuing and acquiring changed after the intervention. To better understand the mechanisms relating the CCFs and acquisition activity, we build a stylized model of firm capital structure and merger decisions. In the model, firms can make capital choices, issue equity and debt, and acquire other firms. We find that a replication of the CCFs in the model can increase the likelihood of cash acquisitions but only if firms have low levels of cash before the acquisition. Our empirical results suggest this was not the case before the announcement of the CCFs, thus supporting our no-effect result.

Keywords: mergers and acquisitions, corporate liquidity, corporate bonds

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1 Introduction

In March of 2020, the Federal Reserve intervened in the corporate bond market for the first time ever with the announcement of the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF)[1]. These facilities granted the Fed the power to purchase corporate bonds on both the primary and secondary markets in an effort to stabilize the markets following turmoil spurred by the COVID-19 pandemic. After the announcement of these programs, a record breaking number of corporate bonds were issued, providing an influx of cash to issuing firms.

The announcement of the Corporate Credit Facilities (CCFs) altered firms with credit ratings' effective access to external financing during a time of macroeconomic uncertainty. Further, the Federal Reserve would only buy bonds issued by firms with investment-grade (IG) ratings, creating additional heterogeneity in this credit market access shock. Harford and Uysal (2014) hypothesize and confirm that firms with access to the corporate bond market engage in more acquisitions than those without. In this paper, we explore the possibility of the CCFs further expanding the credit market access of eligible firms and the impact this has on their acquisition activity.

We build a novel dataset consisting of firm-level financials, credit ratings, bond issuance activity, and acquisition activity. To test how the CCFs affected acquisition activity, we conduct a difference-in-difference analysis of acquisition likelihood by firms with credit ratings, before and after the announcement of the CCFs. We then identify those firms whose bonds were eligible for purchase by the Federal Reserve based on credit rating and study a second difference-in-difference analysis with this threshold. Finally, we determine which firms issued bonds after the CCF announcement and study their acquisition likelihoods before and after that announcement.

Firms with credit ratings are 5.8-6.5% more likely to acquire in a given year than firms

[1]PMCCF: `https://www.federalreserve.gov/monetarypolicy/pmccf.htm`, SMCCF: `https://www.federalreserve.gov/newsevents/pressreleases/files/monetary20200728a1.pdf`

without, aligned with the result found in Harford and Uysal (2014). We find that all firms are significantly less likely to acquire after the announcement of the CCFs, most likely due to the macroeconomic conditions following the start of the COVID-19 pandemic. However, we find no significant difference between the likelihood of acquisition by firms with credit ratings versus firms without after the announcement compared to before.

To study the acquisition likelihood of firms whose bonds are eligible to be purchased under the CCFs, we split firms into those with IG and high-yield (HY) ratings. Both types of firms are more likely to acquire than firms without credit ratings; however, neither are differentially more likely to acquire after the announcement of the CCFs than firms without credit ratings or compared to the other group. This holds true even when we restrict our sample to only firms with credit ratings right around the IG/HY cutoff.

We then focus in on the firms who did issue after the CCF announcement, who we call Covid Issuers. On average, these firms are more likely to acquire than other firms with credit ratings, but there is still not a significant difference in acquisition activity after the announcement of the CCFs compared to other firms with credit ratings or firms without ratings. If we break the Covid Issuers up into those with IG and HY ratings, we find an interesting result that the HY Covid Issuers are actually less likely to acquire after the announcement of the CCFs than firms without credit ratings and compared to HY non-Covid Issuers. This suggests that the HY-rated firms who chose to issue following the CCF announcement may have done so to finance regular operations rather than pursue new investments. We find no significant difference in the likelihood of acquiring by IG Covid Issuers. When looking only at firms with credit ratings just above and just below the IG cutoff, we find no significant difference between the post-CCF acquisition activity of eligible firms (IG) and ineligible firms (HY).

We believe we are unable to identify a significant effect of the CCFs on acquisition activity for at least one of two reasons: 1) the mix of Covid-related relief and market disruptions in the treatment period prevents us from cleanly identifying the impact of only the CCFs and 2) the starting condition of the firms were such that the CCF would not impact acquisition likelihood.

The latter reason is motivated by empirical evidence that the “treated" (aka IG) firms would issue bonds to fund acquisition activity when their cash levels were declining in the pre-CCF period. However, cash levels of these firms were not declining leading up to the announcement of the CCFs and therefore, we may not expect the same relationship between bond issuance and acquisition activity.

To test these channels, we build a stylized model of external financing and acquisition choices of firms. The model consists of an acquirer firm who has access to the bond market and a target firm who does not. The two firms meet according to a known probability during which the acquirer can buy the target firm with cash. Upon solving the model, we introduce a macroeconomic shock based on the Covid shock and study the change in acquisition likelihood. We then replicate the implementation of the CCFs by relaxing the acquirer’s borrowing constraint. Our model demonstrates that such an intervention can increase the likelihood of cash acquisitions. However, there is no effect if the firms already have substantial cash at the start of the intervention. This aligns well with our empirical finding that firms who issued bonds after the implementation of the CCFs had greater cash on hand than in previous quarters in which they issued bonds.

The rest of the paper is as follows. A brief literature review is provided in Section 2 and Section 3 will provide more details on the Fed’s intervention into the corporate bond market. The data is described in Section 4 and Section 5 outlines the methodology strategy for the reduced form analysis and discusses the results. Section 6 discusses the results of our empirical findings. Next, Section 7 introduces our stylized model of the merger and acquisition market and highlights trade-offs associated with cash acquisitions. Last, Section 9 concludes.

2 Literature Review

Our paper will contribute to two strands of literature. The first is the literature on market interventions by the government, specifically the literature on the Primary and Secondary Market

Corporate Credit Facilities. Flanagan and Purnanandam (2020) documents the PMCCF and SMCFF and studies the Federal Reserve's discretion in buying corporate bonds. They find bonds were more likely to be bought if they had a higher rating. Becker and Ivashina (2015) compares corporate bond issuance during the 2020 Covid-19 pandemic and the previous global financial crisis and find that the corporate bond market is very resilient and a key source of funding for firms. Darmouni and Siani (2023) looks at the investment decisions of firms who issued corporate bonds after the announcement of these programs. Rather than find an increase in investment, they found that majority of these firms hoarded cash. Other papers, such as Acharya and Steffen (2020), also study the corporate bond market in March 2020 to show that credit risk had a statistically significant impact on corporate cash holdings. Our paper aligns with the results of these papers in finding that firms did not engage in investment opportunities via acquisitions after issuing a bond during the time period of the CCFs.

The second strand of literature is on the financing on M&A activity. Malmendier et al. (2016) documents the rising proportion of M&A deals executed via cash and Rempel (2020) attributes this change to the speed of completing a M&A deal in cash relative to stock and shows how this speed advantage is driving the increase in cash holdings by firms. Harford (2004) finds that merger waves depend on whether or not there is sufficient capital liquidity to fund such deals. Liquidity is proxied for in this paper using spreads on commercial & industrial loans supplied by banks. Harford and Uysal (2014) then finds that firms with corporate bond market access are more likely to acquire than those without. Our paper studies a shock to firms' effective access to the credit market and its impact on acquisition activity. Furthermore, our paper contributes to the mostly under explored literature of bond issuance and M&A activity. Both Acharya et al. (2024) and Gulen et al. (2022) focus on the effects of cheaper corporate bond prices for firms on their acquisition activity. Acharya et al. (2024) shows that riskier firms benefited from quantitative easing (QE) as they could more easily issue bonds. Further, lower rated firms on the verge of being downgraded took advantage of this QE subsidy to acquire firms and delay the downgrade. While this paper studies the effect of QE on firms' acquisition behavior, our paper directly studies how a subsidy to firm-level debt prices influences acquisition behavior. Gulen et al. (2022) demonstrates that when credit conditions are more favorable, firms issue debt to complete all-cash acquisitions. While their paper focuses on macro-level conditions, our paper isolates credit conditions for individual firms and their specific acquisition activity. Both of these papers are consistent with firms taking advantage of cheap credit and we add to this literature by using a very specific policy that had the direct intention of lowering corporate bond yields.[2]

3 Overview of the PMCCF and SMCCF

In the early onset of the COVID crisis in 2020, foreign investors and money market funds cashed in their US Treasuries. This lead to substantial increases in the balance sheets and supplementary leverage ratios (tier 1 capital/total leverage) of US Treasury Primary Dealers. On March 9, repo rates on 10 Year US Treasuries rose considerably, causing the usual risk-free basis trades held by many large hedge funds to become unprofitable. Between March 9 and March 15, hedge funds unwound their basis trades all at once, leading to illiquidity in the US Treasury market. The US corporate bond market soon followed suit.

On March 15, the Federal Reserve bought $700 billion worth of Treasury notes, which alleviated the selling pressure felt by hedge funds. On March 23, the Federal Reserve bought more US Treasuries and announced the Primary (PMCCF) and Secondary Market Corporate Credit Facilities (SMCCF)[3]. The PMCCF was intended to allow corporations to issue bonds directly to the Federal Reserve and the SMCCF to buy existing investment grade corporate bonds. The purchase of US Treasuries and the announcement alone was enough to stabilize markets on March

[2]While the main purpose of the market intervention was to stabilize the corporate bond market, Fed officials also believed that it would lead to corporate investment and higher employment (of Governors of the Federal Reserve (2020)).

[3]FRBY:https://www.newyorkfed.org/markets/primary-and-secondary-market-faq/corporate-credit-facility-faq

23 ((Smith and Fox, 2020), Darmouni and Siani (2021)), even though corporate bond purchases did not start until June 16th. The bond market surged and lead to record issuance of corporate debt. To fund the purchases, the Treasury Department invested $25 billion into a special Federal Reserve subsidiary that could buy up to $250 billion in corporate debt from bondholders in the secondary market. The Federal Reserve extended the program until December 31, 2020 and on June 2, 2021 announced plans to wind down its corporate debt portfolio. [4]

The qualification rules for the PMCCF and SMCFF changed from the first announcement on March 23, 2020. To qualify for the program when the PMCCF and SMCCF were initially announced, the bond had to be less than 4 years in maturity, rated as investment grade as of March 22, 2020, and from a domestic firm or an international firm that had a significant amount of U.S. employees. However, on April 9th, 2020, the Fed announced it would also purchase bonds from "fallen angel" corporations — firms that were rated as investment grade before the Fed's announcement but had since been downgraded. The selection process for which bonds were going to be purchased was not transparent. For example, some have questioned why the Federal Reserve bought bonds from a large firm such as Apple[5]. Between June and July 2020, the Fed bought 414 out of 1818 potential bonds and as of September 7th, 2020 only $12.5B was used out of the $750B allocated towards the PMCCF and SMCCF. Flanagan & Purnanandam (2020) document bonds that had smaller credit spreads and longer maturity were more likely to be bought by the Federal Reserve.

4 Data

We construct a novel dataset combining firm financials, credit ratings, bond issuance, and acquisitin activity. We obtain firm-level characteristics from Compustat for all firms between 2000 - 2022. The data includes balance sheet information, such as cash holdings, debt holdings,

[4]Federal Reserve Press Release
[5]CNBC Article

PPE, and assets, and income statement variables, including operating income and sales, at the quarterly level. Firm bond issuance data comes from Mergent FISD at the daily frequency. In this dataset, we observe the offering amount, date of issuance, and maturity of each bond that corporations issue between 2000 - 2022. Also using Mergent FISD, we gather the individual rating of each security issued by the firm and any subsequent updating of that security's rating. In the merged Compustat - Mergent FISD sample, we have 1,623 firms that issued bonds between 2000 - 2022. For acquisition activity, we use Securities Data Company (SDC) from Refinitiv to gather data on historical mergers and acquisition deals and characteristics of the deal, such as if the deal was paid for via cash or stock, the date of initiation, and the industry of the target.

4.1 Firm Data: Compustat and CRSP

Our base set of firms consists of Compustat firms from 2000-2022. We drop firms in the financial and regulated utilities industries by dropping those with SIC codes between 6000-6999 and 4900-4999, respectively. For comparison to Harford and Uysal (2014), we also create a "restricted" version of the sample that keeps only firms found in CRSP that we can access stock market data for. To do so, we use the Compustat-CRSP crosswalk provided by Wharton Research Data Services in order to match CRSP data to Compustat. For firms with more than one identifier in the CRSP data (less than 2% of all CRSP firms), we keep the primary identifier designated by WRDS or drop the observations if one is not identified. This drops less than 1% of all firms. 61% of our sample of firms in Compustat match with CRSP.

4.2 Bond Data: Mergent FISD

We use corporate bond issuance data from Mergent FISD. The sample is restricted to bonds issued in US dollars by firms that report in US dollars. Similar to the literature studying the CCCFs, we exclude sovereign debt and debt issued by financial and utility firms. Furthermore, we exclude convertible bonds, capital impact bonds, community bonds, PIK securities, and bonds issued in exchange for a Rule 144A bond.

Data on bonds' credit ratings is obtained from Mergent FISD. There are three companies that report credit ratings in this dataset: Standard & Poor's, Fitch, and Moody's. A mapping between these companies' ratings and the numeric code we use to represent them can be found in the Appendix Table 17. We use ratings that are designated as an initial rating and then any subsequent updated rating of the security. If a bond issuance has either an initial or updated rating from all three companies, we take the median of the three ratings. If only two companies rated the bond, we use the minimum of the ratings as in Becker and Ivashina (2015). If there is a singular company rating the bond, we use that company's rating. Throughout the paper, HY bonds are those with credit rating less than BBB- (numeric code 13) and IG bonds are those with initial credit rating greater than or equal to BBB-.

The COVID-19 induced recession led to both unprecedented monetary and fiscal policies. Spurred by the Fed's Primary and Secondary Corporate Credit Facilities announcement on March 23, 2020, firms issued a record number of issuances compared to previous years. Table 18 shows the number of issuances each week averaged across firms[6]. We show that the number of bond offerings and amount offered greatly differed in each week following March 2, 2020 until June 30, 2020 compared to even the 90% percentile week in 2019. For 2019, we take the distribution of the number of firms offering bonds in any given week and record the 10th, 50th, and 90th percentiles of those weekly offering numbers for IG and HY issuers. We compare this to the number of firms offering bonds in each week from March 2, 2020 to July 5, 2020. Only two of these 18 weeks in 2020 had fewer IG issuers offering bonds than the median week in 2019 and 9 of those weeks had more IG issuers offering bonds than the 90th percentile week in 2019. HY issuers had a slower start to offering bonds during 2020. In fact, there were no HY firms offering bonds from March 9-29, 2020. Offerings really increased starting in mid-April

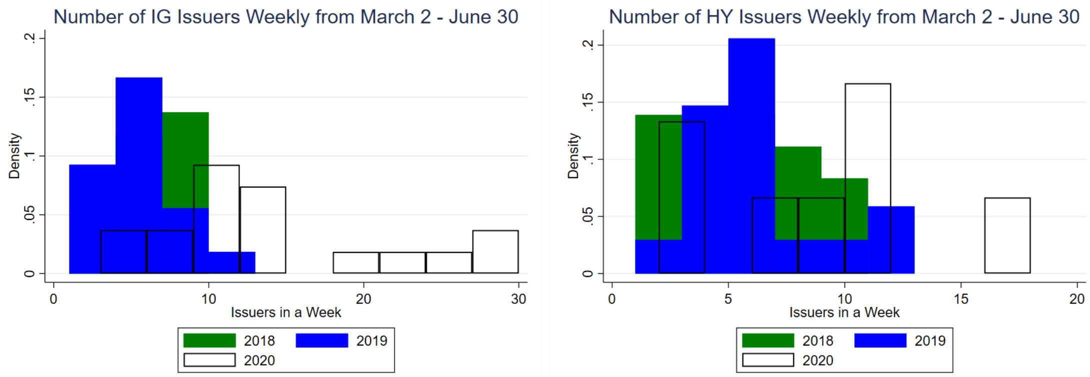
[6]This is the same table as Table IA.1 in Darmouni and Siani (2023) and we replicate this to validate our bond data sample.

Table 1: Weekly Bond Issuances: 2019 versus Post-CCFs Announcement

	Num Offerings	Amount (Bn)	Tenor	Rating	Credit Spread	Yield
IG Issuance: 2019						
10%	2	1.7	5.0	13.5	88	3.03%
50%	6	7.1	11.2	14.8	136	3.73%
90%	11	27.4	29.1	16.7	213	4.66%
IG Issuance: Weeks in 2020						
3/2/2020	13	13.2	14.1	14.7	156	2.64%
3/9/2020	3	3.9	12.2	14.5	211	2.91%
3/16/2020	8	40.5	16.8	17.5	267	3.95%
3/23/2020	27	61.9	13.2	16.1	267	3.63%
3/30/2020	19	63.7	13.6	15.2	342	4.26%
4/6/2020	13	23.0	11.1	15.4	315	3.85%
4/13/2020	11	31.6	13.6	15.6	238	3.38%
4/20/2020	15	17.8	10.2	14.2	291	3.85%
4/27/2020	25	71.1	14.2	15.8	208	2.92%
5/4/2020	28	64.6	12.8	15.4	263	3.39%
5/11/2020	22	46.9	14.4	15.0	239	3.42%
5/18/2020	12	36.9	15.8	16.2	191	2.94%
5/25/2020	10	15.6	15.2	15.6	169	2.51%
6/1/2020	11	21.0	11.0	15.0	166	2.30%
6/8/2020	10	11.2	12.6	14.1	177	2.68%
6/15/2020	12	25.3	11.7	14.3	195	2.53%
6/22/2020	8	11.2	7.9	15.0	178	2.50%
6/29/2020	4	9.3	16.7	14.0	183	2.67%
HY Issuance: 2019						
10%	2	1.5	5.3	6.8	281	4.93%
50%	5	4.2	7.6	9.0	398	6.18%
90%	10	9.8	10.7	11.1	619	8.70%
HY Issuance: Weeks in 2020						
3/2/2020	2	1.8	10.1	10.0	368	4.69%
3/30/2020	3	1.8	5.0	9.7	662	7.00%
4/6/2020	3	1.6	5.0	7.0	814	8.63%
4/13/2020	11	13.8	5.5	10.2	713	7.36%
4/20/2020	16	11.3	5.2	9.4	680	7.15%
4/27/2020	7	3.8	5.0	9.0	555	6.95%
5/4/2020	8	7.1	8.9	10.8	509	6.53%
5/11/2020	9	6.6	6.4	8.3	623	6.98%
5/18/2020	11	5.5	6.3	9.2	663	8.24%
5/25/2020	7	8.6	8.9	9.0	631	7.60%
6/1/2020	11	8.3	6.1	9.3	607	6.61%
6/8/2020	10	7.6	7.8	9.9	403	5.17%
6/15/2020	17	12.1	7.5	9.0	542	6.32%
6/22/2020	10	8.9	7.4	9.3	623	7.53%
6/29/2020	3	2.3	7.7	7.0	584	6.38%

Notes: Data are from Mergent FSID, obtained through WRDS. We exclude sovereign debt and debt issued by financial and utility firms. Furthermore, we exclude financial, sovereign and utility issues as well as convertible bonds, capital impact bonds, community bonds, PIK securities, and bonds issued in exchange for a Rule 144A bond. Counts are average across weeks for all firms, split into either IG or HY rated firms at the time of the CCF announcement, March 23, 2020. This is based on Table IA.I from Darmouni and Siani (2023).

Figure 1: Histograms of Number of Firms Offering Bonds between March 2 - June 30



and then there were 11 weeks in which the number of firms issuing bonds exceeded the median number of firms offering bonds in 2019 while there were five weeks which exceeded the 90th week. Similar patterns can be found by the total dollar amount of the offerings for each week, in billions of USD, in column 2 of the table.

While Table 18 compares all of 2019 to these 18 weeks in 2020, Figure 1 plots histograms of the number of firms offering bonds in these same 18 weeks in 2018, 2019, and 2020 to control for the possibility of March-June being a heavy issuance time regardless of the onset of the Covid pandemic. Especially for the IG issuers, the distribution of firms issuing IG bonds by week in 2020 is to the right of the same distribution in 2018 and 2019. Further, no week exceeds 15 firms issuing in 2018 or 2018, IG or HY, when a significant mass of weeks in 2020 have over 20 IG issuers.

The remaining four columns of Table 18 provide further descriptive statistics of the bond issuances, such as the tenor of the bond, the credit rating, the spread over Treasury bonds, and the yield of the bond. For the 2019 statistics, we solve for the 10th, 50th, and 90th percentiles of each characteristic in each week in 2019, and then report the mean across the weeks in this table. For the weeks in 2020, we solve for the mean of each characteristic in each week. Generally, we see that the mean of each characteristic for weekly IG and HY issuances exceeds the median week in 2019.

After creating the bond sample, we merge the data with Compustat. We find 1,623 unique firms in the Compustat sample that issued a bond between 2000Q1-2021Q3 (the latest quarter for which we currently have Mergent FISD data). There are 6,573 firm-quarter observations in which the firm issued at least one bond that quarter.

We can now compare issuers during the pre-CCFs and post-CCFs times based on Compustat balance sheet items and their issuing habits. This comparison can be seen in Table 2. We also split issuers into IG and HY issuers in the last four columns[7]. For this table, we define the pre-CCFs times issuers as those issuing a bond between 2000 and 2019. We find 1,507 unique issuers in Compustat during this time. We define Covid issuers as those issuing a bond between March 23-June 30, 2020, which results in 262 unique issuers that merge with the Compustat data. 228 of these firms also issue from 2000-2019. Balance sheet characteristics in the table are based on the quarter-end prior to the bond issuance and the table reports the means of these characteristics. On average, Covid issuers are larger, more leveraged, and hold a slightly higher fraction of their assets in cash. Total bonds issued, average bond size, credit rating, and average tenor are calculated over the full dataset back to 2000. Covid issuers have issued significantly more bonds back to 2000 compared to the mean issuer in 2000-2019. They also have a higher credit rating and issue bonds with a higher tenor. We then look at the number of bonds these two groups of issuers issued in 2019 versus Covid times. 103 of the Covid issuers also issued in 2019. Covid issuers issued on average 1.34 bonds in 2019, compared to only 0.61 for pre-CCFs issuers. They also issued 2.02 bonds in Covid times, while pre-CCFs issuers only issued 0.35. This suggests that many of the pre-CCFs issuers did not issue at all from March 23-June 30, 2020.

Breaking the issuers down into IG and HY issuers, we have 548 unique IG and 858 unique HY issuers. However, for Covid issuers, there are 163 unique IG issuers, and only 68 unique

[7]The sum of the number of IG and HY firms does not equal the total number of firms. This is because we are designating firms, not issuances, as IG or HY. If a firm issues both IG and HY firms in the time period, it is difficult to make this designation. We lose some of the issuers in this process. We will continue to update the process until we can keep all issuers.

Table 2: Comparison of pre-CCFs and Covid Times Issuers

	All		IG		HY	
	2000-2019	3/23-6/30	2000-2019	3/23-6/30	2000-2019	3/23-6/30
Total Assets (log)	9.55	10.17	9.99	10.48	9.27	9.92
Leverage	0.36	0.42	0.28	0.39	0.43	0.52
Cash/Assets	0.09	0.10	0.09	0.09	0.07	0.08
Total bonds issued	6.20	15.82	11.56	21.63	3.35	8.63
Average bond size	565.22	882.97	654.08	973.36	457.84	634.37
Credit Rating	12.53	14.19	15.02	15.50	9.04	10.75
Average tenor (years)	10.44	12.83	11.93	13.81	8.55	10.12
Bonds issued 2019 (#)	0.61	1.34	1.11	1.85	0.28	0.72
Bonds issued 2019 ($MM)	214.01	411.46	342.26	518.87	134.81	341.57
Bonds issued COVID (#)	0.35	2.02	0.76	2.54	0.10	1.22
Bonds issued COVID ($MM)	86.91	499.91	145.03	487.60	46.84	591.00
Number of firms	1507	262	548	163	858	68

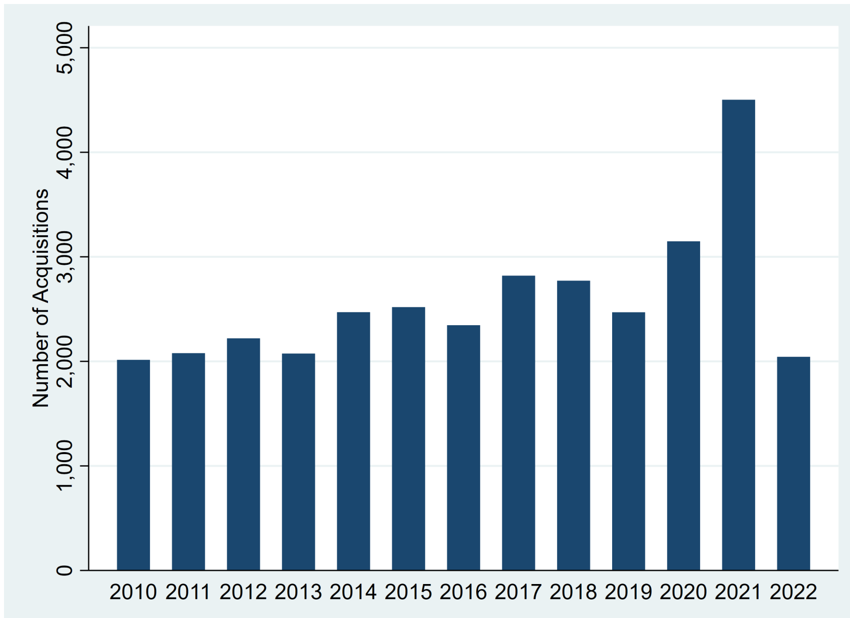
HY issuers. This shows that IG issuers were more likely to issue during Covid than HY issuers. IG issuers are generally larger, less leveraged, and hold more cash than HY issuers. They issue more bonds, which are generally larger and have longer tenor. From March 23-June 30, 2020, for those that did issue, IG issuers issued an average of 2.54 bonds while HY issuers only issued 1.22.

4.3 M&A Data: SDC

Data on acquisition activity comes from the Securities Data Company (SDC) by Refinitiv. We screen for acquisitions performed by firms with headquarters in the U.S. We pull all acquisitions announced from January 2010 - March 2022. We create indicators for the quarter of an announcement of an acquisition deal and merge these into our combined Compustat-Mergent FISD dataset. SDC contains data on both private and public firms while Compustat only contains data on public firms, so our final merged sample only consists of acquisition deals announced by public firms in Compustat. We find 3,507 unique firms that engaged in acquisitions and have 9,345 firm-quarter observations.

While 2020 was unprecedented because of COVID, so was the number of acquisition deals. The total amount of acquisition deals announced in 2020 surpassed the amount of deals in any year in the ten years prior. Figure 2 shows the amount of acquisition activity between 2010Q1 - 2022Q1 based on our sample of firms from SDC. Surprisingly, according to the SDC data sample,

Figure 2: Historic Acquisition Activity



we see an uptick in acquisition deals throughout the entire year. For example, all quarters saw relatively high completion of acquisition deals relative to previous years at 737, 707, 646, and 731 for each quarterly, respectfully. Acquisitions proceeded to break records as 1,188 deals were announced in 2021Q1, the highest ever in our sample. When we merge our sample with Compustat, this dramatic effect is diminished, but we interestingly find that 30% of acquisition deals announced in 2020 for firms in Compustat occurred in 2020Q4. In our merged SDC-Compustat sample, only 144 firms engaged in an acquisition in 2020Q1 and 74 firms engaged in an acquisition deal in 2020Q2. The remainder of 2020 saw an uptick in 2020Q3 and 2020Q4 with 145 and 159 acquisition deals and 153 deals in 2021Q1. These numbers are still higher than the past 3 years' average number of deals per quarter, indicating that the number of acquisitions in 2020 was higher than average. While our data sample does not capture all firms in SDC, given that 2020Q3, 2020Q4, 2021Q4 saw record numbers of acquisition deals, one main goal of this paper is to use firm characteristics to understand why the number of acquisition deals reached an all time high for 2020 and 2021.

The characteristics of these firms are described in more detail in Table 3. While Table 3 looks at the characteristics of firms that engaged in acquisition activity, we find similar results for firms characteristics that engaged in both merger and acquisition deals. These results are in the appendix.

In Table 3, we summarize firms' characteristics by taking averages and medians over the given time frame. All variables are represented as averages except market-to-book, where we take the median of the distribution due to some extreme tail events. Balance sheet characteristics are winsorized at the 1% level. The first column of Table 3 consists of balance sheet items for all firms in our sample that acquired another firm during 2010Q1-2022Q1. The second column represents firms in our sample that acquired during COVID times defined as 2020Q2 - 2022Q1. The third column represents firms in our sample that acquired during pre-CCFs times defined as 2010Q1-2019Q4 and the fourth columns represents the overlap in firms that acquired during pre-CCFs and post-CCFs times. There were 595 firms out of the 3,173 firms during pre-CCFs times that also engaged in acquisitions after the announcement of the CCFs. Surprisingly, there were 312 firms that had never engaged in acquisition activity in pre-CCFs times, but engaged for the first time in the post-period. These firms had slightly higher market-to-book, meaning that those firms were over-valued. The maximum number of deals in the post-CCFs period by a first-timer was 6, which is almost half the maximum number of deals per firm in a year during pre-CCFs times. Table 3 shows that acquisitions after the CCFs announcement were quite different than before in terms of numbers and firm characteristics.

Table 3: Firms Acquiring in pre- and post-CCFs Times

	Full Sample	Post-CCFs	Pre-CCFs	Pre- & Post-	Post-First Time	Only Pre-CCFs
Total Assets (log)	9.313	9.451	9.292	9.483	8.738	9.118
Leverage	0.318	0.318	0.318	0.354	0.2889	0.560
Cash/Assets	0.105	0.140	0.099	0.109	0.198	0.120
CAPX	0.009	0.006	0.010	0.008	0.009	0.009
Market-to-Book	1.959	2.535	1.899	2.082	2.019	1.619
Acquisitions/Year	1.660	1.540	1.679	0.517	0.140	0.256
Max Acquisitions/Year	15	10	15	13	6	15
Firms	3507	944	3173	595	312	3173
Time Period	2010Q1 - 2022Q1	2020Q3 - 2022Q1	2010 - 2019Q4	2020Q3 - 2022Q1	2020Q3 - 2022Q1	2010Q1 - 2019Q4

5 Empirical Methodology

5.1 Acquisition Likelihood

The announcement of the CCFs altered firms' access to external financing by influencing the demand and price for firms' corporate bonds in March 2020. In this paper, we study whether this change to external financing access affects the likelihood of a firm conducting an acquisition. Our analysis can therefore be thought of as an extension of the analysis conducted by Harford and Uysal (2014), which studies if firms with credit ratings conduct more acquisitions than those without, due to their greater access to external financing. Harford and Uysal (2014) proposes that greater access to external financing could lead to more acquisition activity either by 1) relaxing a firm's financial constraints and allowing it to undergo more positive NPV projects or 2) creating more disperse investors for the firm and thus allowing the manager to undergo more negative NPV projects that benefit them. Each of these theories suggest that greater access to external financing leads to more acquisitions, although the quality and returns to these acquisitions may vary. The situation that we study relates more to the first theory: the PMCCF and SMCCF relaxed the borrowing constraints of certain (perhaps all) firms in a tumultuous time and therefore they may have undergone more acquisitions as a result. These firms were primarily bond issuers with other debt already, so it seems unlikely that these programs had a large effect on the dispersion of their investors.

We start our analysis by extending the findings of Harford and Uysal (2014) to study the effect of the CCFs on the likelihood of conducting an acquisition. The specification is

$$\begin{aligned}
\text{Acquisition}_{i,t} = {} & \beta_1 \text{Has Rating}_{i,t-1} + \beta_2 \text{Ln(Sales)}_{i,t-1} + \beta_3 \text{Cash to Assets}_{i,t-1} \\
& + \beta_4 \text{Market Leverage}_{i,t-1} + \beta_5 \text{Stock Return}_{i,t-1} + \beta_6 \text{Market-to-Book}_{i,t-1} \\
& + \beta_7 \text{Operating Income}_{i,t-1} + \beta_8 \text{Industry Liquidity}_{i,t-1} + \beta_9 \text{Herfindahl Index}_{i,t-1} \\
& + \epsilon_{i,t}
\end{aligned} \tag{1}$$

where i designates a firm and t a year. $\text{Acquisition}_{i,t}$ is an indicator for whether a firm i announces an acquisition in year t. Given that $\text{Acquisition}_{i,t}$ is an indicator, we use a probit analysis for this specification, where standard errors are clustered by firm. All independent variables are measured at the year-end of the previous year. $\text{Has Rating}_{i,t-1}$ is an indicator for if the firm had a credit rating in the previous year. Other controls include size (proxied by the natural logarithm of sales), cash ratio, market to book ratio, market leverage, operating income (proxied by EBITDA to assets), and the firm's yearly stock return. Additionally, we add in key variables from Harford and Uysal (2014) representing the industry the firm operates in. Industry liquidity measures the value of all acquisition deals to assets by firms in a 3 digit SIC code each year to capture the liquidity of corporate assets in that industry and therefore an expectation of acquisition activity. To measure industry concentration, the Herfindahl index is calculated based on the sales of firms with the same 3 digit SIC code in a year.

The results of the initial specification in Harford and Uysal (2014) are summarized as marginal effects in Columns 1 and 2, where Column 2 restricts the sample of firms to those with at least $10M in sales as is used in Harford and Uysal (2014). The key coefficient is that of Has Rating, which is positive and significant. Firms with credit ratings are 5.8-6.5% more likely to acquire than firms without access to the corporate bond market, as is also found in Harford and Uysal (2014). Our other coefficients match those of Harford and Uysal (2014) in sign and significance as well, except for that of Cash to Assets. We find a negative coefficient on this when Harford and Uysal (2014) found a positive one, perhaps suggesting a change in

Table 4: Acquisition Likelihood

	1	2	3	4	5	6
Has Rating	0.0581***	0.0647***	0.0592***	0.0649***	0.0521***	0.0585***
	(0.00534)	(0.00649)	(0.00564)	(0.00685)	(0.00600)	(0.00716)
Ln(Sales)	0.0187***	0.0215***	0.0187***	0.0215***	0.0172***	0.0178***
	(0.00225)	(0.00404)	(0.00225)	(0.00404)	(0.00216)	(0.00418)
Cash to Assets	-0.0620***	-0.0770***	-0.0621***	-0.0770***	-0.0620***	-0.0772***
	(0.0147)	(0.0209)	(0.0147)	(0.0209)	(0.0146)	(0.0208)
Market Leverage	-0.105***	-0.134***	-0.106***	-0.134***	-0.0987***	-0.127***
	(0.0108)	(0.0132)	(0.0108)	(0.0132)	(0.0108)	(0.0132)
Stock Return	0.00221***	0.00466***	0.00220***	0.00465***	0.00215***	0.00460***
	(0.000671)	(0.00130)	(0.000668)	(0.00130)	(0.000665)	(0.00129)
Market-to-Book	0.00000574	0.0000167	0.00000572	0.0000166	0.00000529	0.0000146
	(0.00000516)	(0.0000274)	(0.00000525)	(0.0000274)	(0.00000620)	(0.0000274)
Operating Income	0.0254***	-0.00594	0.0255***	-0.00590	0.0278***	-0.00118
	(0.00845)	(0.0175)	(0.00845)	(0.0175)	(0.00839)	(0.0178)
Industry Liquidity	0.396***	0.460***	0.396***	0.460***	0.399***	0.461***
	(0.0746)	(0.0875)	(0.0746)	(0.0875)	(0.0744)	(0.0874)
Herfindahl Index	-0.0340***	-0.0434***	-0.0339***	-0.0434***	-0.0335**	-0.0425***
	(0.0129)	(0.0154)	(0.0129)	(0.0154)	(0.0130)	(0.0155)
Post-CCF			-0.0132*	-0.0235***	-0.0124*	-0.0221**
			(0.00711)	(0.00874)	(0.00709)	(0.00874)
Has Rating X Post			-0.00569	-0.00107	-0.00499	-0.000127
			(0.00837)	(0.00988)	(0.00988)	(0.0115)
Covid Issuer					0.0289***	0.0317***
					(0.00821)	(0.00955)
Covid Issuer X Post					-0.00742	-0.00939
					(0.0135)	(0.0156)
N	30847	25268	30847	25268	30847	25268
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

acquisition behavior compared to the time period of 1990-2011 that they study.

As a first step in studying the effect of the CCFs on acquisition activity, we introduce indicators for the time period after the announcement of the program and the interaction between the Has Rating indicator and this indicator. The new specification is then

$$\begin{aligned}\text{Acquisition}_{i,t} = {} & \beta_1\text{Has Rating}_{i,t-1} + \beta_2\text{Ln(Sales)}_{i,t-1} + \beta_3\text{Cash to Assets}_{i,t-1} \\ & + \beta_4\text{Market Leverage}_{i,t-1} + \beta_5\text{Stock Return}_{i,t-1} + \beta_6\text{Market-to-Book}_{i,t-1} \\ & + \beta_7\text{Operating Income}_{i,t-1} + \beta_8\text{Industry Liquidity}_{i,t-1} + \beta_9\text{Herfindahl Index}_{i,t-1} \\ & + \beta_{10}\text{Post-CCF}_t + \beta_{11}\text{Has Rating}_{i,t-1}X\text{Post-CCF}_t + \epsilon_{i,t}.\end{aligned} \tag{2}$$

The results of this analysis can be seen in Columns 3 and 4 of Table 4. We find significantly negative marginal effects for the indicator representing years after the announcement of the CCF. The interaction term has a negative coefficient as well, but it is not significant. Given the lull in acquisitions in 2020, it is no surprise that acquisitions are less likely for all firms for the Post-CCF period of 2020 and 2021. The insignificant coefficient on the interaction term suggests that in general, firms with credit ratings were not differentially affected by this trend when controlling for other relevant variables, such as size and profitability.

We then add in indicators for firms that issued bonds during the period of March 23-June 30, 2020, or “Covid Issuers". We consider these issuers Covid issuers as they issued in the period shortly after the announcement of the CCFs and therefore the firms most likely to be reacting to the CCF announcement. This specification is

$$
\begin{aligned}
\text{Acquisition}_{i,t} = {} & \beta_1 \text{Has Rating}_{i,t-1} + \beta_2 \text{Ln(Sales)}_{i,t-1} + \beta_3 \text{Cash to Assets}_{i,t-1} \\
& + \beta_4 \text{Market Leverage}_{i,t-1} + \beta_5 \text{Stock Return}_{i,t-1} + \beta_6 \text{Market-to-Book}_{i,t-1} \\
& + \beta_7 \text{Operating Income}_{i,t-1} + \beta_8 \text{Industry Liquidity}_{i,t-1} + \beta_9 \text{Herfindahl Index}_{i,t-1} \\
& + \beta_{10} \text{Post-CCF}_t + \beta_{11} \text{Has Rating}_{i,t-1} X \text{Post-CCF}_t \\
& + \beta_{12} \text{Covid Issuer}_i + \beta_{13} \text{Covid Issuer}_i X \text{Post-CCF}_t + \epsilon_{i,t}.
\end{aligned} \tag{3}
$$

We include an indicator for if the firm is a Covid Issuer as a time-invariant independent variable to test if these firms have an initial likelihood of acquisition that differs from non-Covid issuers with credit ratings and firms without credit ratings. We find a positive and significant coefficient on this indicator. Covid Issuers are 2.9-3.2% more likely to acquire at any point in the time period than firms without credit ratings. We then include an interaction term between this indicator and one for the time period after the announcement of the CCFs. The coefficient on this term is insignificant, suggesting that Covid issuers are not more likely to acquire after the announcement than firms without credit ratings or non-Covid issuers.

For robustness, we replace the dependent variable $\text{Acquisition}_{i,t}$ with the ratio of the sum of acquisition deal values to the firms' assets, $\frac{\text{Total Deal Value}_{it}}{\text{Assets}_{i,t-1}}$ and conduct a tobit analysis with the same regressors as in Equations 1, 2, and 3. The results of this analysis can be found in the Appendix Table 21. The indicator Has Rating is only significant when we restrict the sample to firms with \$10M or more in sales. However, when we include the Covid Issuer indicator and its interaction with the Post-CCF time period, this coefficient is no longer significant, but the new indicators do not have significant coefficients either. This indicates that the indicators cannot capture a significant change in the relative size of the acquisition deals.

In the initial announcement of the CCFs, the Fed stated that it would only purchase bonds issued by firms with an IG rating at the time of purchase. On April 9, 2020, they updated this statement to include bonds that were issued by firms with an IG rating as of the day of the first announcement. Therefore, we can use the IG/HY cutoff of March 22, 2020 to study the effect of the CCFs on acquisition activity for firms eligible for purchase. To do so, we break the Has Rating indicator into two indicators, IG and HY, and repeat the probit analyses summarized in Equations 1, 2, and 3. These results can be found in Tables 5.

From Columns 1 and 2, we see that IG firms are 5.5-5.95% more likely and HY firms are 6.1-6.85% mroe likely to acquire than firms without credit ratings. While the marginal effect for HY firms is slightly larger than that for IG firms, they are not significantly different.

In Columns 3 and 4, we include indicators for the post-CCF announcement period and the interactions between this indicator and IG and between this indicator and HY. While acquisitions are significantly less likely after the announcement, there is no additional effect for either IG or HY issuers compared to firms without credit ratings. Finally, in Columns 5 and 6, we introduce the indicators for firms who issued bonds from March 23 to June 30, 2020 as well as indicators for the interaction with the IG or HY indicators and the indicator for the Post-CCF time period. The coefficient on the interaction between IG, Covid Issuer, and Post-CCF is not significant, but the one on the interaction between HY, Covid Issuer, and Post-CCF is. Surprisingly, this is also negative. Based on the sum of the coefficients on Covid Issuer and Covid Issuer X HY X Post, HY Covid Issuers are actually less likely to engage in acquisitions than other HY firms after the announcement of the intervention. While this may appear to counter our theory about the CCF affecting the rate of acquisitions, bonds issued by HY firms could not be bought by the Fed. Therefore, this could signal that the HY firms that issued from March 23 to June 30 did so for reasons other than an adjustment to the demand for their bonds from the CCF. Perhaps the HY firms who selected into issuing were those that were in greater need of financing to continue normal operations, making them less likely to seek out acquisition opportunities. The results of the equivalent analysis using acquisition size as the dependent variable can be seen in Appendix Table 22.

In further investigation into heterogeneous effects of credit ratings on acquisition likelihood, we break the spectrum of credit ratings down into buckets. By numeric code, the buckets are $[0, 4)$, $[4, 7)$, $[7, 10)$, $[10, 13)$, $[13, 16)$, $[16, 19)$, $[19, 22]$, which correspond to [D, CC], [CCC−, CCC+],

Table 5: Acquisition Likelihood by IG and HY

	1	2	3	4	5	6
IG	0.0550***	0.0595***	0.0554***	0.0589***	0.0417***	0.0459***
	(0.00665)	(0.00824)	(0.00700)	(0.00861)	(0.00779)	(0.00932)
HY	0.0610***	0.0685***	0.0628***	0.0695***	0.0587***	0.0656***
	(0.00639)	(0.00746)	(0.00686)	(0.00801)	(0.00691)	(0.00805)
Ln(Sales)	0.0191***	0.0230***	0.0192***	0.0230***	0.0179***	0.0201***
	(0.00235)	(0.00427)	(0.00235)	(0.00427)	(0.00226)	(0.00433)
Cash to Assets	-0.0619***	-0.0768***	-0.0619***	-0.0767***	-0.0616***	-0.0763***
	(0.0147)	(0.0209)	(0.0147)	(0.0209)	(0.0146)	(0.0208)
Market Leverage	-0.108***	-0.138***	-0.108***	-0.138***	-0.104***	-0.133***
	(0.0112)	(0.0137)	(0.0112)	(0.0137)	(0.0111)	(0.0137)
Stock Return	0.00222***	0.00462***	0.00221***	0.00463***	0.00215***	0.00452***
	(0.000670)	(0.00130)	(0.000667)	(0.00130)	(0.000661)	(0.00129)
Market-to-Book	0.00000588	0.0000178	0.00000587	0.0000177	0.00000561	0.0000163
	(0.00000494)	(0.0000277)	(0.00000501)	(0.0000276)	(0.00000558)	(0.0000279)
Operating Income	0.0248***	-0.00718	0.0249***	-0.00717	0.0268***	-0.00304
	(0.00849)	(0.0175)	(0.00849)	(0.0175)	(0.00843)	(0.0177)
Industry Liquidity	0.395***	0.461***	0.395***	0.461***	0.399***	0.462***
	(0.0746)	(0.0875)	(0.0746)	(0.0875)	(0.0743)	(0.0873)
Herfindahl Index	-0.0339***	-0.0434***	-0.0338***	-0.0433***	-0.0333**	-0.0425***
	(0.0130)	(0.0154)	(0.0129)	(0.0154)	(0.0130)	(0.0155)
Post-CCF			-0.0133*	-0.0238***	-0.0124*	-0.0223**
			(0.00711)	(0.00876)	(0.00709)	(0.00874)
IG X Post-CCF			-0.00247	0.00294	0.00374	0.00858
			(0.0107)	(0.0125)	(0.0151)	(0.0175)
HY X Post-CCF			-0.00907	-0.00528	-0.00289	0.00169
			(0.0107)	(0.0126)	(0.0115)	(0.0134)
Covid Issuer					0.0356***	0.0382***
					(0.00849)	(0.00976)
IG X Covid Issuer					-0.0169	-0.0166
X Post-CCF					(0.0187)	(0.0215)
HY X Covid Issuer					-0.0455**	-0.0516*
X Post-CCF					(0.0230)	(0.0265)
N	30847	25268	30847	25268	30847	25268
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

[B−, BB+], [BB−, BB+], [BBB−, BBB+], [A−, A+], [AA−, AAA] in S&P ratings[8]. We replace the Has Rating indicator in Equations 1, 2, and 3 with indicators for each of these buckets and re-estimate the specifications. The results can be found in Tables 6 and 7 (separated for ease of viewing). In the table, we keep only the coefficients on the credit rating and Post-CCFs variables for brevity.

In the replication of the Harford and Uysal (2014)-style analysis, we find that compared to firms without credit ratings, the probability of acquiring is significantly higher for firms in each credit bucket, except for the lowest bucket. The coefficient for the second lowest bucket $[4, 7)$ is much smaller than the others, at only 2.9-3.2%, while the others range from 5.3-7.9%. For the full sample, this coefficient is actually significantly different from the coefficients on the other credit rating buckets at the 6-15% level, but at the 11% or higher level for the restricted sample. While these firms do have access to credit markets, these results suggest that this access is not as effective at decreasing financial constraints or monitoring to affect their acquisition likelihood.

In Columns 3 and 4, we add in the indicator for the Post-CCFs period and the interaction terms between this indicator and each of the credit rating buckets. The interaction term for the firms with credit rating scores between 4 and 7 are significantly negative at the 1% level. Even more, the sum of the coefficients for this interaction term and the indicator for this bucket, -.3013, is significantly negative at the 9% level. These firms were actually less likely to acquire after the announcement of the CCFs than those firms without credit ratings. The only other significant coefficient in this group is on the interaction term $[7, 10)X$Post, which is significantly positive at the 10% level, suggesting that firms with credit ratings between $[B-, B+]$ were more likely to acquire after the CCFs than before compared to firms without credit ratings.

In the last two columns, we add in indicators for those Covid Issuers and the interaction between being a Covid Issuer, having a credit rating in each bucket, and Post-CCFs. The coefficient on the interaction term Covid Issuer$X[4, 7)X$Post is null as no firms with a credit rating in

[8] See Appendix Table 17 for a full mapping of credit rating scores to credit ratings

this bucket issued during that time period. This supports our finding that these firms were less likely to acquire after the CCFs than firms without credit ratings as these firms did not receive additional funding from the corporate bond market during this time. We find no significance on any of the triple interaction firms. Results of the corresponding analysis with acquisition size as the depending variable can be found in Appendix Tables 23 and 24.

Given the strict cutoff in eligibility of bonds to be purchased in the CCFs, we conduct a further analysis on the sample of firms with credit ratings around this cutoff. Without including firms without credit ratings, we focus on the coefficient on the IG indicator in the specification

$$\begin{aligned}\text{Acquisition}_{i,t} = {} & \beta_1 \text{IG}_{i,t-1} + \beta_2 \text{Ln(Sales)}_{i,t-1} + \beta_3 \text{Cash to Assets}_{i,t-1} + \beta_4 \text{Market Leverage}_{i,t-1} \\ & + \beta_5 \text{Stock Return}_{i,t-1} + \beta_6 \text{Market-to-Book}_{i,t-1} + \beta_7 \text{Operating Income}_{i,t-1} \\ & + \beta_8 \text{Industry Liquidity}_{i,t-1} + \beta_9 \text{Herfindahl Index}_{i,t-1} + \epsilon_{i,t}.\end{aligned} \tag{4}$$

The results of this specification can be found in Columns 1 and 4 of Table 8, where Column 1 uses a sample of firms with credit rating scores from 10 to 16 ([BB−, A−]) and Column 4 from 12 to 14 ([BB+, BBB]). Credit rating score 13 is the lowest score that is considered IG. All firms with ratings in these bands have sales greater than $10M and therefore, we do not need to estimate the specifications separately for that subsample. The coefficient on the IG indicator is not significant, suggesting no differences in acquisition activity by firms just below and just above the cutoff. We then add in indicators for the Post-CCFs time period and the interaction between IG and this indicator, as in Equation 2. We do not find significant coefficients for these indicators either. Finally, we follow along with the specification in Equation 3 and introduce indicators for Covid Issuer and its interactions with IG, HY, and Post-CCFs, but do not find any significant effects here either. Therefore, we can conclude that the CCFs did not significantly affect the acquisition likelihood of eligible firms.

Table 6: Probability of Acquiring by Credit Rating Bucket

	1	2	3	4	5	6
Rating ∈ [0, 4)	0.0139	0.0147	0.00758	0.00677	0.00646	0.00592
	(0.0177)	(0.0206)	(0.0214)	(0.0248)	(0.0214)	(0.0249)
Rating ∈ [4, 7)	0.0286***	0.0316**	0.0400***	0.0446***	0.0392***	0.0435***
	(0.0110)	(0.0127)	(0.0122)	(0.0140)	(0.0122)	(0.0140)
Rating ∈ [7, 10)	0.0568***	0.0643***	0.0515***	0.0573***	0.0488***	0.0546***
	(0.00949)	(0.0109)	(0.0106)	(0.0122)	(0.0107)	(0.0123)
Rating ∈ [10, 13)	0.0531***	0.0589***	0.0534***	0.0581***	0.0464***	0.0514***
	(0.00907)	(0.0106)	(0.00976)	(0.0114)	(0.00968)	(0.0113)
Rating ∈ [13, 16)	0.0506***	0.0546***	0.0523***	0.0555***	0.0397***	0.0433***
	(0.00729)	(0.00883)	(0.00768)	(0.00925)	(0.00816)	(0.00970)
Rating ∈ [16, 19)	0.0570***	0.0606***	0.0538***	0.0560***	0.0369***	0.0399***
	(0.0105)	(0.0126)	(0.0110)	(0.0132)	(0.0120)	(0.0141)
Rating ∈ [19, 22]	0.0737***	0.0788**	0.0757**	0.0802**	0.0561	0.0621
	(0.0278)	(0.0322)	(0.0334)	(0.0385)	(0.0354)	(0.0407)
Post-CCF			-0.0134*	-0.0241***	-0.0126*	-0.0227***
			(0.00710)	(0.00873)	(0.00709)	(0.00873)
[0, 4) X Post			0.0200	0.0261	0.0216	0.0311
			(0.0295)	(0.0343)	(0.0299)	(0.0345)
[4, 7) X Post			-0.0836***	-0.0968***	-0.0746**	-0.0865***
			(0.0287)	(0.0329)	(0.0291)	(0.0333)
[7, 10) X Post			0.0278	0.0371*	0.0289	0.0380*
			(0.0178)	(0.0205)	(0.0186)	(0.0215)
[10, 13) X Post			-0.00149	0.00465	0.00770	0.0145
			(0.0153)	(0.0178)	(0.0170)	(0.0197)
[13, 16) X Post			-0.00855	-0.00400	-0.00220	0.00201
			(0.0125)	(0.0145)	(0.0168)	(0.0194)
[16, 19) X Post			0.0197	0.0285	0.0420	0.0520
			(0.0173)	(0.0199)	(0.0305)	(0.0351)
[19, 22] X Post			-0.0119	-0.00851	-0.0615	-0.0658
			(0.0724)	(0.0832)	(0.101)	(0.117)

Table 7: Probability of Acquiring by Credit Rating Bucket Continued

	1	2	3	4	5	6
Covid Issuer					0.0365***	0.0391***
					(0.00860)	(0.00986)
Covid Issuer X					-0.0360	-0.0486
[0, 4) X Post					(0.0582)	(0.0676)
Covid Issuer X					0	0
[4, 7) X Post					(.)	(.)
Covid Issuer X					-0.0204	-0.0203
[7, 10) X Post					(0.0422)	(0.0486)
Covid Issuer X					-0.0434	-0.0480
[10, 13) X Post					(0.0309)	(0.0355)
Covid Issuer X					-0.0194	-0.0194
[13, 16) X Post					(0.0224)	(0.0256)
Covid Issuer X					-0.0417	-0.0443
[16, 19) X Post					(0.0351)	(0.0403)
Covid Issuer X					0.0755	0.0874
[19, 22] X Post					(0.110)	(0.127)
N	30847	25268	30847	25268	30832	25253
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 8: Probability of Acquiring by IG/HY Cutoff

	1	2	3	4	5	6
IG	-0.0224	-0.0198	-0.0232	-0.0186	-0.000997	-0.00369
	(0.0175)	(0.0186)	(0.0187)	(0.0245)	(0.0285)	(0.0279)
Ln(Sales)	0.0403**	0.0406**	0.0258	0.0342	0.0368	0.00154
	(0.0176)	(0.0176)	(0.0181)	(0.0293)	(0.0295)	(0.0279)
Cash to Assets	-0.0460	-0.0474	-0.0193	-0.0727	-0.0951	-0.0383
	(0.0960)	(0.0958)	(0.0909)	(0.160)	(0.160)	(0.144)
Market Leverage	-0.328***	-0.328***	-0.306***	-0.322***	-0.326***	-0.244***
	(0.0536)	(0.0535)	(0.0529)	(0.0743)	(0.0747)	(0.0735)
Stock Return	0.0192	0.0189	0.0165	0.0329	0.0344	0.0345
	(0.0121)	(0.0121)	(0.0121)	(0.0270)	(0.0269)	(0.0265)
Market-to-Book	0.000240	0.000241	0.000251	0.000293	0.000289	0.000353
	(0.000195)	(0.000195)	(0.000198)	(0.000227)	(0.000231)	(0.000237)
Operating Income	-0.0120	-0.0136	-0.0173	-0.154	-0.163	-0.154
	(0.0961)	(0.0963)	(0.0958)	(0.124)	(0.123)	(0.120)
Industry Liquidity	0.234	0.230	0.233	0.421	0.431	0.452
	(0.279)	(0.277)	(0.275)	(0.546)	(0.547)	(0.532)
Herfindahl Index	0.0361	0.0360	0.0432	-0.0158	-0.0149	-0.0461
	(0.0461)	(0.0461)	(0.0465)	(0.0853)	(0.0868)	(0.0804)
Post-CCFs		0.000224	0.0157		0.0861	0.116*
		(0.0339)	(0.0355)		(0.0634)	(0.0650)
IG X Post		-0.0133	-0.0210		-0.0860	-0.110
		(0.0300)	(0.0365)		(0.0594)	(0.0676)
Covid Issuer			0.0583***			0.104***
			(0.0188)			(0.0299)
Covid Issuer X			-0.0786			-0.102
HY X Post			(0.0518)			(0.0989)
Covid Issuer X			-0.0249			0.00947
IG X Post			(0.0359)			(0.0680)
N	3537	3537	3537	1087	1087	1087
Included Ratings	[10, 16]	[10, 16]	[10, 16]	[12, 14]	[12, 14]	[12, 14]

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

5.2 Relationship between Bond Issuance and M&A Activity

While the results of the previous section do not suggest an effect of the CCFs on acquisition activity, we turn to a more microfounded approach of studying actual bond issuance and acquisition activity. This relationship is not really covered in the literature. Therefore, we begin by studying the relationship between the timing of M&A activity and bond issuance in the pre-CCF times (2010-2019). We start with the event study

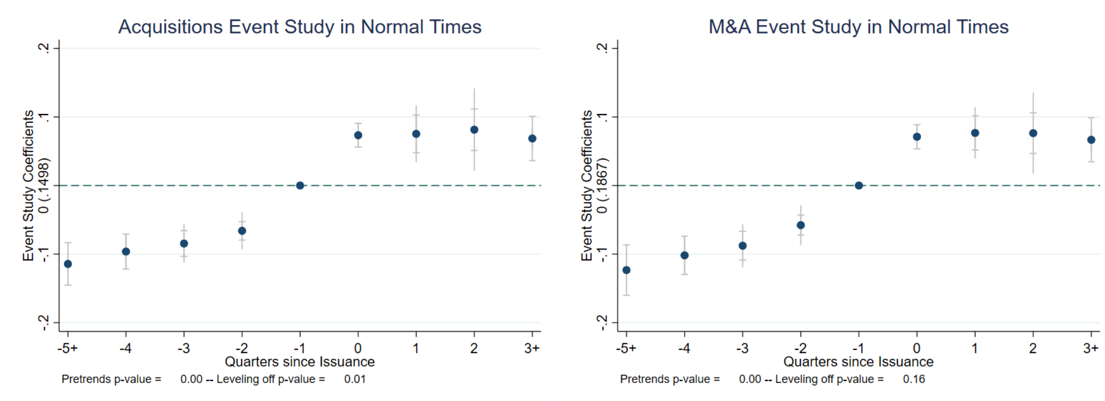
$$Y_{f,q} = \sum_{t=-5}^{4} \beta_t \mathbb{1} Issue_{f,q+t} + \gamma X_{f,q-1} + \alpha_{year} + \alpha_{industry} + \epsilon_{f,q} \tag{5}$$

where $Y_{f,q}$ is either an indicator for firm f announcing an acquisition in quarter q or an indicator for firm f announcing a merger or acquisition in quarter q. We switch to a quarterly level analysis here in order to better understand the timing of bond issuance and acquisition activity. The other controls, X, are the same controls used in Rempel (2020), an analysis we replicate in Appendix Tables 30 and 31: Log(Sales), Market-to-Book, CAPX, Tech, and Biotech. The results of these event studies can be found in Figure 3. We run these event studies only for firms that are both bond issuers and conduct either acquisitions or any type of M&A activity in the time period 2010-2019. The results do not appear different if we do not use this restriction. We also run these event studies separately for IG and HY bond issuers, but there are no significant changes to the results and omit the plotting of these.

The results show that the probability of a firm conducting an acquisition or any M&A deal in a quarter is less in the quarters before a bond issuance, and greater in the 4 quarters following an issuance. As this trend exists when we use only firms that are acquirers and issuers, this suggests that there is a relationship between the timing of a bond issuance and an acquisition.

We can repeat this exercise for the post-CCF period ("Covid times" in the graph) and see if the same relationship between bond issuance and M&A activity appears during those unprecedented times. Figure 4 plots the event study during the post-CCF times using either an indicator for acquisition or any M&A deal as the dependent variable. We start by setting the

Figure 3: Event Study of M&A Activity around a Bond Issuance



indicator Issue equal to one if a firm issued a bond in a post-CCF quarter, where we use the definition of Covid used by Darmouni and Siani (2022) of March 23-June 30, 2020. However, we use the M&A data is from 2019Q1 to 2022Q1. We also test for two different definitions of the post-CCFs time period: 1) 2020Q2-2020Q4, the quarters in which the Fed was buying bonds, and 2) 2020Q2-2021Q3, which captures the corporate bond intervention and the post-period. (We currently only have Mergent FISD data up to 2021Q3). The results are similar regardless of the post period definition used.

The first row of figures is using the full sample of firms. In these graphs, we see similar patterns as in the normal times event study graphs in Figure 3. However, the pre-trends and post-trends are less significant than during normal times. In the second row, we plot the event study only for firms that had an acquisition (left) or any M&A deal (right) after 2020Q2. Here, the pattern disappears. The probability of an acquisition is not significantly different before or after an issuance. This is also true of the final row, which plots the event study only for firms who partook in M&A activity and issued bonds in the post-CCFs period. Our results suggest that the strategy that firms appeared to use in the pre-CCFs period regarding the timing of their M&A activity and bond issuance was not followed in the post-CCF period. This is supported by our finding in Appendix subsection **??** that in pre-CCF times, IG issuers issued bonds when their cash over assets was declining, but the behavior of cash over assets did not predict bond issuance in the post-period. The unprecedented corporate bond intervention and Covid pandemic seems to have led firms to follow new strategies regarding bond issuance and M&A activity.

We next repeat the logistic regressions seen in Appendix Tables 30 and 31 while adding in indicators for the timing of bond issuance. The results are seen in Table 9. We have chosen to use the contemporaneous and three lags of the issue indicator as the event studies in Figure 3 suggest that the probability of M&A activity is significantly higher starting in the same quarter as an issuance, and continuing on for at least 3 quarters. The first column of Table 9 predicts an acquisition for all firms in the pre-CCFs period. The controls from the initial logistic regressions have the same signs and similar magnitudes and significance as in the corresponding column in Appendix Table 30. Further, we find significant and positive coefficients for the contemporaneous issue indicator as well as the first two lags. This suggests that firms issue bonds shortly before announcing an acquisition, most likely to fund the acquisition. In the next two columns, we study the same specification, but only for firms who acquire at some point in the sample, and then only for firms who acquire and issue bonds at some point in the sample. We still find a significantly positive coefficient for the contemporaneous issue indicator. This suggests that firms are more likely to issue bonds in the same quarter as they announce acquisitions. The final three columns repeat this exercise, but using an indicator for any M&A deal instead of an acquisition. The results are similar.

Repeating the same logistic regression for the post-CCF period is more difficult due to the ambiguity in defining the post-period. Darmouni and Siani (2022) use only issuances between March 23-June 30, 2020 to capture Covid issuances due to the strong announcement effect of the CCFs. We hesitate to use this definition as we know that M&A activity slowed in 2020Q2, but picked up at record levels in 2020Q3. We do not want our results to be overinfluenced by this one quarter slump. It is possible that the firms who issued bonds during this time period delayed their M&A activity due to the onset of the pandemic. Further, we believe that there could have been different effects for bonds issued in 2020Q2 versus the following quarters. For

Figure 4: Event Study of M&A Activity around a Bond Issuance Post-CCFs

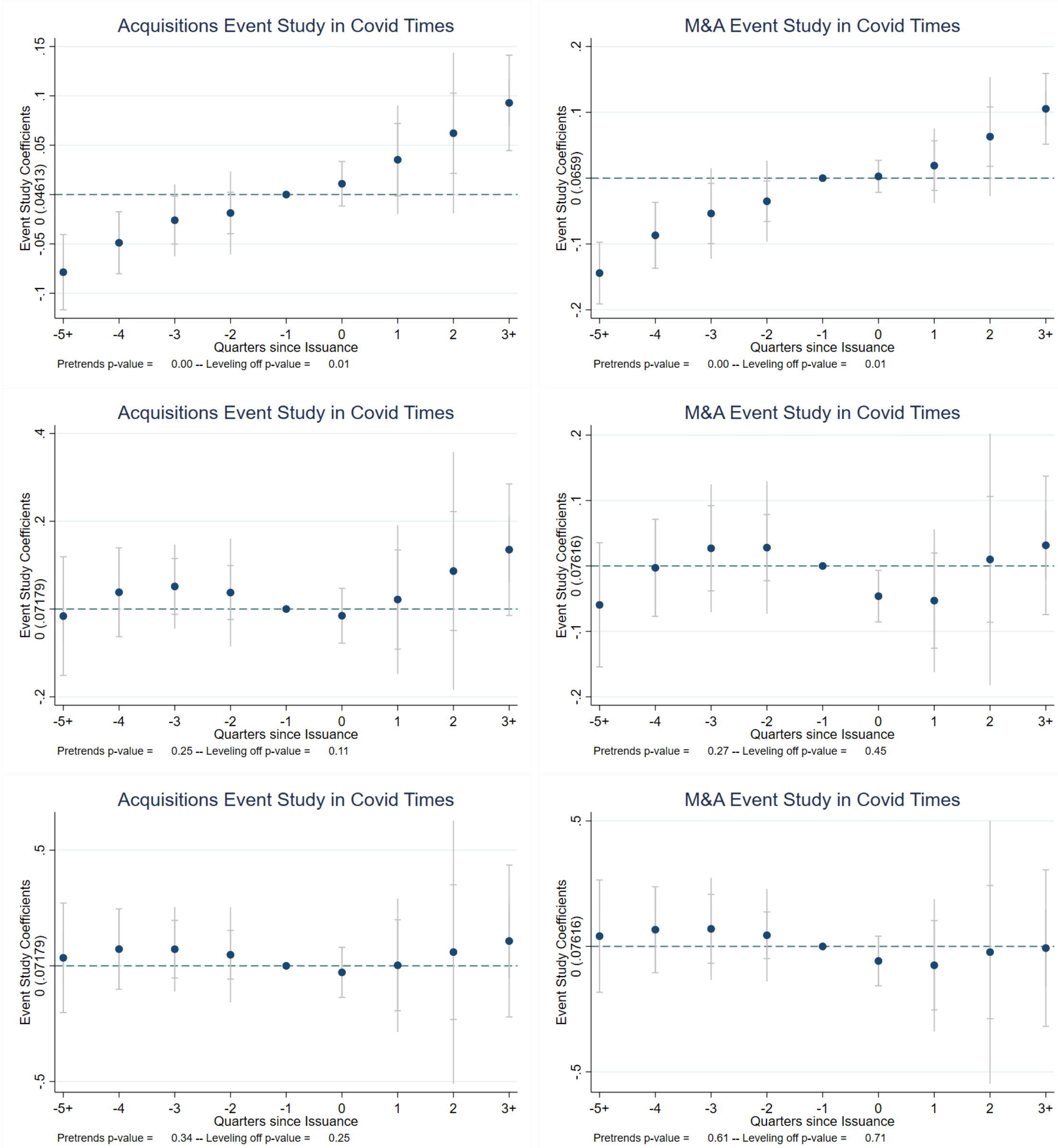


Table 9: Logistic Regression of Acquisitions

	Acquisition	Acquisition	Acquisition	M&A Deal	M&A Deal	M&A Deal
$Issue_t$	0.882***	0.748***	0.730***	0.740***	0.636***	0.552***
	(0.090)	(0.073)	(0.071)	(0.079)	(0.068)	(0.056)
$Issue_{t-1}$	0.257***	0.110	0.068	0.310***	0.191***	0.083
	(0.105)	(0.085)	(0.092)	(0.086)	(0.074)	(0.066)
$Issue_{t-2}$	0.222***	0.090	0.093	0.220***	0.108**	0.016
	(0.100)	(0.089)	(0.072)	(0.056)	(0.043)	(0.045)
$Issue_{t-3}$	0.036	-0.085	-0.088	0.154***	0.051	-0.035
	(0.087)	(0.083)	(0.065)	(0.077)	(0.073)	(0.060)
$\frac{\Delta Cash_{t-1}}{Assets_{t-1}}$	0.842***	0.920**	2.003***	0.719***	0.815***	1.424***
	(0.310)	(0.371)	(0.507)	(0.261)	(0.329)	(0.432)
$Log(Sales)_{t-1}$	0.470***	0.102***	-0.042	0.512***	0.188***	0.194**
	(0.040)	(0.022)	(0.112)	(0.059)	(0.043)	(0.081)
$Market-to-Book_{t-1}$	0.004*	0.004**	0.003	0.005**	0.004**	0.002
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
$CAPX_{t-1}$	-0.001***	-0.000***	-0.000	-0.000***	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tech_{t-1}$	-0.062	0.069	0.497	0.045	0.065	0.283
	(0.235)	(0.203)	(0.615)	(0.171)	(0.103)	(0.366)
$Biotech_{t-1}$	0.649***	0.452***	0.958***	0.334***	0.276***	0.684***
	(0.156)	(0.038)	(0.021)	(0.066)	(0.049)	(0.017)
Constant	-7.060***	-3.200***	-1.421	-6.947***	-3.751***	-3.076***
	(0.312)	(0.177)	(0.988)	(0.452)	(0.329)	(0.770)
N	197,010	77,085	21,984	197,406	99,962	26,463
Sample	All Firms	Acquirers	Acquirer & Issuer	All Firms	M&Aers	M&Aer & Issuer
Time Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

that reason, we include separate indicators for three types of bond issuances in the post-CCFs period: 1) issuances between March 23-June 30, 2020, 2) issuances in 2020Q3 and 2020Q4, and 3) issuances in 2021Q1, 2021Q2, or 2021Q3. The results can be seen in Table 10.

The first column of the table is the specification using all firms from 2020Q2-2022Q1. Using either of the first two definitions of a post-CCFs issue, we find no significant results on any lag of Issue1 or Issue2 in predicting acquisitions. However, using the definition of post-CCFs that includes 2020Q2 to 2021Q3, we find a significantly positive coefficient on $Issue3_t$. These results suggest that firms that issued bonds in 2020 were not issuing to conduct M&A activity, but those who issued in 2021 had returned to their usual behavior of issuing bonds in the same quarter of conducting an acquisition. The other control variables have similar signs and significance as the pre-CCFs period as well.

In the second column, we restrict the sample to only firms who announce an acquisition from 2020Q2 to 2022Q1. The contemporaneous indicator for the third definition of a post-CCFs issue has a positive coefficient once again, but it is less significant. Interestingly, the two lagged version of this indicator has a significantly negative coefficient, suggesting that earlier issuances suggested a decline in acquisitions. The more important coefficient however is the one for the contemporaneous issue using the first definition of post-CCFs issuance. Given that most of these post-CCFs issuances occurred in 2020Q2, we can interpret this to mean that firms that issued in 2020Q2 were less likely to announce an acquisition in 2020Q2 than firms that did not issue in that quarter. This is expected given that 2020Q2 was a very low quarter for M&A activity.

In the final column, we restrict the sample to only firms who announce an acquisition from 2020Q2 to 2022Q1 and issue a bond between 2020Q1 to 2021Q3. We once again find a significantly negative coefficient on the contemporaneous issue indicator using the first definition of post-CCFs issuance. Because we restricted the sample further, we can interpret this as meaning that firms who issued bonds in 2020Q2 were less likely to announce an acquisition in 2020Q2 than firms who did not issue a bond in that period. This is contrary to our results that pre-

CCFs issuing a bond and announcing an acquisition are positively related. We also find that the indicator for issuance using the third post-CCFs issuance definition is significantly positive. This suggests that the relationship between bond issuance and acquisitions from pre-CCFs has returned starting in 2021. Finally, the coefficient on the change in cash is not significant. This is contrary to the pre-period finding that firms announce an acquisition a quarter after having a large change in cash. This does not appear to be true for firms acquiring in the post-CCFs time. We find similar results when we use all M&A deals as the dependent variable instead of only acquisitions, and therefore, omit the results.

While the event study graphs and Tables 9 and 10 suggest that the relationship between bond issuance and M&A activity changed from the pre- to post-period, we can further formalize this idea by conducting a differences-in-differences analysis. This specification will be

$$\begin{aligned} Acquisition_{f,q} = \beta_1 Issue_q + \beta_2 \text{Post-CCFs}_q + \beta_3 \text{Post-CCFs}^*_q Issue_q \\ + \gamma X_{f,q-1} + \alpha_{year} + \alpha_{industry} + \epsilon_{f,q} \end{aligned} \tag{6}$$

where X will consist of the other controls variables we have included in previous logistic regressions of acquisitions. We repeat the same specification using the M&A indicator as the dependent variable instead of the Acquisition indicator. Here, we define Post-CCFs to be 2020Q2 onward. This matches the third definition of post-CCFs in the previous analysis. We do so as we believe this is the most conservative of our possible estimates. We already saw in Table 10 that the relationship between bond issuance and acquisitions appeared to have flipped or became non-existent for issuances in 2020, but resorted back to trend in 2021. Therefore, including all of these issuances will show which effect is quantitatively more important.

The results can be found in Table 11. The key variable to study is the interaction between the issue indicator and the post-CCFs intervention indicator. In all regressions, regardless of the sample used, this interaction is significantly negative. This suggests that firms are less likely

Table 10: Logistic Regression of Acquisitions with Bond Issuance Post-CCFs

	Acquisition	Acquisition	Acquisition
$Issue1_t$	-0.683	-1.216**	-1.172*
	(0.473)	(0.551)	(0.648)
$Issue1_{t-1}$	0.176	0.193	0.408
	(0.341)	(0.396)	(0.526)
$Issue1_{t-2}$	0.296	0.407	0.621
	(0.275)	(0.293)	(0.456)
$Issue1_{t-3}$	-0.186	-0.209	-0.0294
	(0.295)	(0.305)	(0.358)
$Issue2_t$	-0.270	-0.0844	-0.260
	(0.452)	(0.483)	(0.517)
$Issue2_{t-1}$	0.143	0.433	0.200
	(0.450)	(0.524)	(0.542)
$Issue2_{t-2}$	0.353	0.585	0.394
	(0.378)	(0.393)	(0.402)
$Issue2_{t-3}$	0.169	0.340	0.142
	(0.433)	(0.465)	(0.514)
$Issue3_t$	0.815***	0.474*	0.613**
	(0.290)	(0.284)	(0.296)
$Issue3_{t-1}$	0.377	-0.106	0.0319
	(0.353)	(0.412)	(0.421)
$Issue3_{t-2}$	-0.0488	-0.546*	-0.426
	(0.307)	(0.329)	(0.334)
$Issue3_{t-3}$	0.135	-0.317	-0.140
	(0.413)	(0.462)	(0.478)
$\frac{\Delta Cash_{t-1}}{Assets_{t-1}}$	0.778**	1.126***	0.262
	(0.332)	(0.295)	(1.456)
$Log(Sales)_{t-1}$	0.357***	0.0356*	-0.0872
	(0.0386)	(0.0198)	(0.123)
$Market-to-Book_{t-1}$	0.00446**	0.00166	0.000325
	(0.00206)	(0.00212)	(0.00680)
$CAPX_{t-1}$	0.0000264	-0.0000997	-0.00000267
	(0.000229)	(0.000137)	(0.000262)
$Tech_{t-1}$	-0.154	0.0904	-0.620***
	(0.154)	(0.0704)	(0.0854)
$Biotech_{t-1}$	0.601***	-0.0345	0.508***
	(0.0605)	(0.0542)	(0.0697)
Constant	-6.583***	-1.958***	-0.965
	(0.313)	(0.138)	(1.072)
N	48,464	6,545	1,027
Sample	All Firms	Acquirers	Acquirer & Issuer
Time Period	2020Q2-2022Q1	2020Q2-2022Q1	2020Q2-2022Q1

Table 11: Change in Relationship between M&A and Bond Issuance

$Issue_t$	0.962***	0.765***	0.730***	0.866***	0.694***	0.558***
	(0.109)	(0.0845)	(0.0720)	(0.107)	(0.0786)	(0.0587)
$Post-CCFs_t$	-0.0821	-0.0980	-0.0312	-0.153	-0.175	-0.100
	(0.119)	(0.125)	(0.186)	(0.120)	(0.118)	(0.161)
$Issue\#Post-CCFs_t$	-0.429**	-0.417**	-0.387**	-0.530**	-0.482**	-0.354**
	(0.204)	(0.207)	(0.187)	(0.209)	(0.199)	(0.178)
$\frac{\Delta Cash_{t-1}}{Assets_{t-1}}$	0.841***	0.925***	1.465***	0.697***	0.788***	1.161***
	(0.304)	(0.330)	(0.432)	(0.249)	(0.299)	(0.426)
$Log(Sales)_{t-1}$	0.476***	0.110***	0.0376	0.478***	0.167***	0.248***
	(0.0443)	(0.0223)	(0.0849)	(0.0841)	(0.0509)	(0.0630)
$Market-to-Book_{t-1}$	0.00611***	0.00518***	0.00179	0.00669***	0.00534***	0.00277*
	(0.00150)	(0.00148)	(0.00191)	(0.00128)	(0.00128)	(0.00150)
$CAPX_{t-1}$	-0.000426***	-0.000279**	-0.000177	-0.000403**	-0.000145	-0.000165*
	(0.000163)	(0.000109)	(0.000136)	(0.000188)	(0.000101)	(0.0000927)
$Tech_{t-1}$	-0.0449	0.176	0.361	0.120	0.167	0.284
	(0.255)	(0.207)	(0.552)	(0.198)	(0.107)	(0.358)
$Biotech_{t-1}$	0.653***	0.429***	0.917***	0.305***	0.205**	0.657***
	(0.113)	(0.0528)	(0.0432)	(0.0944)	(0.0815)	(0.0124)
$Constant$	-7.265***	-3.507***	-2.223***	-6.720***	-3.678***	-3.829***
	(0.347)	(0.179)	(0.791)	(0.645)	(0.402)	(0.620)
N	314,810	112,537	33,839	315,253	141,357	39,200
Sample	All Firms	Acquirers	Acquirer & Issuer	All Firms	M&Aers	M&Aer & Issuer
Time Period	2010Q1-2022Q1	2010Q1-2022Q1	2010Q1-2022Q1	2010Q1-2022Q1	2010Q1-2022Q1	2010Q1-2022Q1

to engage in any M&A activity following a bond issuance in the post-period than in the pre-period.

6 Discussion of Empirical Results

The key innovation of our paper is to study the relationship between bond issuance and M&A activity. We first show that there is a statistically significant positive relationship between bond issuance and acquisition activity from 2010-2019. From the event studies in Figure 3, we see that the probability of announcing an acquisition in a quarter increases starting in the quarter of a bond issuance. This is further supported by the regression results in Table 9. Even when restricting the sample to only firms who both acquisitions and issue bonds at some point in 2010-2019, we still find a significant coefficient for a bond issuance in that quarter. This confirms our hypothesis that the corporate bond market plays a role in the merger & acquisition market.

We next study how this relationship may have changed due to the Fed's intervention in the corporate bond market. We first classified post-CCFs issuances into three categories: those affected by the Fed announcement, or from March 23-June 30, 2020, those during the time the Fed was buying bonds from 2020Q2-2020Q4, and those in the post-intervention time period from 2020Q2-2021Q3. Using different indicators for each type of issuance, we find that firms who issued in 2020Q2 were actually less likely to acquire in the same period and there were insignificant effects for acquisitions in later quarters. In fact, the only issue indicator that maintained the same sign and significance as in the pre-period was the contemporaneous indicator using the third definition of post-period issuance. This suggests that the relationship between bond issuance and M&A activity was broken during 2020, but may have been restored in 2021.

We further also investigate this change in the relationship by conducting a differences-in-differences analysis. We find a significantly negative relationship between post-CCF intervention issuances and M&A activity, suggesting that firms were less likely to issue and acquire in the same period. This result is driven by the large number of issuances in the first two quarters of 2020 but a lack of acquisitions in those quarters.

In the next section, we try to explain this change in the relationship between bond issuance and acquisition activity in the presence of the macroeconomic shock from Covid and the Fed's intervention in the corporate bond market. We propose that the data may not suggest an effect due to either confounding forces from other government support or macroeconomic conditions or that the intervention may only affect acquisition likelihood under certain firm conditions. To test these, we build a stylized model of acquirer and target's external financing and acquisition decisions and replicate both the Covid shock and the CCFs.

7 Model

Due to the unique economic and financial conditions at the start of the Covid pandemic and the following year, it is difficult to disentangle the effects of the Fed's intervention in the corporate bond market on acquisition activity from other channels in the data. For this reason, we build a stylized model to examine the role of a government intervention in credit markets on the acquisition market. The government intervention relaxes firms' borrowing constraints, which can play a role in the likelihood of cash acquisitions due to the availability of funding at such a time.

7.1 Baseline Model (No Mergers)

The model is based on that of Hennessy and Whited (2005) with additions and changes to capture the acquisition market and the impacts of the CCFs. Let us first describe the model in which there is no acquisition market. The model consists of two firms: an acquirer a and a target t. The acquirer has access to the bond market while the target does not. There are two beginning periods followed by an infinite horizon problem. In period 1, both firms make their initial capital investments, k. Firms invest this capital into a one-period risky project. In period 2, the project produces output $Az(s)k^{\alpha}$, in which A is an aggregate productivity and $z(s)$ is an idiosyncratic, state-dependent productivity. The shock is i.i.d., but differs for the acquirer and target such that the acquirer's shock distribution stochastically dominates that of the target. In period 1, the acquirer also chooses a quantity of one-period debt, p. The debt is structured as a discount bond such that the firm receives $\frac{p}{1+r}$ today to repay p tomorrow. Borrowing has a tax advantage. Firms pay corporate taxes τ_c on the proceeds of the project but are able to deduct depreciation and interest payments. Therefore, the tax function is $g(z(s), k, p) = \max\{0, Az(s)k^{\alpha} - \delta k - \frac{rp}{1+r}\}$. The acquirer is able to borrow at the risk-free rate r due to a borrowing constraint such that the acquirer must be able to pay back all of the debt, even with the lowest realization of the $z(s)$ shock. The firm can sell off its undepreciated capital to assist in paying the debt but only receives a firesale value of the capital, γ. Therefore, the borrowing constraint is $p \leq Az(\underline{s})k^{\alpha} + s\gamma(1-\delta)k - \tau_c g(z(\underline{s}), k, p)$. If firms have negative cash flow this period, they must raise equity in order to pay these outflows. Equity issuance is subject to a flotation cost, λ. If cash flow is positive, however, it is paid as a dividend to shareholders, which is subject to a dividend tax τ_d. Finally, the firms are held by shareholders who would be taxed at the individual tax rate of τ_i if they kept their funds in their individual accounts rather than in the firm. Therefore, the effective discount factor for the shareholders is $\frac{1}{1+r(1-\tau_i)}$.

The acquirer's problem in period 1 can be written as

$$V_{a1} = \max_{k_a,p_a}(1+\phi_i\lambda - \phi_d\tau_d)(-k_a + \frac{p_a}{1+r}) + \frac{1}{1+r(1-\tau_i)}\mathop{\mathbb{E}}_{s'\in S}(\pi_s V_{a2}(k_a,p_a,s'))$$

$$\text{s.t.}$$

$$p_a \leq Az_a(\underline{s})k_a^{\alpha} + \gamma(1-\delta)k - \tau_c g(z_a(\underline{s}),k_a,p_a) \tag{7}$$

$$\phi_i = \{-k_a + \frac{p_a}{1+r} < 0\}$$

$$\phi_d = \{-k_a + \frac{p_a}{1+r} \geq 0\}.$$

ϕ_i and ϕ_d are indicators for if the firm issues equity or dividends, respectively. No issuance of either type is treated as a dividend with value of \$0. The target's problem is similar, but does not include the choice to borrow

$$V_{t1} = \max_{k_t}(1+\lambda)(-k_t) + \frac{1}{1+r(1-\tau_i)}\mathop{\mathbb{E}}_{s'\in S}(\pi_s V_{t2}(k_t,s')). \tag{8}$$

Without borrowing, it is clear that the target will be issuing equity in the initial period to cover its investment.

In period 2, both firms realize the returns on their projects. They each pay taxes and choose new capital investment. The acquirer must pay back its debt and can choose new borrowing. The acquirer problem is then

$$V_{a2}(k_a, p_a, s) = \max_{k'_a, p'_a}(1 + \phi_i\lambda - \phi_d\tau_d)(Az_a(s)k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r})$$
$$+\frac{1}{1+r(1-\tau_i)}\mathop{\mathbb{E}}_{s'\in S}(\pi_s V_{ai}(k'_a, p'_a, s'))$$
$$\text{s.t.}$$
$$p'_a \leq Az_a(\underline{s})k'^\alpha_a + \gamma(1-\delta)k'_a - \tau_c g(z_a(\underline{s}), k'_a, p'_a)$$
$$\phi_i = \{Az_a k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r} < 0\}$$
$$\phi_d = \{Az_a k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r} \geq 0\}. \tag{9}$$

Similarly, the target's problem is

$$V_{t2}(k_t, s) = \max_{k'_t}(1 + \phi_i\lambda - \phi_d\tau_d)(Az_t(s)k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta)k_t - k'_t$$
$$+\frac{1}{1+r(1-\tau_i)}\mathop{\mathbb{E}}_{s'\in S}(\pi_s V_{ti}(k'_t, s'))$$
$$\text{s.t.} \tag{10}$$
$$\phi_i = \{Az_t(s)k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta)k_t - k'_t < 0\}$$
$$\phi_d = \{Az_t(s)k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta)k_t - k'_t \geq 0\}.$$

In the model without mergers, the problem for every period after period 2 takes the same form as that of the second period, or

$$V_{ai}(k_a, p_a, s) = \max_{k'_a, p'_a}(1 + \phi_i\lambda - \phi_d\tau_d)(Az_a(s)k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r})$$
$$+\frac{1}{1+r(1-\tau_i)}\mathop{\mathbb{E}}_{s'\in S}(\pi_s V_{ai}(k'_a, p'_a, s'))$$
$$\text{s.t.}$$
$$p'_a \leq Az_a(\underline{s})k'^\alpha_a + \gamma(1-\delta)k'_a - \tau_c g(z_a(\bar{s}), k'_a, p'_a)$$
$$\phi_i = \{Az_a k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r} < 0\}$$
$$\phi_d = \{Az_a k_a^\alpha - \tau_c g(z_a(s), k_a, p_a) - p_a + (1-\delta)k_a - k'_a + \frac{p'_a}{1+r} \geq 0\} \tag{11}$$

and

$$
\begin{aligned}
V_{ti}(k_t, s) = \max_{k_t'} & (1 + \phi_i \lambda - \phi_d \tau_d)(A z_t(s) k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta) k_t) - k_t' \\
& + \frac{1}{1 + r(1-\tau_i)} \mathop{\mathbb{E}}_{s' \in S} (\pi_s V_{ti}(k_t', s')) \\
& \text{s.t.} \\
\phi_i &= \{A z_t(s) k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta) k_t - k_t' < 0\} \\
\phi_d &= \{A z_t(s) k_t^\alpha - \tau_c g(z_t(s), k_t) + (1-\delta) k_t - k_t' \geq 0\}.
\end{aligned}
\tag{12}
$$

Example model parameters can be found in Table 12. Using these parameters, we solve for the capital, debt, and value of the target and acquirer, as described in Table 13. We find that the acquirer increases its capital investment when the project generates the higher return $z(\bar{s})$, due to the relaxed equity constraint associated with earning cash from the previous investment. Further, the acquirer chooses a lower value of capital after the project generates the lower return $z(\underline{s})$. The target also increases its capital upon realizing the higher return, but chooses the same level of capital if it receives the lower return. The target actually has more cash on hand after receiving the lower return than the acquirer does because the acquirer chose to borrow up to its borrowing constraint and therefore must use all cash proceeds to repay its debt. Without being able to borrow, the target does not face this issue. The ability to borrow is very useful though, as seen by the substantial difference in V_{a1} and V_{t1}.

7.2 Merger Model

In this section, we introduce mergers into the model. All mergers are modeled as cash acquisitions. When the acquirer and the target choose to merge, the following happen:

1. The acquirer pays the target a price P and receives the target's undepreciated capital

Table 12: Model Parameters

Parameter	Description	Value
α	Capital Return	0.551
δ	Depreciation Rate	0.145
λ	Equity Issuance Cost	0.028
τ_i	Investor Tax Rate	0.296
τ_d	Dividend Tax Rate	0.12
τ_c	Corporate Tax Rate	0.35
r	Risk Free Rate	0.025
A	Aggregate Productivity	1.0
$z_a(\bar{s})$	Acquirer High Productivity	0.95
$z_a(\underline{s})$	Acquirer Low Productivity	0.425
$z_t(\bar{s})$	Target High Productivity	0.75
$z_t(\underline{s})$	Target Low Productivity	0.375
$\pi(\bar{s})$	Probability of High Productivity	0.95
η	Target Bargaining Power	0.5
σ	Merger Gains	0.55
c_M	Fixed Cost of Merging	2.0

Table 13: Example Results in No Merger Model

Variable	Value
V_{a1}	50.7922
k_a	4.898
p_a	2.980
$k'_a(\bar{s})$	7.3469
$p'_a(\bar{s})$	4.3059
$k'_a(\underline{s})$	6.1224
$p'_a(\underline{s})$	3.4666
V_{t1}	29.5038
k_t	3.6735
$k'_t(\bar{s})$	4.898
$k'_t(\underline{s})$	3.6735

$(1-\delta)k_t$. The acquirer must also pay a fixed cost c_M, representing administrative, legal, and other fees associated with merging.

2. The target exits with final value of any remaining cash flow and the price P, all subject to dividend taxes.

3. The acquirer makes its new capital and debt choices.

4. In the next period, the idiosyncratic productivity of the merged firm is $z_m(\bar{s}) = (z_a(\bar{s}) + z_t(\bar{s}))^\sigma$ with probability $\pi(\bar{s})$ and $z_m(\underline{s}) = (z_a(\underline{s}) + z_t(\underline{s}))^\sigma$ with probability $1-\pi(\bar{s})$.

5. The acquirer continues in the infinite horizon problem.

The price of the merger is set by Nash bargaining, in which the target's bargaining power parameter is η. Essentially, both the acquirer and target need to earn at least the value they would receive from not merging and split the additional gains, leading to the price

$$
\begin{aligned}
P(k_a, p_a, s_a, k_t, s_t) = (1-\delta)k_t + &\frac{1}{1+r(1-\tau_i)}[\pi(\bar{s})V_{ti}(k_t', \bar{s}) + (1-\pi(\bar{s}))V_{ti}(k_t', \underline{s})] \\
&+\frac{\eta}{1+r(1-\tau_i)}[\pi(\bar{s})(V_{mi}(k_m', p_m', \bar{s}) - V_{ai}(k_a', p_a', \bar{s}) - V_{ti}(k_t', \bar{s})) \\
&+(1-\pi(\bar{s}))(V_{mi}(k_m', p_m', \underline{s}) - V_{ai}(k_a', p_a', \underline{s}) - V_{ti}(k_t', \underline{s})) - c_M]
\end{aligned}
\tag{13}
$$

where the choices of $k_t', k_m', k_a', p_m', p_a'$ are all depend on the set $(k_a, p_a, s_a, k_t, s_t)$ including the states $\bar{s}$ or $\underline{s}$ for the acquirer s_a and target s_t. The first line of Equation 13 represents the value of continuing as a standalone firm for the target. The target will only agree to the merger if they receive at least this amount of cash. The next two lines represent the target's share of the gains from the merger, which must include the fixed cost of merging c_M the acquirer will pay. The acquirer pays this price in cash, i.e. it must use its cash flow, debt, and equity issuance to pay this price in period 2 if it would like to merge and may be subject to large equity issuance costs to complete the merger.

The value of the merged firm in the remaining infinite horizon problem is now

$$V_{mi}(k_m, p_m, s) = \max_{k'_m, p'_m} (1 + \phi_i \lambda - \phi_d \tau_d)(Az_m(s)k_m^\alpha - \tau_c g(z_m(s), k_m, p_m) - p_m + (1-\delta)k_m - k'_m + \frac{p'_m}{1+r})$$

$$+ \frac{1}{1 + r(1-\tau_i)} \mathop{\mathbb{E}}_{s' \in S} (\pi_s V_{mi}(k'_m, p'_m, s'))$$

s.t.

$$\begin{aligned}
p'_m &\leq Az_m(\underline{s}){k'}_m^\alpha - \tau_c g(z_m(\underline{s}), k'_m, p'_m) + \gamma(1-\delta)k'_m \\
\phi_i &= \{Az_m(s)k_m^\alpha - \tau_c g(z_m(s), k_m, p_m) - p_m + (1-\delta)k_m - k'_m + \frac{p'_m}{1+r} < 0\} \\
\phi_d &= \{Az_m(s)k_m^\alpha - \tau_c g(z_m(s), k_m, p_m) - p_m + (1-\delta)k_m - k'_m + \frac{p'_m}{1+r} \geq 0\}.
\end{aligned} \tag{14}$$

If the acquirer and target match at the start of the second period, the acquirer's problem is

$$V_{a2}^m(k_a, p_a, s_a, k_t, s_t) = \max\{V_{a2}(k_a, p_a, s_a), \max_{k'_m, p'_m} (1 + \phi_i \lambda - \phi_d \tau_d)(Az_a(s_a)k_a^\alpha - \tau_c g(z_a(s_a), k_a, p_a) - p_a$$

$$+ (1-\delta)k_a + (1-\delta)k_t - k'_m + \frac{p'_m}{1+r} - P(k_a, p_a, s_a, k_t, s_t) - c_M)$$

$$+ \frac{1}{1 + r(1-\tau_i)} \mathop{\mathbb{E}}_{s' \in S} (\pi_s V_{mi}(k'_m, p'_m, s'))\}$$

s.t.

$$\begin{aligned}
p'_m &\leq Az_m(\underline{s}){k'}_m^\alpha - \tau_c g(z_m(\underline{s}), k'_m, p'_m) + \gamma(1-\delta)k'_m \\
\phi_i &= \{Az_a(s_a)k_a^\alpha - \tau_c g(z_a(s_a), k_a, p_a) - p_a \\
&\quad + (1-\delta)k_a + (1-\delta)k_t - k'_m + \frac{p'_m}{1+r} - P(k_a, p_a, s_a, k_t, s_t) - c_M < 0\} \\
\phi_d &= \{Az_a(s_a)k_a^\alpha - \tau_c g(z_a(s_a), k_a, p_a) - p_a \\
&\quad + (1-\delta)k_a + (1-\delta)k_t - k'_m + \frac{p'_m}{1+r} - P(k_a, p_a, s_a, k_t, s_t) - c_M \geq 0\}.
\end{aligned} \tag{15}$$

The value of the target is simply

$$V_{t2}^{m}(k_a, p_a, s_a, k_t, s_t) = \max\{V_{t2}(k_t, s), (1 + \phi_i\lambda - \phi_d\tau_d)(Az_t(s_t)k_t^{\alpha} - \tau_c g(z_t(s_t), k_t) + P(k_a, p_a, s_a, k_t, s_t))\}$$

$$\text{s.t.}$$

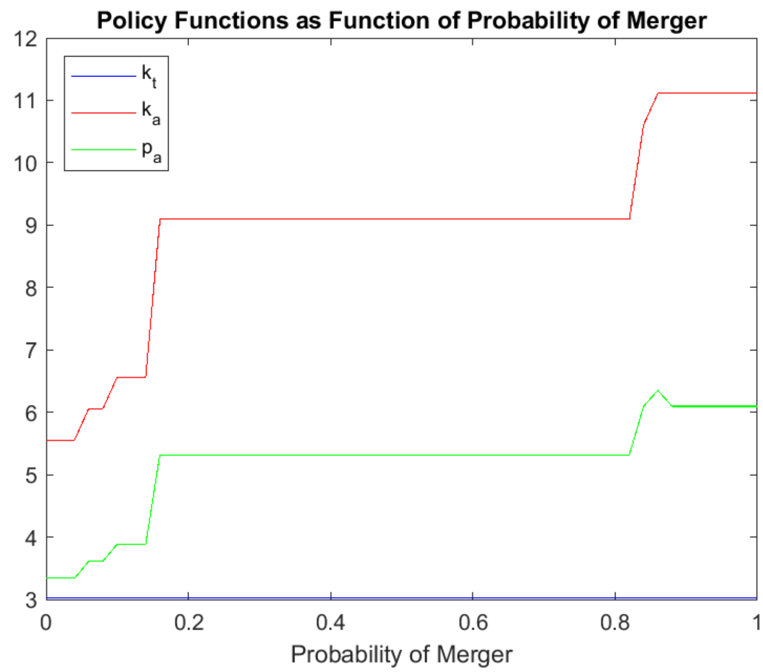
$$\phi_i = \{Az_t(s_t)k_t^{\alpha} - \tau_c g(z_t(s_t), k_t) + P(k_a, p_a, s_a, k_t, s_t) < 0\}$$

$$\phi_d = \{Az_t(s_t)k_t^{\alpha} - \tau_c g(z_t(s_t), k_t) + P(k_a, p_a, s_a, k_t, s_t)\} \geq 0\}. \tag{16}$$

To solve the first period problems of the acquirer and target, we must make assumptions about their expectations of merging. We assume that the probability of merging is π_M and that the acquirer and target have perfect insight into the choices of the other party. This is because the acquirer knows the parameters of the target's problem and therefore can infer the decisions it would make, and vice versa. In practicality, this would map to the acquirer and target studying financial information about the other prior to merging. However, these assumptions do not guarantee a unique equilibrium. For a given π_M, there may be multiple (k_t, k_a, p_a) combinations that are consistent with value function optimization. In this case, we assume that the acquirer has a form of first mover advantage and will always choose the (k_a, p_a) that maximizes their own utility. The target is aware of this and will choose the corresponding equilibrium policy choice. The acquirer's first period problem is then

$$\begin{gathered} V_{a1} = \max_{k_a, p_a}(1 + \phi_i\lambda - \phi_d\tau_d)(-k_a + \frac{p_a}{1+r}) \\ +\frac{1}{1 + r(1 - \tau_i)}[(1 - \pi_M)\mathop{\mathbb{E}}_{s' \in S}(V_{a2}(k_a, p_a, s')) \\ +\pi_M \mathop{\mathbb{E}}_{s' \in S}(V_{a2}^{m}(k_a, p_a, s', k_t, s_t))] \\ \text{s.t.} \\ p_a \leq Az_a(\underline{s})k_a^{\alpha} - \tau_c g(z_a(\underline{s}), k_a, p_a) + \gamma(1 - \delta)k_a \\ \phi_i = \{-k_a + \frac{p_a}{1+r} < 0\} \\ \phi_d = \{-k_a + \frac{p_a}{1+r} \geq 0\} \end{gathered} \tag{17}$$

Figure 5: Initial Period Policy Functions - Target Choice Constant



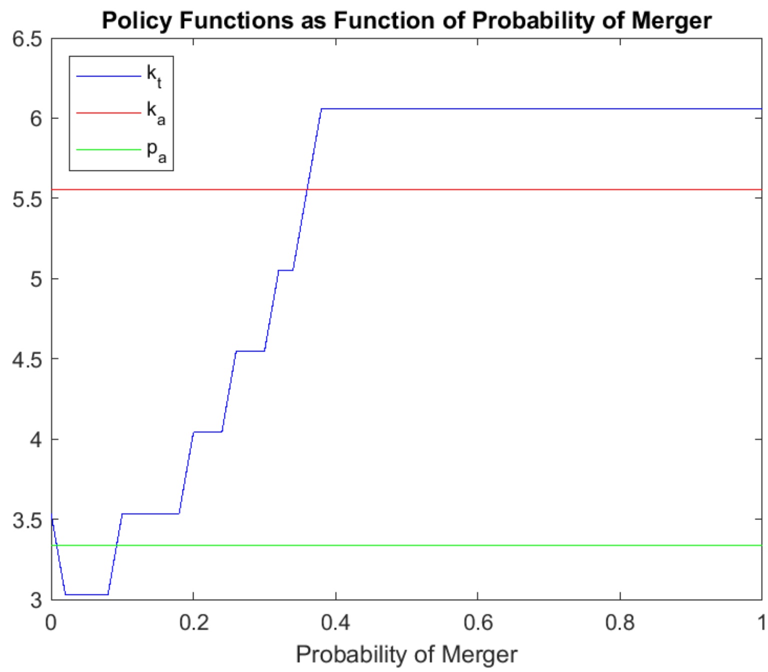
and the target's

$$V_{t1} = \max_{k_t} -(1+\lambda)k_t + \frac{1}{1+r(1-\tau_i)}[(1-\pi_M)\mathop{\mathbb{E}}_{s'\in S}(V_{t2}(k_t,s')) \\ +\pi_M \mathop{\mathbb{E}}_{s'\in S}(V^m_{a2}(k_a,p_a,s_a,k_t,s'))]. \tag{18}$$

We once again use the parameters in Table 12 to solve for the capital and debt choices of the acquirer and target in each period. In Figure 5, we plot the acquirer's initial period capital and borrowing decisions as a function of the probability of merger while holding the target's capital decision constant at the value the target chooses when the probability of merger is zero. This plots highlights how the acquirer alone reacts to the greater probability of merger. Figure 6 plots the target's decisions while keeping the acquirer's decisions constant while Figure 9 plots the true equilibrium in which each firm will optimally adjust to the decisions of the other firm.

Focusing solely on the acquirer's choices in Figure 5, the acquirer increases its capital as the probability of merger increases. Further, the acquirer slightly decreases its leverage (debt over capital) when the probability of merger passes 85%. There are two effects from a merger

Figure 6: Initial Period Policy Functions - Acquirer Choice Constant



that encourage this behavior. First, an increase in the probability of the merger increases the continuation value of the acquirer as the value of the merged firm is greater than the value of the acquirer alone. An increase in continuation value allows the firm to have a lower cash flow (or higher outflow of cash) in the first period, which occurs when the acquirer chooses more capital and/or less borrowing. Second, paying for the merger in cash can incur large equity issuance costs for the firm in the second period. Therefore, investing in more capital today and decreasing borrowing today both increase the firm's remaining cash after the returns of the project are realized and the debt is repaid next period. This cash can then be used to help pay for the merger.

In Figure 6, we see that the target also increases its capital when the probability of merger increases. The increased value of the second period allows the target to better stomach the high equity issuance cost in the first period. The corresponding value functions for Figures 5 and 6 can be seen in Figures 7 and 8. Value functions are strictly increasing in the probability of merging.

Figure 7: Initial Period Value Functions - Target Choice Constant

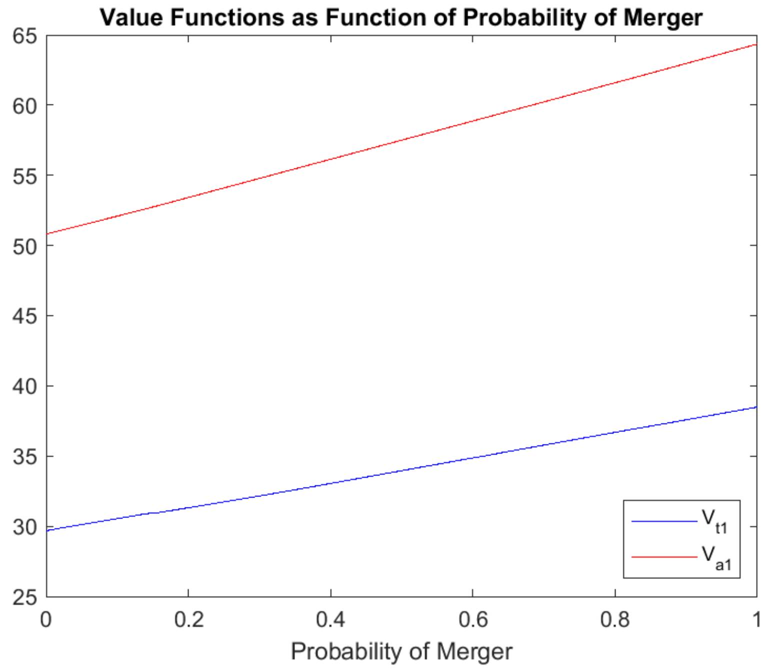


Figure 9 plots the equilibrium policy functions and value functions in the initial period for both firms. The equilibrium responses are approximately the same as the firms' choices when the other firm's choice is held constant. This is due to each firm absorbing a share of gains from the merger and therefore each benefiting from making the optimal decision. The value functions of the two firms can be found in the right plot. They are still increasing with the probability of merger. Figures 10 and 11 plot the second period choices and value functions of the acquirer and target, keeping the choice of the other one fixed. These choices are a function of the probability of merger because they depend on the capital and borrowing decisions from the initial period, which depended on the probability of merger. As seen in the left plot of Figure 10, the acquirer increases its capital as the probability of merger increases. When the firm merges, however, it always chooses the same level of capital and debt, despite the capital and debt that were brought into the period. This is because the cost of the merger is quite substantial for the acquirer and they must pay large equity issuance costs to afford it. As the acquirer generally borrows up to its borrowing constraint, $-k_m' + \frac{p_m'}{1+r}$ is decreasing in k_m'. Therefore, the acquirer

Figure 8: Initial Period Value Functions - Acquirer Choice Constant

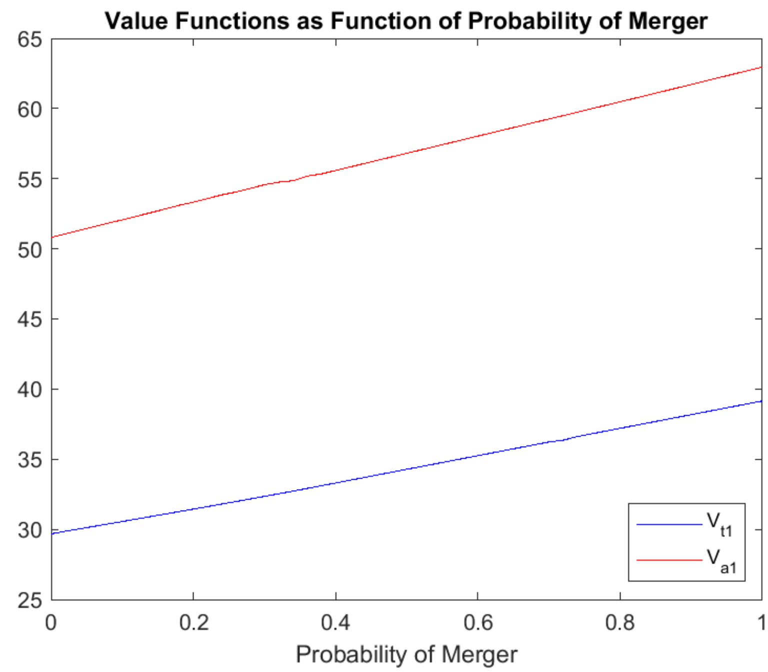


Figure 9: Initial Period Policy and Value Functions

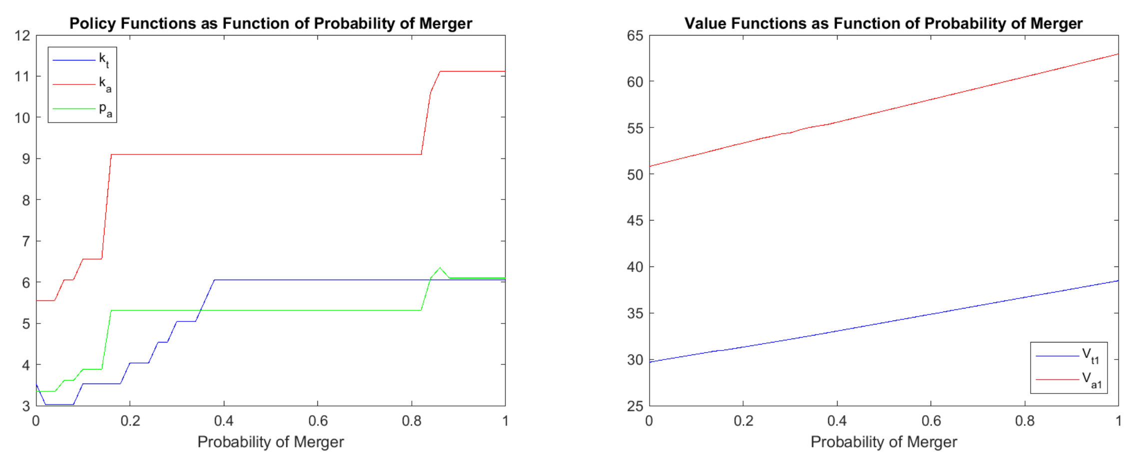


Figure 10: Second Period Functions - Target Choice Constant

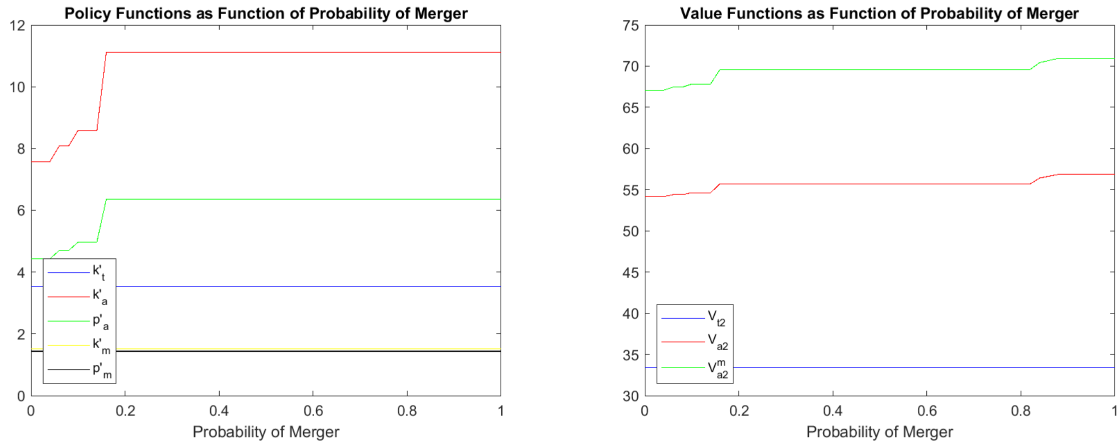
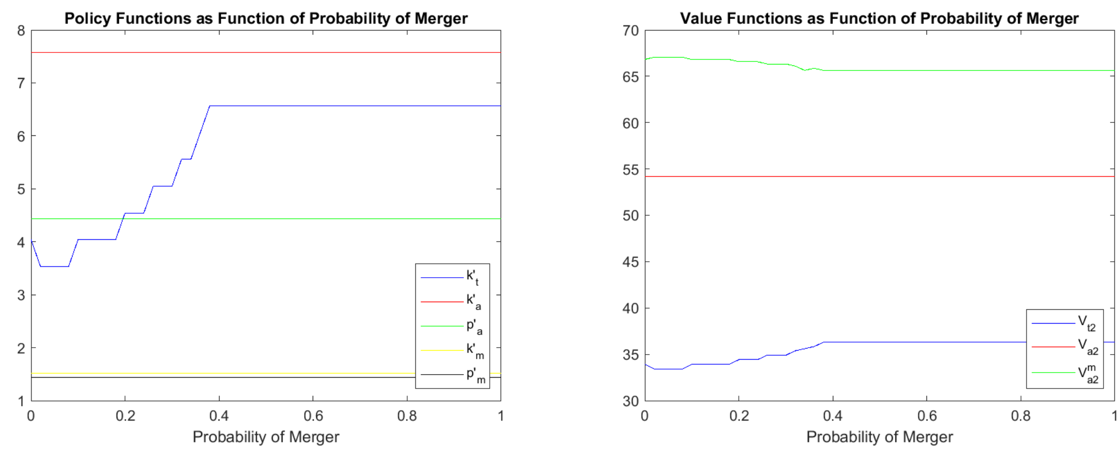


Figure 11: Second Period Functions - Acquirer Choice Constant



chooses to minimize this expenditure in this period in order to focus on paying the price of the merger itself. In the following period, the merged firm greatly increases its capital investment.

In the left plot of Figure 11, we see the second period capital decisions of the target and the capital and debt decisions of the merged firm, holding the initial choices of the acquirer constant. The standalone target increases its capital investment as its initial period capital increases. The merged firm once again does not change its capital and debt investment. An increase in the capital investment of the target actually increases the value of the target and therefore the price that the acquirer must pay for the target. This binds the merged firm's borrowing contraint even more and they need to keep capital investment low in order to finance it.

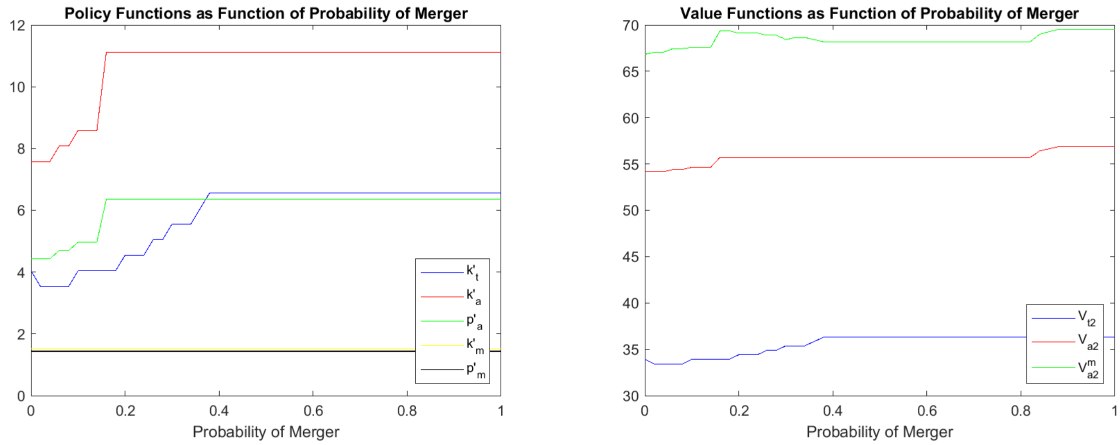
Figures 10 and 11 also show the value functions associated with the second period for the target, acquirer, and merged firm, first when the target's choices are kept constant and then when the acquirer's are. The acquirer's and merged firm's values increase with the probability of merger when the target's choices (and thus value) are held constant. However, only the target's value increases when the acquirer's choices are held constant. The value of the merged firm decreases initially. This is due to the increase in the target's value needing to be incorporated into the price that is paid to the target in the merger, decreasing the value of the merging firm.

Finally, Figure 12 plots the equilibrium k'_t, k'_a, k'_m, p'_a, and p'_m choices of the acquirer and target after the realization of the merger shock in its lefthand plot. The capital and borrowing decisions of the three firms are about the same as in the previous decisions. The value functions depicted in the right plot are more interesting. The value of the merged firm initially increases, due to a large bump in the acquirer's initial capital investment that produces cash to help the payment of the merger. However, there is a slight decline in the merger as the target then increases its capital investment and must be compensated for its value in the merger price. As the probability approaches one, the value of the merged firm increases again due to the reduction in leverage in the initial period by the acquirer, again providing the firm with more cash flow in the second period to pay for the merger.

7.3 The Shock

March 2020 consisted of many macroeconomic and financial shocks, all of which could have impacted the corporate bond and merger markets. In this section, we focus on changes that can be made to our model to highlight the most relevant shocks and their effects.

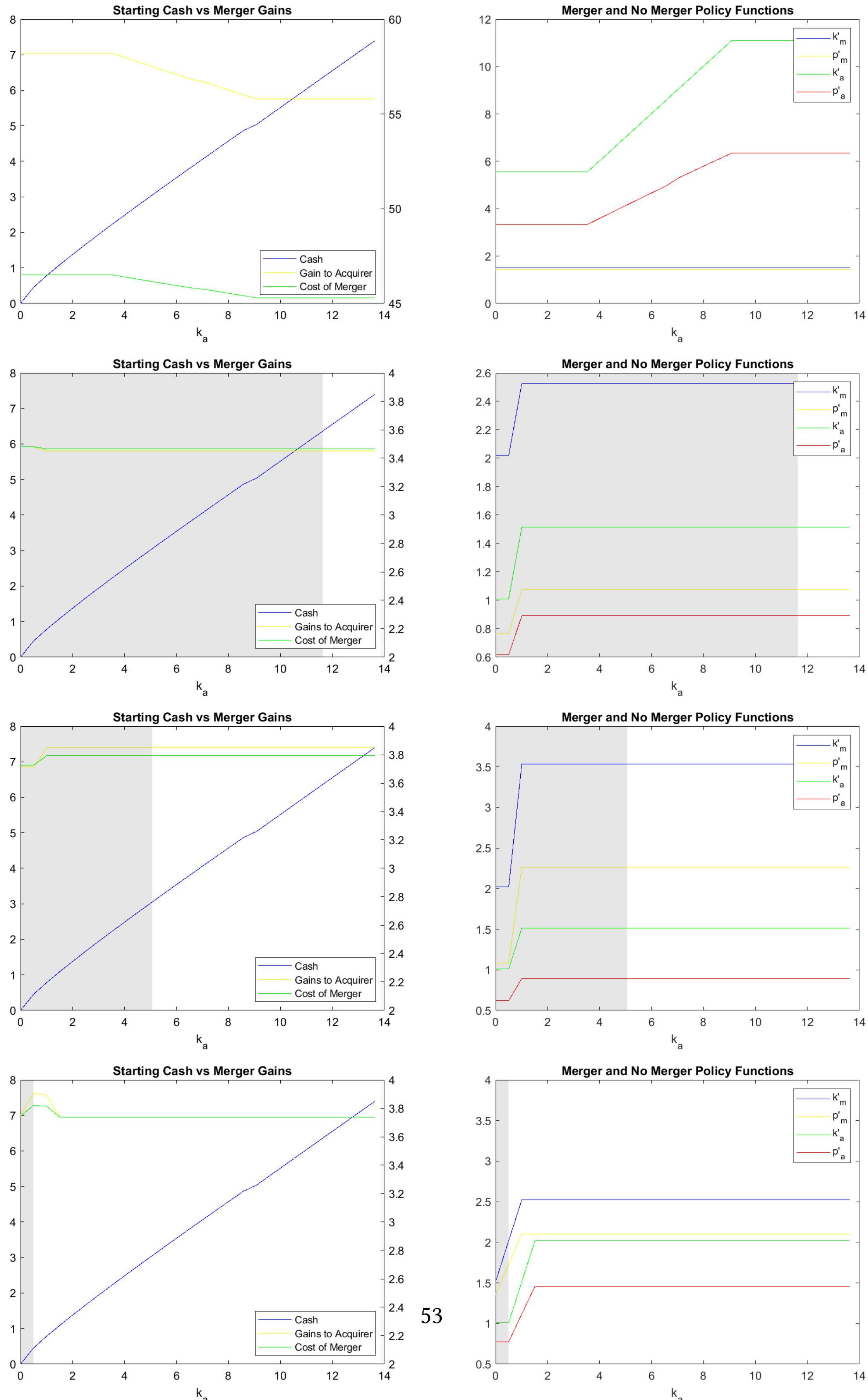
Figure 12: Second Period Policy and Value Functions



First, the onset of the COVID-19 pandemic impacted demand for the service industry, the operations of supply chains, and the availability of labor. In our simple model, these effects translate to a decrease in the aggregate productivity A. Not only does aggregate productivity affect the future returns of the firms, but it is also a factor in the borrowing constraint. A lower aggregate productivity translates to a lower fraction of debt that can be borrowed.

The second row of Figure 13 plots the impact of the aggregate productivity shock on the acquirer's capital and borrowing decisions and the effect on mergers compared to the baseline model show in the first row. The lefthand plot displays the "starting cash" of the acquirer in the second period in the higher idiosyncratic productivity state, equal to $Az_a(\bar{s})k_a^\alpha - \tau_c g(z_a(\bar{s}), k_a, p_a) - p_a + (1-\delta)k_a$, with values of k_a on the x-axis. In our previous analysis, we generally found that the acquirer would max out its borrowing constraint, so we assume that $p_a = Az_a(\underline{s})k_a^\alpha + s(1-\delta)k_a - \tau_c g(z_a(\underline{s}, k_a, p_a)$. We also hold constant the value of k_t and the idiosyncratic return of the target at X and $z_t(\bar{s})$, respectively. Cash is increasing in the value of k_a that the acquirer entered the period with. The yellow line plots the next period gains to the acquirer from the merger, or $\beta(V_{mi}(k'_m, p'_m) - V_{ai}(k'_a, p'_a))$ where k'_m, p'_m, k'_a, p'_a are all optimally chosen based on the k_a, p_a, k_t, and all parameter values. The green line represents the total cost of the merger to the acquirer, which includes the price it must pay $P =$

Figure 13: Merger, Capital, and Borrowing Choices in Various Macroeconomic Conditions



$\beta(V_{ti}(k'_t) + \eta(V_{mi}(k'_m, p'_m) - V_{ai}(k'_a, p'_a) - V_{ti}(k'_t) - c_M))$ and the cost of merging c_M. In the right-hand plot, the optimal choices of k'_m, p'_m, k'_a, p'_a as a function of k_a are plotted for each scenario. Finally, in both plots, the grey shaded area represents state spaces in which the acquirer and/or target would choose not to merge.

In comparing the baseline results (first row) to the lowered aggregate productivity shock results (second row), the first thing to note is the much reduced gain and cost of merging. Due to the lowered aggregate productivity indefinitely, the value functions of each firm are greatly reduced, also resulting in lowered price of merging. With such a low aggregate productivity, the increased idiosyncratic productivity associated with the merger is less of a benefit to the acquirer. The second major difference is that the firms choose not to merge for most of the state space. In the baseline, the firms always merge under the parametrization plotted here. However, in the lowered aggregate productivity scenario, the acquirer needs to have entered the period with substantial cash in order to be willing to merge. This is due to both the fixed cost of merger and the cost of raising equity to pay the cash price of the merger to the target in this period.

The righthand plot shows that the standalone acquirer will invest in much less capital now that the aggregate productivity is lower. The merged firm, however, will invest in slightly more. This actually demonstrates the choice the merged firm makes when financing the merger. In the baseline scenario, the price of the merger is very high. Even though the gains are also large, the acquirer must pay substantial equity issuance costs. This incentivizes the acquirer to save money in the current period on capital investment and instead spend it on the cost of the merger itself. The merged firm increases its capital investment in the periods following the merger. In the lowered aggregate productivity state however, the cost of the merger is lowered. Therefore, the acquirer is actually willing to invest in a little more capital today.

Lowered aggregate productivity does not fully capture the ways in which the Covid shock has impacted corporate firms and their merger decisions. As a reaction to the shock, in March 2020, the Federal Reserve cut its benchmark rate twice, including a 50 bps cut on March 3 and a

100 bps cut on March 16. We represent these cuts by decreasing r, the risk-free rate in the model, from 2.5% to 1.0%. As rate cuts are seen as persistent and because we permanently decreased aggregate productivity A, we solve for the infinite horizon problem with this new risk-free rate as the new permanent risk-free rate as well as with the new lowered aggregate productivity.

The third row of Figure 13 plots the merger, capital, and borrowing decisions of the acquirer and merged firm under this scenario. The lowered risk-free rate has a few effects: 1) it decreases the cost of borrowing 2) it increases the firm's discount factor and 3) it increases the borrowing constraint. These factors should attenuate the impact of the lowered aggregate productivity and lead to more investment and more mergers. This is what we see in the lefthand plot as the shaded area has been substantially reduced. The non-merger part of the state space is still greater than it was in the baseline scenario. In the righthand plot, the acquirer chooses similar capital investment as in the previous, but the merged firm chooses higher capital investment. The increases borrowing constraint helps offset the price of this investment while still paying for the cost of the merger.

7.4 PMCCF and SMCCF Effects

On March 16, 2020, the Federal Reserve announced the Primary and Secondary Market Corporate Credit Facilities (PMCCF and SMCCF). The Fed promised to purchase corporate bonds using the PMCCF that 1) had 4 or less years of maturity and 2) were issued by issuers with an investment grade rating at the time of issuance. Additionally, the Fed promised to purchase corporate bonds on the secondary market using the SMCCF if the bonds 1) had 4 or less years of maturity remaining and 2) were issued by issuers with a current rating of investment grade. This announcement was the first time the Fed promised to purchase corporate bonds and a record-breaking issuance wave soon followed.

To model the effects of the PMCCF and SMCCF, we relax the acquirer's borrowing constraint, in order to represent an increase in demand for corporate bonds or that the government may be more relaxed in its willingness to lend to the firms in this situation. In the model, we multiply the right-hand side of the borrowing constraint by ϵ. For the merged firm, this translates to the constraint

$$p'_m \leq \epsilon[z_m(\underline{s})k'^{\alpha}_m - \tau_c g(z_m(\underline{s}), k'_m, p'_m) + s(1-\delta)k'_m]. \tag{19}$$

The acquirer's borrowing constraint will be adjusted in the same way.

We test this effect using the scenario in which in the second period, the interest rate is lowered to $r = .01$ and the aggregate productivity is reduced to $A = 0.5$. The results can be seen in the final row of Figure 13. While there is little impact on the cost or gains from merger, the no-merger state space is greatly reduced, almost to there being no such space at all. The increased borrowing limit assists the standalone acquirer in investing in more capital. However, this leads to the merged firm slightly decreasing its investment in order to have more gains from the merger to offset the cost.

The latter exercise demonstrates the exact mechanism we hope to show: an interference in the corporate bond market can lead to a greater rate of acquisition activity. However, this impact greatly depends on the starting level of cash of firms. We find that those firms that already had large amounts of cash were willing to merge in the adverse macroeconomic scenario, even without the CCFs.

8 Support of Model Prediction

Our replication of the CCFs suggests that the intervention will not affect the likelihood of bond issuance-induced acquisitions if the firms already had substantial cash to fund acquisitions. We therefore return to the data to study the relationship between cash and bond issuance before and after the announcement of the CCFs.

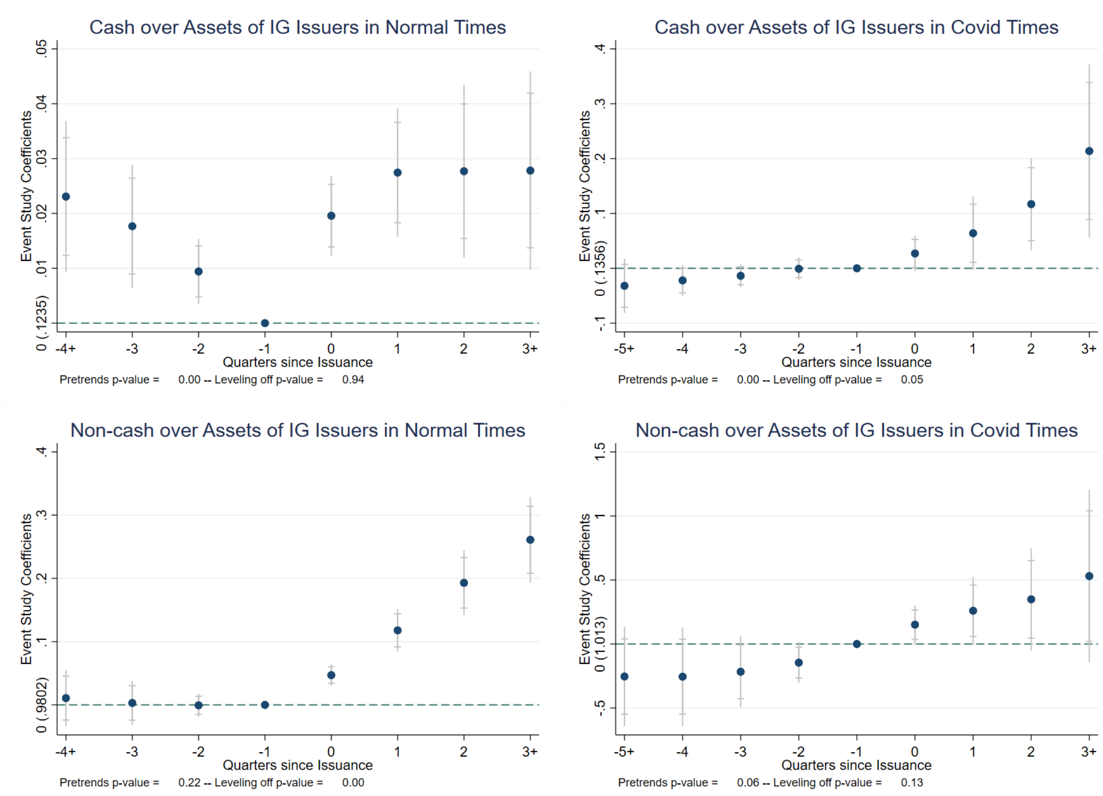
We start with an event study analysis of cash over assets for firms surrounding a bond issuance, first during the pre-CCF period and then in the post-CCF period. The specification is

$$\frac{Y_{f,q}}{Assets_{f,q-4}} = \sum_{t=-5}^{4} \beta_t \mathbb{1}\{Issue\}_{f,q+t} + \alpha_f + \alpha_{indxyear} + \epsilon_{f,q}.$$

The left hand side outcome variable, $Y_{f,q}$, is a firm-quarter observable balance sheet characteristic normalized by a one year lag in Assets to control for firm size. For this exercise, we compare the effect of bond issuance on two different outcomes: cash and non-cash assets. Cash is defined as cash and short-term investments while non-cash assets are all other assets and serves as a proxy for real investment. We use indicator variables up to 5 quarters before issuance and 4 quarters after issuance. To control for heterogeneity within industry and year, we include a industry-year fixed effect, using 2 digit NAICs codes for industry. Similarly to control for heterogeneity within firms, we include a firm fixed effect. To explore how bond issuance pre-CCF ("Normal") times defined as January 2010 - December 2019 and for post-CCF ("Covid") times defined as March 23 - June 30, 2020. The Fed announced the CCFs on March 23, so any β_t after that day would capture the effect of bond issuance on cash holdings after the announcement. Additionally, to account for across-firm heterogeneity, we run this specification for IG firms and HY firms. The cash over assets and non-cash over assets ratios are winsorized at the 1% level. Figures 14 and 16 plot the results of the event studies for IG and HY issuers, respectively.

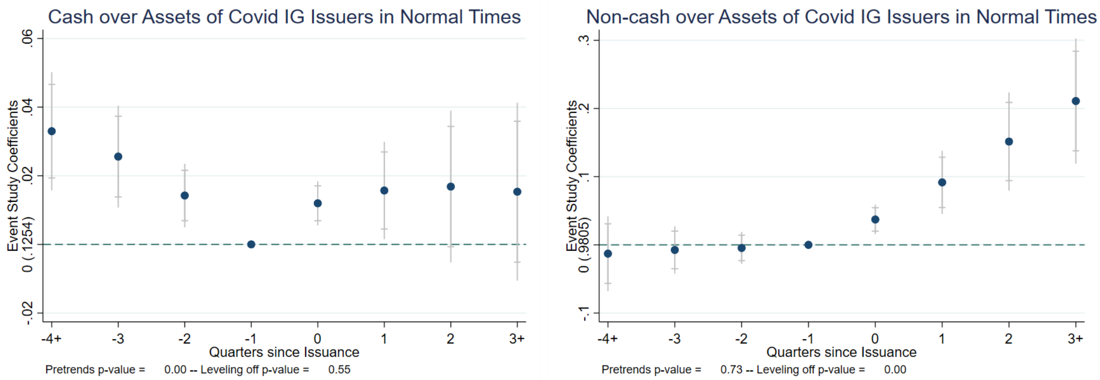
The first row of Figure 14 plots the event study of cash over assets, for IG issuers in the pre-CCF period on the left and in the post-CCF on the right. In the pre-CCF period, IG issuers issue bonds after quarters of decreasing cash. Following issuance, cash over assets reaches a new, seemingly steady value. This suggests that bond issuance is very strategic — IG firms issue bonds and deplete the cash by using it for their operating activities. Once the cash has reached a low enough level, they will issue again. This is supported by the rise in non-cash over assets for IG issuers following an issuance in the bottom left graph of Figure 14. Importantly, the

Figure 14: Balance Sheet Items Surrounding IG Bond Issuance



decreasing trend in cash over assets prior to a bond issuance does not exist for the post-CCF IG issuers. Cash over assets did not differ or was slightly lower in the quarters leading up to an issuance than it was in the quarter before this issuance. This suggests that IG issuers did not follow their previous strategy of issuing a bond following the depletion of cash over assets as they did in normal times. Instead, they seemed to be induced to issue due to Fed intervention, the Covid crisis, or some other event, such as the decrease in the interest rates in March 2020, as suggested by the findings of our model that a decrease in r leads to greater borrowing. To further dive into this, we look at the same issuers who issued in post-CCFs period and their issuances during the pre-period, for both cash and non-cash as the dependent variables. A plot of the coefficients from the event study can be found in Figure 15. The figure in the left panel demonstrates the behavior of cash over assets of post-CCF IG issuers during the pre-period. Comparing to the top right figure in Figure 14, we see that cash over assets behaves differently for these issuers in the pre and post periods, not only after the issuance, but before the issuance as well. Cash does seem to continue to rise following an issuance in the post-period, suggesting that the firm is holding onto the cash instead of investing in real investment (non-cash increasing). However, cash over assets was not declining prior to an issue as it was in the pre-period. This suggests that these issuers had other reasons for issuing the bonds following the announcement of the CCFs. Further, this supports the finding of our model that if the firm already had more cash, the CCF would not impact its likelihood of acquisition. Figure 16 repeats the results from the same event study as Figure 14, but for HY issuers. Interestingly, HY issuers do not have the same pre-trend for cash over assets as IG issuers do. Cash over assets is not significantly different in two to four quarters before issuance than it is one quarter before issuance. Cash is then greater following an issuance and is still slightly significant as late as two quarters after issuance. In the post-period, however, cash over assets is actually significantly less two to four quarters before issuance than it is one quarter before. Cash is then significantly higher and increasing after the issuance. For non-cash, the figures support the story told in Darmouni and Siani (2022). Non-cash over assets increases following a bond issuance in the

Figure 15: Balance Sheet Items Surrounding IG Bond Issuance - Post-CCFs Issuers Only



pre-period, but does not significantly change after the announcement of the CCFs. Therefore, it seems that HY issuers use bond issuance for real investment in the pre-period, but did not do so in the post-period. While we were not able to replicate the post issuance cash hoarding found by Darmouni and Siani (2022), our new result presented in Figures 16 and 14 is aligned with one strand of literature analyzing why firms are holding more cash. Acharya (2012) studies the precautionary savings of firms with different bond credit ratings and find that firms with lower ratings tend to have higher precautionary savings as they face more financing risk than higher rated firms. In the left panel of Figure 14, we can see this relationship. Our results suggest that IG firms are decreasing in their cash balances before issuance, indicating that their precautionary motives are not as strong leading up to issuance. This contrasts greatly with HY firms who do not have a significant pre trend prior to issuance.

To ensure the effect seen in Figure 16 is not due to a change in the composition of issuers from the pre to post periods, we repeat the pre-CCF event studies for only HY post-CCF issuers, seen in Figure 17. HY post-CCF issuers seem to follow the same patterns as HY non-post issuers.

We further investigate this pre-trend of cash over assets before an issuance by studying a bond issuance indicator as a function of cash over assets. These regressions take the form of

$$Issue_{f,q} = \beta X_{f,q} + \alpha_f + \alpha_{indxyear} + \epsilon_{f,q}. \tag{20}$$

Figure 16: Balance Sheet Items Surrounding HY Bond Issuance

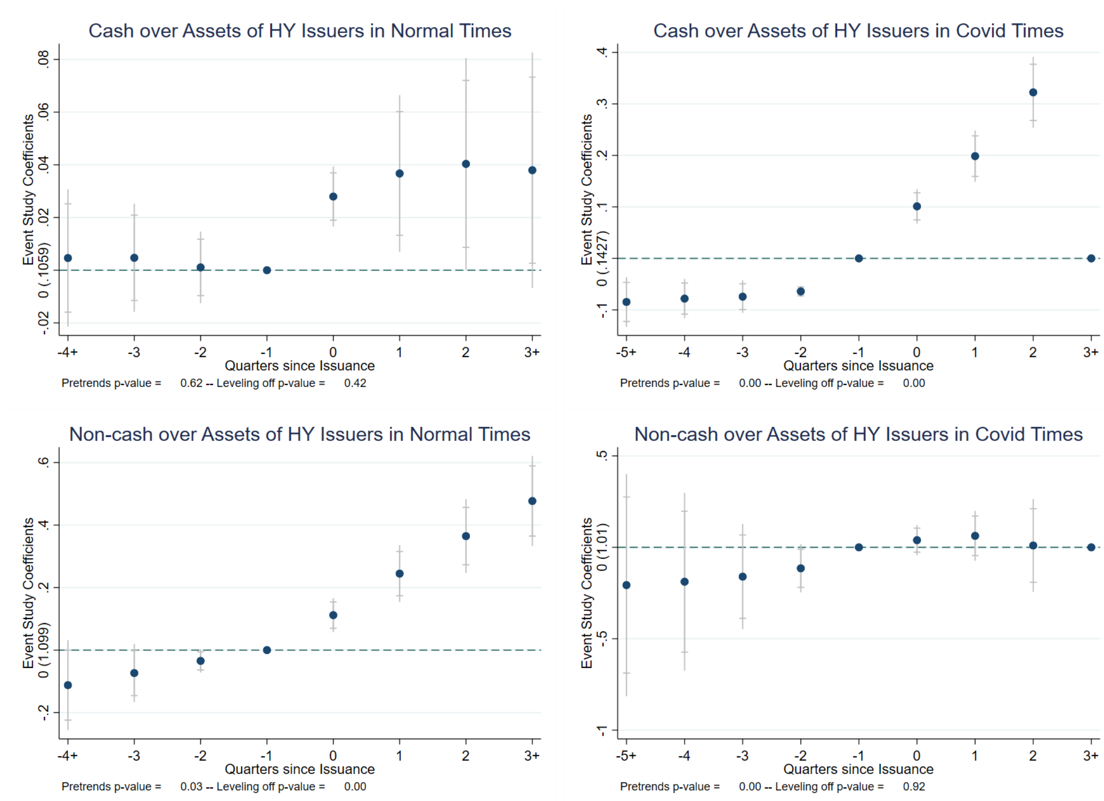


Figure 17: Balance Sheet Items Surrounding HY Bond Issuance - Post-CCF Issuers Only

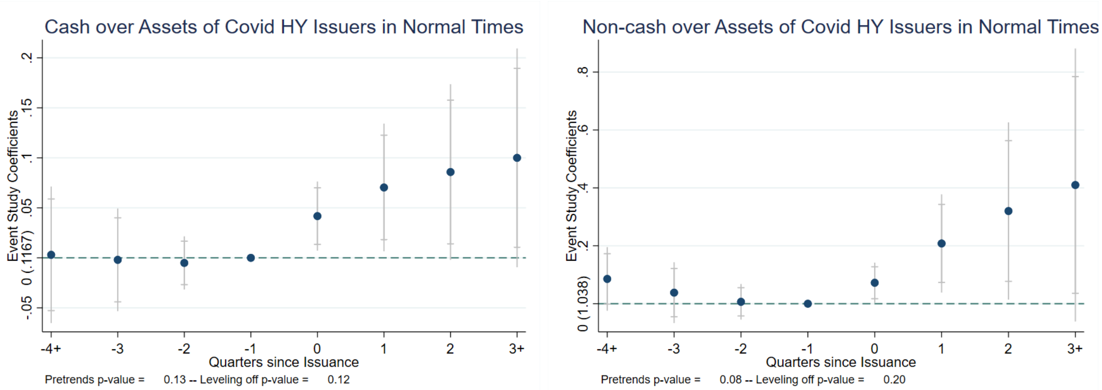


Table 14 shows the results for IG issuers. The first column shows that there is significantly negative relationship between last period's cash and the probability of issuing a bond in this period for all IG issuers during the period 2010-2019. Last period's cash is the most important predictor, as controlling for other lags does not significantly change the results. We can also look at change in cash instead of the level of lag cash. Column 3 shows that an increase in the change of cash from 2 periods ago to last period is associated with a significant decrease in the probability of issuing a bond this period. Therefore, IG firms issue bonds in the pre-CCFs period when cash had declined. Columns 4-6 repeat 1-3 but using only IG issuers who issued following the announcement of the CCFs. The direction is the same, but the magnitude on lag cash is higher. The coefficient for lag change in cash is less significant, however. In the final three columns, we replicate the specifications in Columns 1-3, but add in an interaction between the independent variables and an indicator for being a post-CCFs issuer. This is to test if there is a difference in the bond issuance strategies of those IG firms who did and did not issue following the announcement of the CCFs in the pre-period. The indicator for being a post-CCF Issuer is absorbed in the firm fixed effects. The only interaction term that is significant is that in Column 7 for lagged cash. This suggests that the decline in cash is an even stronger predictor for post-CFF issuers than other issuers in the pre-period.

Table 15 shows the results for HY issuers. As we saw in the event study, there does not appear to be a relationship between previous cash and the decision to issue a bond for HY issuers in the pre-period. This holds true for both those HY firms who issued after the CCFs announcements and those who did not.

Now, we can compare the relationship between previous cash and bond issuance in the pre and post periods. As seen in Table 14, one lag of cash is the best predictor for bond issuance out of the predictors we have studied for IG issuers. No function of cash seems to predicts bond issuance for HY issuers. Therefore, we run a diff-in-diff to compare lag cash, interacted with an indicator for the post-period, on bond issuance, or

Table 14: IG Bond Issuance as a Function of Cash

	1	2	3	4	5	6	7	8	9
$\frac{Cash_{t-1}}{Assets_{t-5}}$	-0.162***	-0.186***		-0.237***	-0.247***		-0.109***	-0.127***	
	(0.301)	(0.0418)		(0.0526)	(0.0791)		(0.0395)	(0.0529)	
$\frac{Cash_{t-2}}{Assets_{t-6}}$		0.0124			0.0342			0.0110	
		(0.400)			(0.0791)			(0.0489)	
$\frac{\Delta Cash_{t-1}}{Assets_{t-5}}$			-0.0940***			-0.144*			-0.0709
			(0.0391)			(0.0781)			(0.0503)
Post Issuer# $\frac{Cash_{t-1}}{Assets_{t-5}}$							-0.124**	-0.143	
							(0.0597)	(0.0874)	
Post Issuer# $\frac{Cash_{t-2}}{Assets_{t-6}}$								0.0257	
								(0.0853)	
Post Issuer# $\frac{\Delta Cash_{t-1}}{Assets_{t-5}}$									-0.0728
									(00.839)
Constant	0.135***	0.136***	0.115***	0.188***	0.188***	0.184***	0.135***	0.135***	0.115***
	(0.00461)	(0.00531)	(0.00572)	(0.00914)	(0.0101)	(0.0108)	(0.00461)	(0.00534)	(0.00239)
N	16,736	15,966	16,702	6,007	5,817	5,674	16,736	15,966	16,702
Issuer Group	All IG	All IG	All IG	Post IG	Post IG	Post IG	All IG	All IG	All IG
Time Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

Table 15: HY Bond Issuance as a Function of Cash

	1	2	3	4	5	6	7	8	9
$\frac{Cash_{t-1}}{Assets_{t-5}}$	-0.0166	-0.0177		-0.0900	-0.105		-0.0155	-0.0114	
	(0.0140)	(0.0219)		(0.0774)	(0.114)		(0.0144)	(0.0225)	
$\frac{Cash_{t-2}}{Assets_{t-6}}$		-0.00361			0.00833			-0.0948	
		(0.400)			(0.114)			(0.0602)	
$\frac{\Delta Cash_{t-1}}{Assets_{t-5}}$			0.00093			-0.0376			-0.00235
			(0.0216)			(0.116)			(0.0221)
Post Issuer# $\frac{Cash_{t-1}}{Assets_{t-5}}$							-0.0948	-0.108	
							(0.0602)	(0.0949)	
Post Issuer# $\frac{Cash_{t-2}}{Assets_{t-6}}$								0.00189	
								(0.0945)	
Post Issuer# $\frac{\Delta Cash_{t-1}}{Assets_{t-5}}$									0.0276
									(0.0974)
Constant	0.135***	0.136***	0.115***	0.188***	0.188***	0.184***	0.0785***	0.0807***	0.0751***
	(0.00461)	(0.00531)	(0.00572)	(0.00914)	(0.0101)	(0.0108)	(0.00228)	(0.00250)	(0.00170)
N	22,926	21,967	23,920	2,900	2,805	2,730	22,926	21,967	23,920
Issuer Group	All HY	All HY	All HY	Post HY	Post HY	Post HY	All HY	All HY	All HY
Time Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

$$Issue_{f,q} = \beta_1 \frac{Cash_{f,q-1}}{Assets_{f,q-5}} + \beta_2 \text{Post-CCFs}_{q-1} + \beta_3 \text{Post-CCFs}^*_{q-1} \frac{Cash_{f,q-1}}{Assets_{f,q-5}} \\ + \alpha_f + \alpha_{indxyear} + \epsilon_{f,q}. \tag{21}$$

We define $Post - CCFs_{q-1} = 1$ if the date $q-1$ is at least 2020Q1. The results of this regression for IG and HY issuers alike can be found in Table 16. As before, we find a significantly negative relationship between lag cash and the probability of issuing a bond for IG issuers, but an insignificant relationship for HY issuers. For all four regressions, the coefficient on Post-CCFs is significantly positive. As detailed in Section 4, issuances were much higher following the Fed intervention into corporate bond markets than in historical times, for both IG and HY issuers. The coefficient of interest is the interaction between Post-CCFs and the lagged value of cash over assets. When using all IG issuers, we find that this coefficient is significantly positive. This suggests that the relationship between lag cash and issuing a bond differs in the Post-CCFs time period, as it is now firms with more cash that are more likely to issue in the Post-CCFs time. However, if we look at only post-CCFs IG issuers, we find an insignificant effect from this interaction. For the firms who did issue bonds during the Post-CCFs time, their lag cash had no impact on their decision to do so. When we look at all HY issuers, we see a slightly significant positive effect on this interaction term, suggesting that there is a small relationship between cash and the probability of issuing a bond during Covid times. This does not hold true when we only look at HY post-CCFs issuers though. This suggests that the HY issuers who issue following the announcment simply have more lagged cash than other HY issuers.

We repeat the above exercise using lagged non-cash and change in non-cash instead of cash. We find no significant results for any of the regressors. This suggests that non-cash levels or changes are not a predictor of the issuance of bonds, during the pre or post-period.

Table 16: Differences-in-differences in Cash and Issuance

	1	2	3	4
$\frac{Cash_{t-1}}{Assets_{t-5}}$	-0.173***	-0.239***	-0.0155	-0.0729
	(0.0299)	(0.0515)	(0.0140)	(0.0755)
Post-CCFs$_{t-1}$	0.0732**	0.517***	0.0623***	0.764***
	(0.0300)	(0.225)	(0.0220)	(0.0648)
Post-CCFs$^{*}_{t-1}\frac{Cash_{t-1}}{Assets_{t-5}}$	0.424***	0.116	0.303**	0.232
	(0.130)	(0.225)	(0.146)	(0.354)
Constant	0.141***	0.194***	0.0776***	0.128***
	(0.00458)	(0.00895)	(0.00222)	(0.0101)
N	17,412	6,292	23,779	3,048
Issue Group	All IG	Covid IG	All HY	Covid HY
Time Period	2010Q1-2020Q2	2010Q1-2020Q2	2010Q1-2020Q2	2010Q1-2020Q2

9 Conclusion

In this paper, we investigate the relationship between corporate bond issuance and firm acquisition activity. Further, we study the impact of the Fed's first ever intervention in the corporate bond market on this relationship and whether a rise in acquisitions can be an unintended consequence of such interventions. To investigate this relationship, we combine data from Compustat, Mergent FISD, and SDC to create a dataset of firms with information on bond issuances and M&A deals. We first conduct a differences-in-differences analysis of the likelihood of acquisitions by firms with credit ratings and without before and after the announcement of the CCFs. Due to the Fed's specification of buying only IG-rated firm's bonds with the CCFs, we repeat the analysis comparing IG, HY, and nonrated firms before and after the announcement. The likelihood of acquiring is 1.3-2.4% less likely after the announcement of the CCFs than before. The interaction terms between the IG and Post-CCFs indicators and between the HY and Post-CCFs indicators are not significant, suggesting that there were no additional effect on acquisition activity by firms with any credit rating in the post-period. We next study a differences-in-differences specification with an indicator for a firm that issued a bond following the announcement of the CCFs. These firms are more likely to acquire at all times in the sample, but overall do not see a significant change in the Post-CCFs period. However, when we break these firms down into post-CCFs issuers with IG ratings and post-CCF issuers with HY ratings, we find a significantly negative effect for the interaction term for HY post-CCFs issuers in the post-period. Firms with HY ratings who issued bonds from March 23-June 30, 2020 were actually less likely to engage in acquisitions than firms with HY ratings who did not issue. However, firms with HY ratings who issued bonds from March 23-June 30, 2020 were still more likely to acquire than firms without credit ratings in the Post-CCFs time. This suggests that the HY firms issuing following the CCFs announcement more likely did so to finance their normal operations than to pursue acquisitions.

We then study the relationship between actual bond issuance and M&A activity. During the pre-CCF times, we find a significantly positive relationship between a bond issuance and an acquisition in the same period. However, this relationship does not hold up when we look at post-CCF times. In fact, for issuances that occur in 2020Q2, the relationship is significantly negative. These results suggest that the relationship between bond issuance and acquisition announcement changed in the time following the CCFs' announcement. To better understand the mechanisms at play, we build a stylized model of external financing and acquisition decisions of firms. Upon solving the model, we replicate both the Covid shock and the CCFs in the model. We find that the CCFs can increase the likelihood that acquisitions will occur, but only if the acquiring firm does not have a high level of cash at the time of the announcement. Returning to the data, we find that the IG firms in our sample had higher than average levels of cash before their post-CCF bond issuance compared to pre-CCF issuances. This suggests that the CCF would not impact the probability of acquisitions given the starting conditions of firms, but that this channel could become relevant if a similar intervention is used in the future.

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A Additional Summary Statistics

Table 17: Credit Rating Mapping

S&P	Moody	Fitch	Numerical
AAA	Aaa	AAA	22
AA+	Aa1	AA+	21
AA	Aa2	AA	20
AA-	Aa3	AA-	19
A+	A1	A+	18
A	A2	A	17
A-	A3	A-	16
BBB+	Baa1	BBB+	15
BBB	Baa2	BBB	14
BBB-	Baa3	BBB-	13
BB+	Ba1	BB+	12
BB	Ba2	BB	11
BB-	Ba3	BB-	10
B+	B1	B+	9
B	B2	B	8
B-	B3	B-	7
CCC+	Caa1	CCC+	6
CCC	Caa2	CCC	5
CCC-	Caa3	CCC-	4
CC	Ca	CC	3
C	C	C	2
D	D	D	1

B Acquisition Size Analysis

Table 18: Weekly Bond Issuances: 2019 versus Post CCF Announcement

	Num Offerings	Amount (Bn)	Tenor	Rating	Credit Spread	Yield
IG Issuance: 2019						
10%	2	1.7	5.0	13.5	88	3.03%
50%	6	7.1	11.2	14.8	136	3.73%
90%	11	27.4	29.1	16.7	213	4.66%
IG Issuance: Weeks in 2020						
3/2/2020	13	13.2	14.1	14.7	156	2.64%
3/9/2020	3	3.9	12.2	14.5	211	2.91%
3/16/2020	8	40.5	16.8	17.5	267	3.95%
3/23/2020	27	61.9	13.2	16.1	267	3.63%
3/30/2020	19	63.7	13.6	15.2	342	4.26%
4/6/2020	13	23.0	11.1	15.4	315	3.85%
4/13/2020	11	31.6	13.6	15.6	238	3.38%
4/20/2020	15	17.8	10.2	14.2	291	3.85%
4/27/2020	25	71.1	14.2	15.8	208	2.92%
5/4/2020	28	64.6	12.8	15.4	263	3.39%
5/11/2020	22	46.9	14.4	15.0	239	3.42%
5/18/2020	12	36.9	15.8	16.2	191	2.94%
5/25/2020	10	15.6	15.2	15.6	169	2.51%
6/1/2020	11	21.0	11.0	15.0	166	2.30%
6/8/2020	10	11.2	12.6	14.1	177	2.68%
6/15/2020	12	25.3	11.7	14.3	195	2.53%
6/22/2020	8	11.2	7.9	15.0	178	2.50%
6/29/2020	4	9.3	16.7	14.0	183	2.67%
HY Issuance: 2019						
10%	2	1.5	5.3	6.8	281	4.93%
50%	5	4.2	7.6	9.0	398	6.18%
90%	10	9.8	10.7	11.1	619	8.70%
HY Issuance: Weeks in 2020						
3/2/2020	2	1.8	10.1	10.0	368	4.69%
3/30/2020	3	1.8	5.0	9.7	662	7.00%
4/6/2020	3	1.6	5.0	7.0	814	8.63%
4/13/2020	11	13.8	5.5	10.2	713	7.36%
4/20/2020	16	11.3	5.2	9.4	680	7.15%
4/27/2020	7	3.8	5.0	9.0	555	6.95%
5/4/2020	8	7.1	8.9	10.8	509	6.53%
5/11/2020	9	6.6	6.4	8.3	623	6.98%
5/18/2020	11	5.5	6.3	9.2	663	8.24%
5/25/2020	7	8.6	8.9	9.0	631	7.60%
6/1/2020	11	8.3	6.1	9.3	607	6.61%
6/8/2020	10	7.6	7.8	9.9	403	5.17%
6/15/2020	17	12.1	7.5	9.0	542	6.32%
6/22/2020	10	8.9	7.4	9.3	623	7.53%
6/29/2020	3	2.3	7.7	7.0	584	6.38%

Notes: Data are from Mergent FSID, obtained through WRDS. We exclude sovereign debt and debt issued by financial and utility firms. Furthermore, we exclude financial, sovereign and utility issues as well as convertible bonds, capital impact bonds, community bonds, PIK securities, and bonds issued in exchange for a Rule 144A bond. Counts are average across weeks for all firms, split into either IG or HY rated firms at the time of the CCF announcement, March 23, 2020. This is Table IA.I from Darmouni and Siani (2023).

Table 19: Firms M&A Activity in Normal and Covid Times

	Full Sample	COVID	Normal	COVID & Normal	COVID-First Time	Only Normal Times
Total Assets (log)	9.360	9.460	9.343	9.488	8.821	9.010
Leverage	0.286	0.286	0.286	0.318	0.260	0.641
Cash/Assets	0.114	0.137	0.111	0.111	0.178	0.128
CAPX	0.009	0.006	0.009	0.007	0.009	0.009
Market-to-Book	1.897	2.086	1.872	1.915	1.527	1.571
M&As/Year	1.020	0.882	1.004	0.416	0.067	0.178
Max M&As/Year	15	10	15	13	6	15
Firms	4821	1658	4298	912	693	3417
Time Period	2010Q1 - 2022Q1	2020Q3 - 2022Q1	2010 - 2019Q4	2020Q3 - 2022Q1	2020Q3 - 2022Q1	2010Q1 - 2019Q4

Table 20: Firms M&A Activity in Normal and Covid Times & Bond Issuance

	Issuance Anytime		Covid Issuance	
	Normal & COVID MA	Normal MA	COVID MA	COVID MA-First MA
Total Assets (log)	9.879	9.857	9.722	9.842
Leverage	0.335	0.433	0.453	0.418
Cash/Assets	0.0918	0.099	0.116	0.110
CAPX	0.011	0.008	0.010	0.008
Market to Book	2.621	2.169	1.316	2.418
M&As/Year	0.06632	0.194	0.082	0.641
Max M&As/Year	9	5	3	3
Firms	288	545	225	79

Table 21: Acquisition Size

	1	2	3	4	5	6
Has Rating	0.00589	0.00494***	0.00541	0.00411**	0.00358	0.00270
	(0.00409)	(0.00162)	(0.00359)	(0.00162)	(0.00353)	(0.00217)
Ln(Sales)	-0.00633	-0.00223**	-0.00634	-0.00222**	-0.00646	-0.00281***
	(0.00563)	(0.000968)	(0.00563)	(0.000968)	(0.00566)	(0.000885)
Cash to Assets	-0.0408	-0.00703	-0.0408	-0.00704	-0.0407	-0.00707
	(0.0371)	(0.00564)	(0.0371)	(0.00564)	(0.0371)	(0.00563)
Market Leverage	-0.0311**	-0.0191***	-0.0311**	-0.0190***	-0.0300**	-0.0179***
	(0.0123)	(0.00338)	(0.0123)	(0.00337)	(0.0121)	(0.00348)
Stock Return	-0.000107	0.000841*	-0.000101	0.000855*	-0.000104	0.000845*
	(0.00118)	(0.000461)	(0.00118)	(0.000464)	(0.00118)	(0.000462)
Market-to-Book	4.31e-08	0.00000341	4.04e-08	0.00000356	1.81e-08	0.00000315
	(0.000000597)	(0.00000489)	(0.000000594)	(0.00000491)	(0.000000609)	(0.00000492)
Operating Income	0.0110	0.00497	0.0110	0.00485	0.0111	0.00560
	(0.00721)	(0.00860)	(0.00720)	(0.00862)	(0.00724)	(0.00868)
Industry Liquidity	0.145*	0.0812***	0.145*	0.0815***	0.146*	0.0816***
	(0.0820)	(0.0256)	(0.0823)	(0.0256)	(0.0825)	(0.0256)
Herfindahl Index	-0.0185**	-0.00857***	-0.0186**	-0.00861***	-0.0185**	-0.00852***
	(0.00722)	(0.00308)	(0.00724)	(0.00308)	(0.00724)	(0.00309)
Post-PMCCF			0.0119	0.000380	0.0120	0.000634
			(0.00851)	(0.00283)	(0.00851)	(0.00282)
Has Rating X Post			0.00241	0.00412	0.00341	0.00547
			(0.00698)	(0.00374)	(0.00742)	(0.00476)
Covid Issuer					0.00789	0.00751
					(0.00512)	(0.00477)
Covid Issuer X Post					-0.00498	-0.00623
					(0.00719)	(0.00706)
N	30839	25264	30839	25264	30839	25264
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.
Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table 22: Acquisition Size by IG and HY

	1	2	3	4	5	6
IG	0.00461	0.00244	0.00476	0.00226	0.00120	-0.000582
	(0.00537)	(0.00191)	(0.00490)	(0.00202)	(0.00504)	(0.00316)
HY	0.00698**	0.00653***	0.00599**	0.00519***	0.00504*	0.00444**
	(0.00341)	(0.00210)	(0.00288)	(0.00191)	(0.00291)	(0.00208)
Ln(Sales)	-0.00628	-0.00171	-0.00629	-0.00170	-0.00638	-0.00218**
	(0.00568)	(0.00109)	(0.00569)	(0.00109)	(0.00570)	(0.00101)
Cash to Assets	-0.0408	-0.00701	-0.0408	-0.00706	-0.0408	-0.00705
	(0.0371)	(0.00564)	(0.0371)	(0.00563)	(0.0371)	(0.00563)
Market Leverage	-0.0317***	-0.0203***	-0.0316***	-0.0202***	-0.0310***	-0.0193***
	(0.0119)	(0.00372)	(0.0118)	(0.00370)	(0.0117)	(0.00373)
Stock Return	-0.000110	0.000822*	-0.000106	0.000830*	-0.000112	0.000811*
	(0.00118)	(0.000457)	(0.00117)	(0.000458)	(0.00118)	(0.000456)
Market-to-Book	5.30e-08	0.00000374	4.83e-08	0.00000386	2.83e-08	0.00000350
	(0.000000588)	(0.00000488)	(0.000000586)	(0.00000491)	(0.000000599)	(0.00000491)
Operating Income	0.0110	0.00451	0.0110	0.00438	0.0111	0.00509
	(0.00725)	(0.00859)	(0.00725)	(0.00861)	(0.00727)	(0.00866)
Industry Liquidity	0.145*	0.0815***	0.145*	0.0816***	0.146*	0.0819***
	(0.0822)	(0.0256)	(0.0825)	(0.0256)	(0.0826)	(0.0256)
Herfindahl Index	-0.0185**	-0.00858***	-0.0185**	-0.00863***	-0.0185**	-0.00851***
	(0.00724)	(0.00308)	(0.00726)	(0.00308)	(0.00725)	(0.00308)
Post-PMCCF			0.0119	0.000283	0.0120	0.000538
			(0.00851)	(0.00284)	(0.00852)	(0.00283)
IG X Post-PMCCF			-0.000715	0.000968	-0.000226	0.00165
			(0.00658)	(0.00299)	(0.00688)	(0.00389)
HY X Post-PMCCF			0.00482	0.00653	0.00637	0.00767
			(0.00832)	(0.00581)	(0.00878)	(0.00662)
Covid Issuer					0.00936*	0.00863*
					(0.00523)	(0.00504)
IG X Covid Issuer					-0.00240	-0.00279
X Post-PMCCF					(0.00681)	(0.00678)
HY X Covid Issuer					-0.0126	-0.0102
X Post-PMCCF					(0.0121)	(0.0121)
N	30839	25264	30839	25264	30839	25264
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 23: Acquisition Size by Credit Rating Bucket

	1	2	3	4	5	6
Rating ∈ [0, 4)	-0.00263	-0.00124	-0.00574**	-0.00559***	-0.00609**	-0.00588***
	(0.00408)	(0.00370)	(0.00257)	(0.00200)	(0.00255)	(0.00198)
Rating ∈ [4, 7)	0.00227	0.00210	0.00587*	0.00581*	0.00566*	0.00557*
	(0.00339)	(0.00331)	(0.00334)	(0.00332)	(0.00333)	(0.00331)
Rating ∈ [7, 10)	0.00838*	0.00786**	0.00532	0.00458	0.00463	0.00400
	(0.00438)	(0.00379)	(0.00333)	(0.00287)	(0.00336)	(0.00295)
Rating ∈ [10, 13)	0.00469	0.00348	0.00404	0.00252	0.00233	0.00113
	(0.00389)	(0.00213)	(0.00351)	(0.00228)	(0.00360)	(0.00261)
Rating ∈ [13, 16)	0.00420	0.00243	0.00471	0.00268	0.00146	-0.0000181
	(0.00459)	(0.00193)	(0.00408)	(0.00208)	(0.00436)	(0.00306)
Rating ∈ [16, 19)	0.00563	0.00169	0.00502	0.000744	0.000521	-0.00298
	(0.00716)	(0.00292)	(0.00680)	(0.00303)	(0.00695)	(0.00420)
Rating ∈ [19, 22]	-0.00157	-0.00710**	-0.00134	-0.00732**	-0.00695	-0.0118**
	(0.00933)	(0.00328)	(0.00902)	(0.00331)	(0.00919)	(0.00498)
Post-PMCCF			0.0120	0.000443	0.0121	0.000594
			(0.00847)	(0.00278)	(0.00848)	(0.00279)
[0, 4) X Post			0.0110	0.0154	0.00582	0.00749
			(0.0118)	(0.0104)	(0.00706)	(0.00459)
[4, 7) X Post			-0.0199*	-0.0207*	-0.0208	-0.0217*
			(0.0119)	(0.0117)	(0.0131)	(0.0130)
[7, 10) X Post			0.0155	0.0166	0.0184	0.0195
			(0.0156)	(0.0148)	(0.0171)	(0.0164)
[10, 13) X Post			0.00302	0.00446	0.00447	0.00602
			(0.00716)	(0.00409)	(0.00725)	(0.00457)
[13, 16) X Post			-0.00227	-0.00103	-0.00219	-0.000892
			(0.00694)	(0.00345)	(0.00710)	(0.00383)
[16, 19) X Post			0.00390	0.00583	0.00822	0.0111
			(0.00778)	(0.00520)	(0.0103)	(0.00892)
[19, 22] X Post			-0.00132	0.00122	-0.00129	0.00184
			(0.00632)	(0.00335)	(0.00748)	(0.00525)

Table 24: Acquisition Size by Credit Rating Bucket Continued

	1	2	3	4	5	6
Covid Issuer					0.00969*	0.00906*
					(0.00525)	(0.00510)
Covid Issuer X [0, 4) X Post					0.00991	0.0208
					(0.0355)	(0.0369)
Covid Issuer X [4, 7) X Post					0.00552	0.00670
					(0.0130)	(0.0129)
Covid Issuer X [7, 10) X Post					-0.0307*	-0.0310*
					(0.0170)	(0.0169)
Covid Issuer X [10, 13) X Post					-0.00829	-0.00891
					(0.00978)	(0.00965)
Covid Issuer X [13, 16) X Post					-0.00182	-0.00193
					(0.00777)	(0.00774)
Covid Issuer X [16, 19) X Post					-0.00894	-0.0103
					(0.0111)	(0.0111)
Covid Issuer X [19, 22] X Post					0.000246	-0.000774
					(0.00766)	(0.00722)
N	30839	25264	30839	25264	30839	25264
Sample	Full	Restricted	Full	Restricted	Full	Restricted

Restricted sample drops firms with sales less than $10M.

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table 25: Acquisition Size at IG/HY Cutoff

	1	2	3	4	5	6
IG	-0.000524	0.000587	0.000682	0.00214	0.00373	0.00371
	(0.00222)	(0.00252)	(0.00254)	(0.00362)	(0.00455)	(0.00459)
Ln(Sales)	-0.00512**	-0.00500**	-0.00577***	-0.00600	-0.00580	-0.00714*
	(0.00212)	(0.00211)	(0.00215)	(0.00397)	(0.00398)	(0.00401)
Cash to Assets	-0.0138	-0.0143	-0.0133	-0.0255	-0.0275	-0.0257
	(0.0141)	(0.0141)	(0.0138)	(0.0214)	(0.0220)	(0.0221)
Market Leverage	-0.0309***	-0.0312***	-0.0300***	-0.0340***	-0.0341***	-0.0310***
	(0.00565)	(0.00564)	(0.00556)	(0.00865)	(0.00865)	(0.00890)
Stock Return	0.00123	0.00113	0.00123	0.00107	0.00121	0.00154
	(0.00161)	(0.00163)	(0.00168)	(0.00459)	(0.00460)	(0.00464)
Market-to-Book	0.0000571	0.0000573	0.0000567	0.0000189	0.0000181	0.0000174
	(0.0000431)	(0.0000434)	(0.0000443)	(0.0000210)	(0.0000213)	(0.0000222)
Operating Income	-0.00207	-0.00280	-0.00274	-0.0167	-0.0173	-0.0165
	(0.0114)	(0.0116)	(0.0116)	(0.0173)	(0.0174)	(0.0176)
Industry Liquidity	0.00308	0.00174	0.00216	-0.0334	-0.0328	-0.0313
	(0.0414)	(0.0409)	(0.0406)	(0.0731)	(0.0733)	(0.0730)
Herfindahl Index	0.00284	0.00272	0.00310	-0.0190**	-0.0193**	-0.0201**
	(0.00645)	(0.00648)	(0.00647)	(0.00943)	(0.00958)	(0.00912)
Post-PMCCF		0.00665	0.00692		0.00841	0.0104
		(0.00477)	(0.00529)		(0.00678)	(0.00749)
IG X Post		-0.00528	-0.00838*		-0.00773	-0.0124*
		(0.00471)	(0.00481)		(0.00703)	(0.00732)
Covid Issuer			0.00159			0.00302
			(0.00248)			(0.00451)
Covid Issuer X			-0.00157			-0.00887
HY X Post			(0.00856)			(0.00762)
Covid Issuer X			0.00657			0.00969
IG X Post			(0.00620)			(0.00855)
N	3537	3537	3537	1087	1087	1087
Included Ratings	[10, 16]	[10, 16]	[10, 16]	[12, 14]	[12, 14]	[12, 14]

Standard errors in parentheses

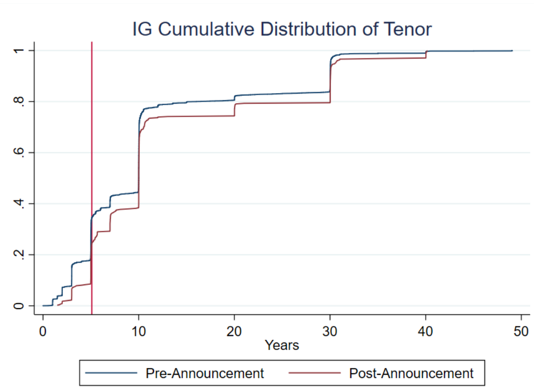
* p<0.10, ** p<0.05, *** p<0.010

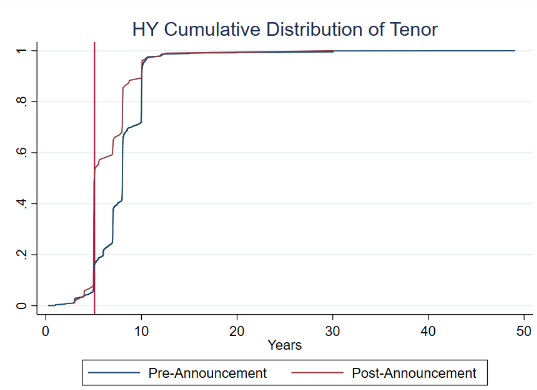
C Identification of Treatment

In this section, we explore different definitions of treatment of the announcement of the Corporate Credit Facilities on firm bond issuance and subsequent acquisition behavior. We explore multiple ways of assigning a treatment group: rating of firm at time of announcement, maturity of bond issued, refinance risk, and CDS spreads.

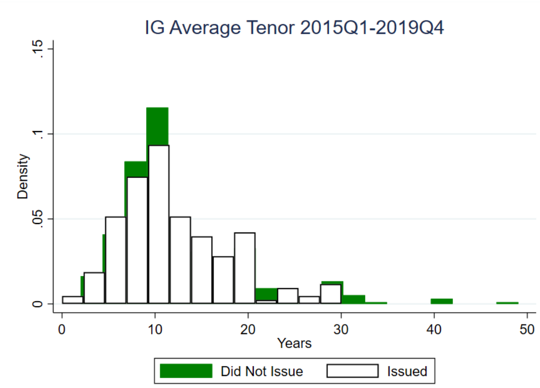
C.1 Maturity of Bond Issued

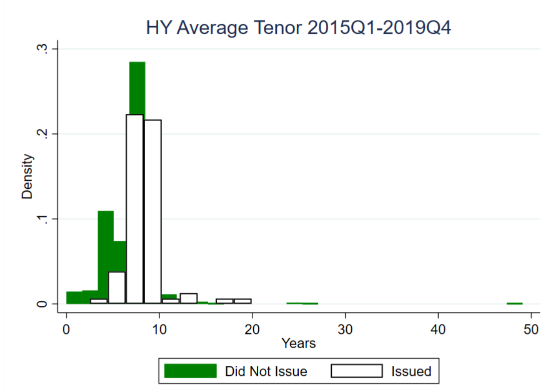
Given the Fed's criteria for buying bonds, we would expect issuers, especially IG issuers, to issue many bonds with a maturity of less than 5 years. However, as we plot the cumulative distribution of the maturity of bonds by IG and HY issuer before and after the announcement, we do not see this. There is a jump at 5 years for IG, but the jump is actually there for the pre-announcement as well and the cumulative distribution at 5 years is higher for pre-announcement bonds. HY issuers, on the other hand, were the ones who were significantly more likely to issue bonds with a maturity of 5 years. These results are robust to looking at a shorter time period in 2019. The graph below is for our control time period 2010 - 2019. Issuers, especially IG issuers, did not seem to be very influenced by the Fed's maturity criteria in their issuances.





Of those who issue after the announcement, about 50% of them issue at least one bond with maturity less than or equal to 5 years. This is true for both IG and HY issuers. However, IG issuers are very likely to also issue a longer maturity bond. HY issuers do not generally issue other bonds. We then tried to identify a continuous treatment by defining issuers based on their previous choice of maturity. However, we do not find an obvious pattern. In Figure **??**, we plot the average tenor of IG and HY issuers from 2015Q1-2019Q4, splitting the issuers based on if they issued after the announcement or not. In general, the two groups appear to be the same. In fact, for HY, the ones who did issue after the announcement appear to have issued longer bonds in the past, not shorter ones. These results are robust to looking at averages over a longer period of time and looking at the share of issues under 5 years.





C.2 Refinance Risk

An alternative explanation for the mass issuance of bonds is that firms were simply refinancing debt that was already coming due, rather than taking advantage of this lowered cost of capital. To rule out this explanation, we define a measure of Refi Exposure

$$\text{Refi Exposure} = \frac{\text{LT Debt} < \text{1yr} + \text{Current Debt}}{\text{LT} + \text{Current Debt}}. \tag{22}$$

In Equation 22, we define a firm's refinancing need as the fraction of its total debt (long-term and current) that is either long-term debt due in one year or current debt to capture the fraction of all debt that is due within a year.

To test the importance of refinancing need on post-announcement bond issuance, we run

Table 26: Bond Issuance as a Function of Refinancing Need

	$\text{Issue}_{i,t}$
Refi $\text{Exposure}_{i,t-1}$	0.043***
	(0.006)
Post Announcement_t	0.036***
	(0.011)
Refi $\text{Exposure}_{i,t-1}\text{XPost}_t$	-0.005
	(0.016)
N	36,548
Includes firm and 2-digit industry fixed effects.	

the following specification

$$\begin{aligned} \text{Issue}_{i,t} = \alpha_i + \gamma_{j(i)} + \beta_1 \text{Refi Exposure}_{i,t-1} + \beta_2 \text{Post Announcement}_t \\ + \beta_3 \text{Refi Exposure}_{i,t-1} \text{XPost Announcement}_t + \epsilon_{i,t} \end{aligned} \tag{23}$$

where i represents a firm, t a quarter, and $j(i)$ the 2-digit industry of the firm.

Table 26 summarizes the results of the specification in Equation 23. The Refi Exposure measure positively and significantly predicts bond issuance in the following quarter. The coefficient on Post Announcement is also positive and significant, as firms are more likely to issue in the period after the Fed's announcement of the CCFs. However, the indicator between the Refi Exposure measure and the Post Announcement is negative and insignificant. This suggests that firms with refinancing needs before the announcement were actually less likely to issue than in normal times, although not significantly so. The mass of issuances was not driven by firms needing to refinance.

C.3 Treatment of Targets

In this paper, we hypothesize that the lower cost of capital from the Fed intervention led to more acquisitions by these firms than would have occurred otherwise. However, if the targets

Table 27: Target Characteristics by Acquirer Treatment

	Percent of Targets that are		
Acquirer Type	Public	Rated	Rated IG
No Credit Rating	6.2%	0.6%	0%
Credit Rating, but not CCF Issuer	8.3%	2.6%	1.3%
CCF Issuer	16.7%	6.3%	2.1%

of these acquisitions were also “treated" by the Fed intervention, it seems unlikely that the intervention changed the likelihood of these acquisitions as the targets themselves would have had a lowered cost of capital. To test our theory, we investigate the corporate bond market activity of the targets. Table 27 below summarizes characteristics of the targets, split by their acquirer type. In general, very few of the targets are public firms, and even fewer have a credit rating as of 2019Q4. This implies that they were not affected by the Fed intervention. Additionally, IG firms were most treated by the Fed intervention, and a smaller percentage of the targets are rated IG at the end of 2019Q4. We rule out the story that the targets were also treated, and for extra precaution, we will control for the acquisitions in which targets had a credit rating in future analysis. The percentages of public targets, rated targets, and IG rated targets are higher for CCF issuers. This is most likely because CCF issuers are on average larger firms, and therefore would be most capable of acquiring larger, public firms. We will control for those characteristics of acquirers in the analyses.

C.4 Credit Default Swaps Spreads

We gather firm-level data on Credit Default Swaps spreads as a proxy to firm level bond prices. We use 5 Year CDS spreads from Bloomberg as Poeschl and Yamarthy (2023) document that 5 Year CDS spreads are more sensitive to aggregate risk and that investors thought the COVID pandemic posed greater short-run risk than long-run risk.

Figure 18 shows the CDS in basis points for a variety of different firm-level ratings. The first dashed line represents the first announcement on March 23, 2020. One reason that we believe that all firms were treated is that even firms rated B- experienced a large drop in CDS spreads following the Fed's announcement despite the credit rating of B- being excluded in the Fed's initial criteria for purchase of bonds. As seen in Figure 19, there is also large variation in the

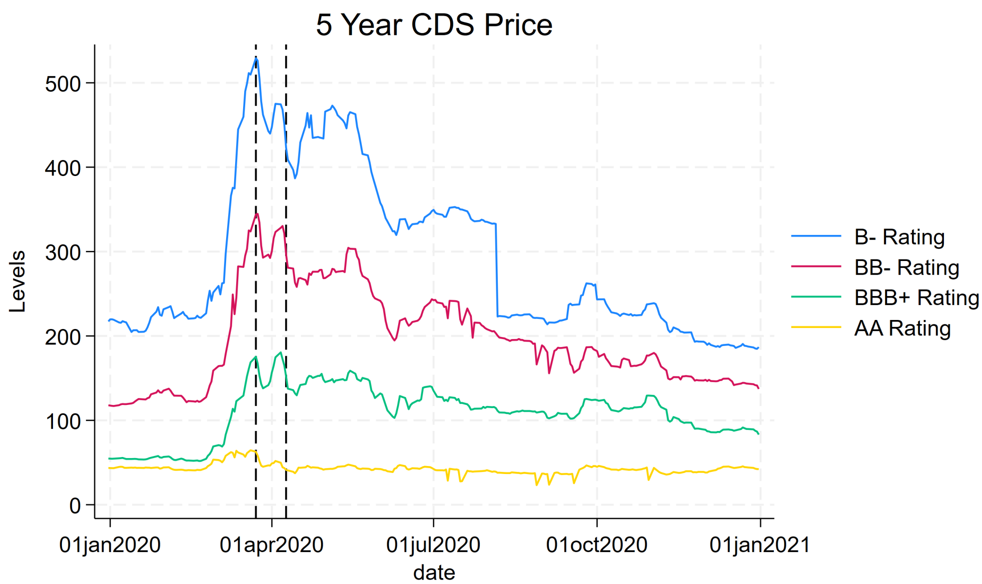


Figure 18: CDS Levels Across Firm Rating Classes

industry-level CDS spreads around the announcement dates.

Due to data limitations, only 414 of the firms in our sample have CDS available from Bloomberg. However, in the next section, we run preliminary analysis that supports the hypothesis that firms issued mass amounts of bonds due to a lowered cost of capital.

Our results studying bond issuance during the Corporate Credit Facilities suggests that the effect of this program on firms' bond issuances began before the Fed started buying bonds. Most issuances occurred before the first purchase on the secondary market and no purchases were ever made on the primary market. Aligned with Gilchrest et al. (2020), we believe the program influenced firms' debt issuance behavior at the onset of the announcement. While a natural control group would be the qualifications set by the Fed to be in the Primary or Secondary

Market Corporate Credit Facilities [9], our results and summary statistics suggest that these are not appropriate treatment and control groups. First, all firms appear to have been affected by the first announcement on March 23, 2020. Figure 18 shows the CDS spreads for a wide range of firm ratings as of March 22, 2020 announcement. If only firms rated BBB- and above were truly treated, then we would not expect firms who had lower ratings also experience a change in their CDS spreads. Gilchrest et al. (2020) also emphasize that the announcement had a strong effect on decreasing credit spreads due to increasing market sentiment. We argue that essentially all firms were at least partially treated. We therefore use the one week change in firm-level CDS spreads around the announcement as an instrument for the firm's exposure to the treatment. Figure 20 demonstrates that both IG and HY firms had similar run ups in the CDS spreads prior to the announcement on March 23, 2020. When we normalize these spreads to be equal the day before the announcement, we see that IG firms had a larger relative drop than HY firms. However, if HY firms were not truly treated, then we would not expect them to experience any change in their underlying valuation.

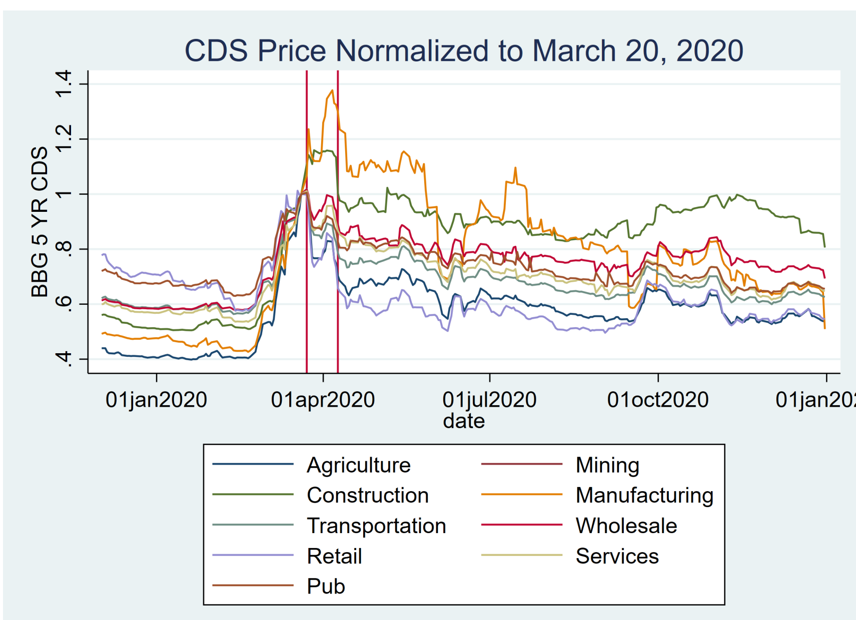


Figure 19: CDS Levels Across Industries

[9]PMCCF: Rated 13 or above as of March 22, 2020 and maturity less than 5 years or less. SMFFF: Rated 13 or above as of March 22, 2020 but downgraded and maturity less than 5 years or less.

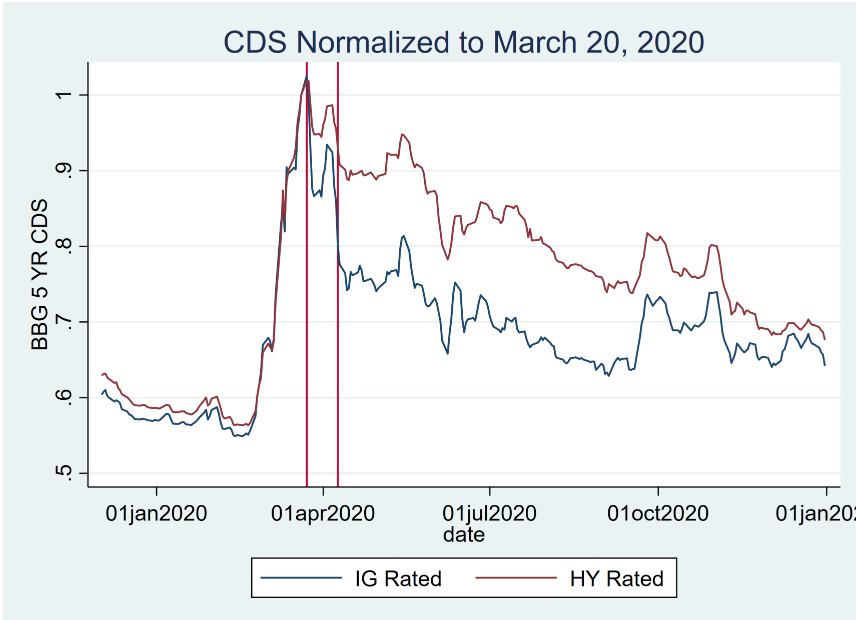


Figure 20: IG vs. HY CDS Spreads Around Announcement

We also see a large variation in the change in the CDS spreads around the announcement, as demonstrated in Figure 21 using one-week changes in the spreads and in Figure 22 using two-week changes.

In order to test the cost of capital theory, we run a regression on the sum of issuances over a specified horizon on firm-level changes in CDS spreads around the announcement. Equation 24 below is our first stage for a given firm f in time period t where x is the duration of the future horizon days. We are interested in seeing that the coefficient β_2 is positive, implying that a larger percent change in a firm's CDS spreads after the announcement, the more likely they are to issue. We include other controls, such as time since last issuance and cash normalized by assets. In the next section, we show why these are important predictors for firm bond issuance. The variable Treatment Time is an indicator for if t is within a set number of days after the first announcement on March 23, 2020. The time period for the regressions specified in Table 28 is January 1, 2016 - June 30, 2020. The left hand side variable is the two week or 10 business day sum of issuances for a given firm.

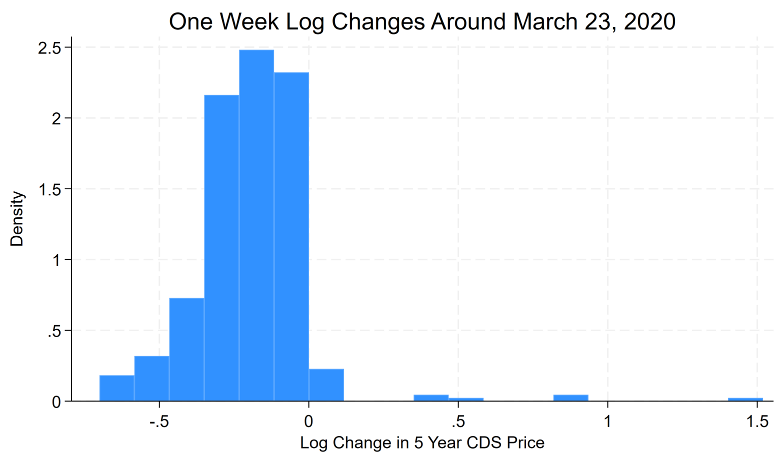


Figure 21: One Week Log CDS Price Change

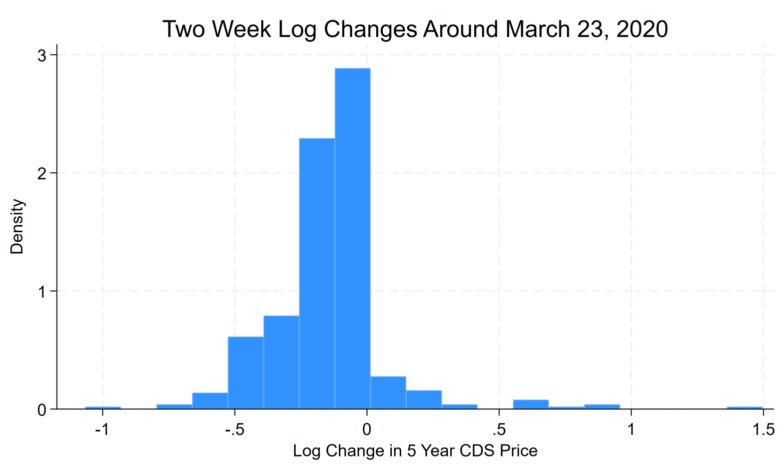


Figure 22: Two Week Log CDS Price Change

$$
\begin{aligned}
\sum_{t}^{t+x} Issuances_f = \alpha + \beta_1(\Delta\text{CDS Price})_{f,t-1} + \beta_2(\Delta\text{CDS Price})_{f,t-1} \cdot \{TreatmentTime\} \\
+ \beta_3(\text{Days Since Last Issuance}_{f,t-1}) + \beta_4(\text{Days Since Last Issuance}_{f,t-1}) \cdot \{TreatmentTime\} \\
+ \beta_5(\frac{Cash_{f,q(t)-2}}{Assets_{f,q(t)-2}}) + \beta_6(\frac{Cash_{f,q(t)-2}}{Assets_{f,q(t)-2}}) \cdot \{TreatmentTime\} \\
+ \beta_7\{March22, 2020Rating\}_f + \beta_8\{March22, 2020Rating\}_f \cdot \{TreatmentTime\} + \epsilon_t
\end{aligned} \tag{24}
$$

The results from the first stage regression using a two week Treatment Time around the announcement are below. In almost all of these specifications, the coefficient on the rating of the firm at March 22, 2020 β_7 is significant but β_8, the coefficient on the interaction between this rating and the Treatment Time, is not. The rating taken as of March 22, 2020 reflects the direct treatment of the CCF. We find that the coefficient β_8 is only significant and positive for very low rated firms (CCC-) or very high rated firms (AAA and above) in specifications where we use each individual rating. These full table results are available upon request. What is surprising in Table 28 is that the one week or 5 business day change in firm-level CDS spreads has positive predictive power for bond issuance that there is not an additional effect of the change in CDS spreads during the Treatment Time. However, the two week change in CDS price becomes significant for predicting issuance after the Federal Reserve's announcement. The first set of results highlights an important aspect about the announcement effect of this program and supports our hypothesis that firms issued to due a lowered cost of capital. We run the same specification but for a one week treatment time after the announcement and taking the cumulative sum for 30 days. We find that the two week change in firm level price is no longer significant, but the one week price change during this one week is significant in predicting the sum of issuances 30 days out. This is a new result that we do not believe has been explored yet in the literature. This finding also supports our cost of capital story. Furthermore, the coeffi-

Table 28: 10 Day Treatment Period Around Announcement: March 23 - April 7, 2020

			10 Day Cum. Sum Issuances			
5 Day ΔCDS	0.0310*	0.0326*				
	(0.0156)	(0.0170)				
Days Since Last Issue	-0.0195***	-0.0138**	-0.0194***	-0.0137**	-0.0196***	-0.0139**
	(0.00605)	(0.00534)	(0.00610)	(0.00536)	(0.00614)	(0.00544)
Treatment Time*5 Day ΔCDS	0.0815	0.110				
	(0.0669)	(0.0662)				
Treatment Time*Days Since Last Issue	-0.0229	-0.00606	-0.0246	-0.00870	-0.0220	-0.00467
	(0.0331)	(0.0395)	(0.0337)	(0.0398)	(0.0348)	(0.0398)
Treatment Time	0.133**	0.177	0.129**	0.168	0.121**	0.142
	(0.0497)	(0.171)	(0.0496)	(0.173)	(0.0511)	(0.182)
Lagged Quarterly Cash/Assets		0.0847		0.0861		0.0859
		(0.0568)		(0.0572)		(0.0584)
Treatment Time*Lagged Quarterly Cash/Assets		-0.997**		-0.956**		-0.990**
		(0.438)		(0.409)		(0.427)
10 Day ΔCDS			0.0208	0.0216		
			(0.0146)	(0.0156)		
Treatment Time*10 Day ΔCDS			0.0812	0.134**		
			(0.0577)	(0.0638)		
Constant	0.0628***	0.0410***	0.0627***	0.0410***	0.0630***	0.0406***
	(0.00770)	(0.0142)	(0.00781)	(0.0143)	(0.00790)	(0.0145)
N	205,185	194,032	204,553	193,435	201,908	190,940

Standard errors in parentheses

* p<0.10, ** p<0.05, *** p<0.010

cient on the interaction between Treatment Time and the Days since last issuance is negative but not significant, supporting the fact that this is not a story about refinance risk.

Table 29: 5 Day Treatment Period Around Announcement: March 23, - March 30, 2020

	30 Day Cum. Sum Issuances					
5 Day ΔCDS	0.0909***	0.0929***				
	(0.0332)	(0.0344)				
Days Since Last Issue	-0.0299	-0.0119	-0.0298	-0.0119	-0.0314*	-0.0134
	(0.0184)	(0.0166)	(0.0184)	(0.0166)	(0.0185)	(0.0168)
Treatment Time*5 Day ΔCDS	0.185	0.273*				
	(0.145)	(0.147)				
Treatment Time*Days Since Last Issuance	-0.0325	-0.0128	-0.0293	-0.0107	-0.0258	-0.00141
	(0.0790)	(0.0880)	(0.0794)	(0.0870)	(0.0799)	(0.0860)
[1em] Treatment Time	0.278**	0.400	0.251**	0.356	0.216*	0.284
	(0.107)	(0.286)	(0.104)	(0.289)	(0.120)	(0.322)
Lagged Quarterly Cash/Assets		0.221		0.222		0.218
		(0.146)		(0.148)		(0.150)
Treatment Time*Lagged Quarterly Cash/Assets		-1.458*		-1.465*		-1.341
		(0.865)		(0.841)		(0.855)
10 Day ΔCDS			0.0681**	0.0690*		
			(0.0338)	(0.0348)		
Treatment Time*10 Day ΔCDS			0.0431	0.183		
			(0.131)	(0.135)		
30 Day ΔCDS					0.0796**	0.0803**
					(0.0383)	(0.0386)
Treatment Time*30 Day ΔCDS					-0.0162	0.0923
					(0.117)	(0.111)
Constant	0.161***	0.0889	0.161***	0.0892	0.163***	0.0907
	(0.0228)	(0.0534)	(0.0229)	(0.0535)	(0.0232)	(0.0544)
N	205,185	194,032	204,553	193435	201,908	190,940

Standard errors in parentheses
* p<0.10, ** p<0.05, *** p<0.010

For the rest of the paper, we do not use this as our treatment effect. For one, there is variation in significance of the treatment time and the window in which the price change occurs. For example, in Table 29, we see that firms' one month change in their CDS price also has significant power in predicting issuance. Additionally, in Tables 28 and 29, we control for firm-level rating as of March 22, 2020. The coefficient on each rating is on average insignificant so the results are excluded. The variable Lagged Cash/Assets is negative, meaning that once you control for individual firm-level rating, the lower cash on hand, the more likely the firm was to issue a bond.

Furthermore, when we run our second stage regression ultimately predicting firm-level acquisition behavior, we do not find significant results. We believe this is because the window in which the first stage occurs is very small. Let **Z** denote the vector of variables from the first stage regression in 24, then Equation 25 shows our second stage regression which has very similar timing to our first stage.

$$\sum_{t}^{t+x} Acqusitions = \alpha + \gamma_1 Issu\hat{ances}_t + z\mathbf{Z}_t + \gamma_2 log(sales_{t-1}) +$$

$$\gamma_3 CAPX_{t-1} + \gamma_4 Market - to - Book_{t-1} + \epsilon_t \qquad (25)$$

Let t denote any time period after June 30, 2020 and similar to Equation 24, x represents the cumulative sum of acquisitions occurring over the horizon. It is important to note that the predicted values $Issu\hat{ances}_t$ and variables in vector $\mathbf{Z}_t$ must be lagged by the difference of days from when t starts in Equation in 25 and when x ends in Equation 24. Studying the impact of the CCF on firms' acquisition behavior is a challenge as there is no obvious "control" group. We run this regression but we do not find significant results. This could be because of the timing. In the next part of the paper, Section **??**, we find that firms issue debt one to three quarters before acquiring. However, we do not believe that firms issued bonds with the intent of acquiring. We believe that this is one of the unintended consequences of the announcement of the CCF program.

D Determinants of M&A Activity

Before we study the relationship between M&A activity and bond issuance, we first replicate the results of Rempel (2020) that a firms' change in cash is a significant predictor of M&A activity. Table 30 shows the regression results of a logistic regression of announcing an acquisition in a quarter from 2010-2019 on multiple balance sheet and income statement characteristics of the firm. Omitted from the table but included in the regressions are fixed effects for year and

Table 30: Logistic Regression of Acquisitions

	Acquisition	Acquisition	Acquisition	M&A Deal	M&A Deal	M&A Deal
$\frac{\Delta Cash_{t-1}}{Assets_{t-1}}$	0.848***	0.922**	1.887***	0.736***	0.825***	1.361***
	(0.308)	(0.362)	(0.544)	(0.257)	(0.316)	(0.437)
$Log(Sales)_{t-1}$	0.502***	0.119***	0.014	0.544***	0.208***	0.232***
	(0.042)	(0.025)	(0.105)	(0.059)	(0.045)	(0.076)
$Market-to-Book_{t-1}$	0.046***	0.004**	0.003	0.005***	0.004***	0.003
	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
$CAPX_{t-1}$	-0.000***	-0.000*	-0.000	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tech_{t-1}$	-0.067	0.065	0.505	0.065	0.085	0.304
	(0.241)	(0.202)	(0.630)	(0.177)	(0.106)	(0.385)
$Biotech_{t-1}$	0.644***	0.456***	0.981***	0.311***	0.257***	0.674***
	(0.157)	(0.041)	(0.022)	(0.066)	(0.050)	(0.019)
Constant	-7.280***	-3.309***	-1.778*	-7.129***	-3.854***	-3.299***
	(0.326)	(0.175)	(0.988)	(0.465)	(0.357)	(0.746)
N	203,388	79,116	22,567	203,797	102,629	27,170
Sample	All Firms	Acquirers	Acquirer & Issuer	All Firms	M&Aers	M&Aer & Issuer
Time Period	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019	2010-2019

SIC 2-digit industry codes. Standard errors are clustered at the SIC 2-digit level. The industry indicators Tech and Biotech are defined using Ritter's classification.

As in Rempel (2020), we find a positive and significant coefficient for lagged change in cash. This suggests that firms increase their cash prior to an acquisition or other M&A activity. Firms that have higher market-to-book ratios, representing that they may be overvalued, are also more likely to acquire. In addition to controlling for broad industries using 2-digit SIC, we include indicators specifically for biotech and other tech firms, which are more likely to engage in M&A activity due to their business models.

We then repeat this exercise, but focusing only on M&A activity starting in 2020Q3. We aim to determine if the same relationship between lagged balance sheet and income statement variables and M&A activity exists during the Covid period as during "normal" times. The regression results can be found in Table 31.

Table 31: Logistic Regression of Acquisitions during Covid

	Acquisition	Acquisition	Acquisition	M&A Deal	M&A Deal	M&A Deal
$\frac{\Delta Cash_{t-1}}{Assets_{t-1}}$	0.835***	1.061***	-0.722	0.532	0.712***	0.713
	(0.325)	(0.268)	(1.187)	(0.324)	(0.335)	(1.042)
$Log(Sales)_{t-1}$	0.407***	0.037***	-0.003	0.297***	0.023	0.085
	(0.048)	(0.020)	(0.119)	(0.010)	(0.030)	(0.106)
$Market-to-Book_{t-1}$	0.004*	0.001	-0.009	0.006***	0.003	-0.003
	(0.002)	(0.002)	(0.006)	(0.002)	(0.002)	(0.005)
$CAPX_{t-1}$	-0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Tech_{t-1}$	-0.126	0.103*	-0.394***	0.175	0.149***	0.106
	(0.138)	(0.059)	(0.114)	(0.117)	(0.042)	(0.080)
$Biotech_{t-1}$	0.595***	-0.040	0.300**	0.127	-0.172**	-0.094
	(0.091)	(0.026)	(0.057)	(0.219)	(0.086)	(0.066)
Constant	-6.696***	-1.553***	-1.283	-5.209***	-1.978***	-2.966***
	(0.397)	(0.156)	(0.949)	(0.803)	(0.273)	(0.899)
N	42,463	5,766	690	42,941	8,965	1,068
Sample	All Firms	Acquirers	Acquirer & Issuer	All Firms	M&Aers	M&Aer & Issuer
Time Period	2020Q3-2022Q1	2020Q3-2022Q1	2020Q3-2022Q1	2020Q3-2022Q1	2020Q3-2022Q1	2020Q3-2022Q1