Unconventional Monetary Policy and Labor Demand: Evidence from the Secondary Market Corporate Credit Facility

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Abstract

We estimate the effects of unconventional monetary policy on firms' labor demand. Using two policy discontinuities of the Secondary Market Corporate Credit Facility (SMCCF), we show the SMCCF increased vacancies by 42% for fallen angels, and was associated with a 23% and 19% increase for BBB and A firms. Every $1 million purchase implies a 7.1%, 3.9%, and 2.7% increase, respectively, implying approximately $5,000 purchase per additional vacancy. Eligible firms experienced increases in borrowing, expenditure, and market value without being liquid constrained, consistent with the SMCCF providing liquidity to the firms.

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1 Introduction

Unconventional monetary policy (UMP) has become an important part of the policy toolkit of most Central Banks around the world for stabilizing financial markets and supporting economic growth when short-term rates reached the zero lower bound. However, UMP consists of numerous policy approaches and programs, and its effects on the real economy must yet be fully understood.

We study the effects of unconventional monetary policy on firms' labor demand through the Secondary Market Corporate Credit Facility (SMCCF), which aimed to provide liquidity to outstanding corporate bonds during the COVID-19 Pandemic, and the program purchased $14 billion parvalues of bonds which belong to about 600 firms. We estimate the effects of the SMCCF on firms' vacancy postings, and we examine the economic channels through changes in firms' balance sheet.

We find that the SMCCF increased vacancy postings of BBB firms which were downgraded to BB (fallen angels) by 42%. The SMCCF is also associated with a 23% increase in vacancy postings of firms with BBB bond ratings (BBB firms), and a 19% increase of firms with AAA/AA/A ratings (A firms).[1] The point estimates decrease when firms' credit ratings increase, which is consistent with a higher responsiveness of more liquid-constrained firms. Using variation in the treatment dose suggests that a $1 million bond purchase associates with increases in vacancy postings of the fallen angels by 7.1%, of BBB firms by 3.9%, and of A firms by 2.7%, respectively, which implies that approximately every $5,000 purchase is associated with one more vacancy. We examine the mechanism and find that the treated firms experienced an immediate increase in borrowings, expenditure, and market value without change in liquidity, which suggests that the SMCCF supported credit to the firms, and it allowed these firms to increase expenditure and relax credit constraints.

Our identification leverages two policy discontinuities in the SMCCF which required

[1]We obtain the credit ratings time series of firms according to their bond ratings time series at the majority of the NRSROs. Importantly, ratings of bonds issued by the same firm are consistent under the same NRSRO.

that the eligible bonds must i) have at least a BBB- rating as of March 22, 2020, when the Board of Governors of the Federal Reserve System (the Fed) voted for the measure unanimously; and ii) have a maturity of five years or less at the time of purchase. We propose a primary identification strategy based on the arguably arbitrary date cutoff, which allows us to compare firms who had some of their bonds purchased by the SMCCF and whose ratings were BBB on March 22, 2020, but were subsequently downgraded to BB, referred to as the fallen angels, with the firms whose ratings were BB on March 22, 2020, and at least BB throughout 2020, referred to as the control BB firms. These firms are similar in this case because they are borderline eligible/ineligible for the SMCCF, and the Fed arguably cannot know with certainty which firms would satisfy the rating requirement on March 22, 2020.[2]

As a second exercise, while aware that the maturity cutoff could imply selection, we also compare firms with the same bond ratings but different maturities for completeness, controlling for firm fixed effects and a range of firm time-varying characteristics for robustness. We apply this identification approach to BBB and A firms. Treated BBB (A) firms had at least some of their bonds with remaining maturities fewer than five years purchased by the SMCCF, whereas control firms had the same credit rating but no bond that satisfied the maturity requirement, because these firms tend to issue long-term bonds. As this is in principle a weaker identification, we refrain from claiming full causality in this case, even though we fairly corroborate the plausibility of the identification with an exhaustive series of empirical tests.

We merge the SMCCF disclosures with the Mergent Fixed Income Securities Database (FISD), the Burning Glass Technology (BGT) online vacancy postings data, and the Compustat Capital IQ (Compustat) data, which results in a unique dataset of 736 firms from 2019m1 to 2022m12. We use a Difference-in-Difference (DiD) regression and show that the fallen angels had an insignificant initial response, which increased to over 40% and

[2]In this case, the maturity cutoff, although a necessary requirement for treatment, is not sufficient as firms with short-term debt but BB rating would be included in the control group.

became significant after one year. The results are robust to using sharper control groups which further tighten the similarity to the fallen angels. The treated BBB firms displayed similar trends in their vacancy postings, whereas the treated A firms immediately saw a 19% increase in vacancy postings.

Further analysis shows that the effects are larger for firms in more affected industries, which suggests that the SMCCF eased industry-specific responses to the shock. Meanwhile, vacancy postings did not differ in their skill content or posted salaries after the SMCCF, which implies the program did not change the type of labor demand.

We measure borrowings, expenditure, and market value using the debt-to-asset ratio, expense-to-asset ratio, and market-value-to-asset ratio, respectively, and we use three measures of firms' liquidity, namely the cash-to-asset ratio, cash-holdings-to-asset ratio, and KZ-index (Kaplan and Zingales, 1997). We show that the fallen angels and the treated BBB firms saw increases in their borrowings and expenditure temporarily, and their measure of liquidity experienced no change. Meanwhile, the SMCCF is associated with increases in the market value of the treated A and BBB firms, which could imply fewer credit constraints because the market viewed them to provide safer assets.

Thus, we argue that the SMCCF increased firms' labor demand, measured by vacancy postings, through liquidity provision to firm bonds, at least for the more constrained firms. One question is whether the potential gain in the labor market could be large if the Fed had launched a program similar to the SMCCF during the Great Recession, instead of providing liquidity to financial institutions.[3] We posit that the external validity depends on whether liquidity shocks are temporary. If instead these shocks are persistent, firms might not increase labor demand regardless of the intervention. Future research along this line is needed.

The current study contributes to the literature on the labor market effect of unconventional monetary policy (See, e.g., Luck and Zimmermann, 2018; Hohberger et al., 2020;

[3] In particular, the median bond spreads remained elevated during the Great Recession even after Quantitative Easings (Kozlowski et al., 2021).

Zens et al., 2020, besides the studies cited above). By focusing on the SMCCF, we are able to use various empirical tools to estimate the causal effect of the intervention, which differs from the VAR approach (e.g., Gertler and Karadi, 2015; Gambacorta et al., 2014) or event-study method (e.g., Joyce et al., 2011). While the studies on the financial market outcomes show that most of the effects on bond spreads happened shortly following the announcement of the SMCCF (e.g., Gilchrist et al., 2021; D'Amico et al., 2020; Kargar et al., 2021; Haddad et al., 2021; Nozawa and Qiu, 2021; O'Hara and Zhou, 2021), we show that the effects on labor demand could be long lasting and delayed, which resembles the hump-shaped employment response to conventional monetary policy (e.g., Christiano et al., 1999).[4]

More broadly, the current study is related to the labor market effect of credit provision to firms. Most past studies focus on small firms (e.g., Brown and Earle, 2017) or firm-bank relations (e.g., Chodorow-Reich, 2014; Caglio et al., 2021).[5] Because of the nature of the SMCCF, we show that the effects of direct liquidity provision by the monetary authority could be large for large employers. Specifically, we find that A firms which include Amazon and Walmart responded to the SMCCF, whereas Chodorow-Reich (2014) find no employment effect of bank credit provision for the largest firms.

We note that one key mechanism, namely that unconventional monetary policy affects "safety premium," was present in the Quantitative Easing (QE) by the Fed from 2008 to 2014 (e.g., Gagnon et al., 2011). In particular, the "Baa Index" declined following the announcement of QEs. Therefore, the current study provides an evaluation to asset purchase programs more broadly (For a survey, see Bhattarai and Neely, 2022). As more central banks launched programs similar to the SMCCF, it is important to understand the real effects of such monetary policy and how it compares to existing programs such

[4]Compared to the studies on the effects of the SMCCF on the financial market outcomes, our identification strategy that utilizes both of the policy discontinuities in DiD or synthetic control is novel and more comprehensive. We also use actual treated firms instead of firms that were likely to be treated, allowing us to estimate the causal response.

[5]For a recent survey on the real effects of banks' corporate credit supply, see Güler et al. (2021).

as the Small Business Administration (SBA) loans. Our results suggest that despite the observation that large employers tend to direct funds to non-labor related activities such as buying back stocks, their increase in vacancy postings is substantial.

The focus on the labor demand, besides data availability, is useful in a period when the labor supply was dampened due to, e.g., health concerns. The counterfactual estimate of the effects of the SMCCF on employment would be zero in the extreme case of inelastic labor supply. Therefore, our estimates of labor demand serve as a useful benchmark for analyzing the effects of future interventions under different labor supply elasticity.

In addition, the large labor demand effects are consistent with the conventional wisdom in the New Keynedian framework that the effects of monetary policy mainly operate through the labor demand channel (e.g., Galí, 2013; Broer et al., 2020).

The organization of the rest of the paper is: Section 2 describes the SMCCF and our data in detail. Section 3 show the results on labor demand and Section 4 show the effects on firms' balance sheet. Section 5 concludes. Robustness analysis are relegated to the Appendix.

2 Data and Empirical Methods

2.1 Institutional Background

On March 13, 2020, the Trump Administration declared a nationwide emergency because of the outbreak of the COVID-19 pandemic. Against the backdrop, on March 23, the Federal Reserve (Fed) announced extensive new measures to support the economy. Among them is the Corporate Credit Facility (CCF) which includes the Primary Market Corporate Credit Facility (PMCCF) and the Secondary Market Corporate Credit Facility (SMCCF), and they aim to support credit to large employers. The PMCCF is intended to support new bond and loan issuance and the SMCCF is for providing liquidity to outstanding corporate bonds.[6] The timeline of the CCF program is[7]

- March 23, 2020: The Fed announced the PMCCF and the SMCCF. The program would start in 2020m6 and end in 2020m9. Eligible corporate bonds must meet the following criteria *at the time of bond purchase*: (i) issued by US companies headquartered in the US with material operations in the US; (ii) issued by an issuer that is rated at least BBB-/Baa3 by a major nationally recognized statistical rating organization (NRSRO) and, if rated by multiple major NRSROs, rated at least BBB-/Baa3 by two or more NRSROs; and (iii) have a maturity of four years or less.

- April 9, 2020: The Fed expanded the PMCCF and the SMCCF. Under the new terms, the program would run until 2020m12, and the second and third criteria updated to: (ii) the issuer was rated at least BBB-/Baa3 *as of March 22, 2020*, by a major NRSRO. If rated by multiple major NRSROs, the issuer must be rated at least BBB-/Baa3 by two or more NRSROs as of March 22, 2020. An issuer that was rated at least BBB-/Baa3 as of March 22, 2020, but was subsequently downgraded, must be rated at least BB-/Ba3 as of the date on which the Facility makes a purchase. If rated by multiple major NRSROs, such an issuer must be rated at least BB-/Ba3 by two or more NRSROs at the time the Facility makes a purchase; and (iii) have a maturity of five years or less.

- June 16, 2020: The Fed began buying individual corporate bonds under the SMCCF.

- December 31, 2020: The Fed ceased buying individual corporate bonds under the SMCCF but continued to hold the bonds.

- September 2, 2021: The Fed sold the bonds through 2021m1 to 2021m9. The last set of sales were settled on September 2, 2021, when the total outstanding amount of the SMCCF reached 0. No transactions occurred under the PMCCF during the period it was operational.

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[6]See https://www.federalreserve.gov/newsevents/pressreleases/monetary20200323b.htm.

[7]See the SMCCF's March 2020, January 2021, and October 2021 announcements.

We utilize two policy discontinuity of the program for identification. First, the expansion of the program on April 9 allowed some firms whose bond ratings were subsequently downgraded after March 22, 2020 to be eligible. These firms were arguably similar to the ones who were just ineligible. Second, the cutoff for bond maturity was five years, which means that firms who tend to issue bonds with longer maturities were ineligible even if they satisfied the rating requirements. In the next subsection, we describe our data and empirical methods in detail.[8]

2.2 Data

Our data consists of four sources: the SMCCF transaction-specific disclosures, the Mergent Fixed Income Securities (FISD) Database, the Burning Glass Technology (BGT) online vacancy postings data, and the Compustat Capital IQ (Compustat) data.

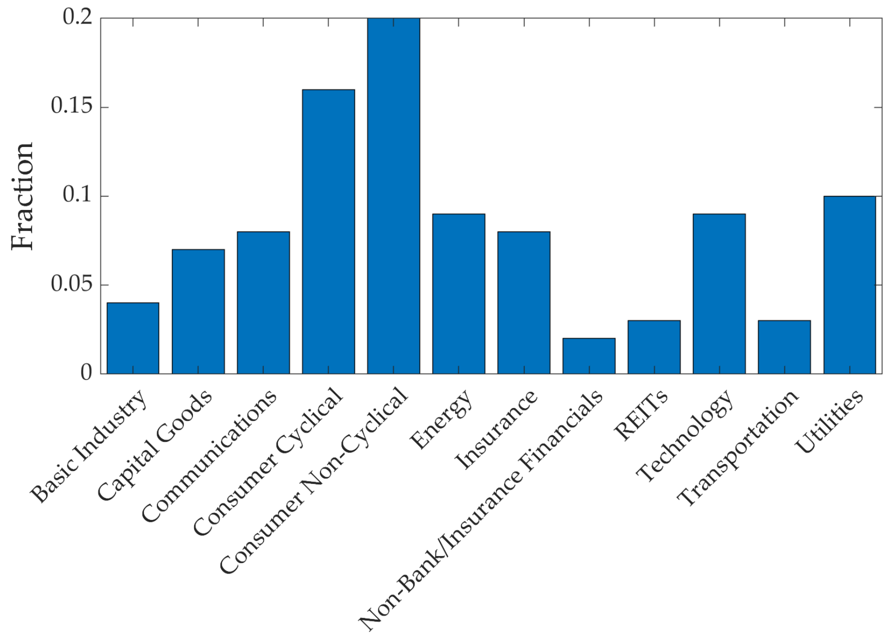
The SMCCF transaction-specific disclosures are monthly balance sheets for the SMCCF, which contain information on the par-value of bond holdings for each firm. The size of the SMCCF is large: In 2020m12, the total outstanding amount of the Fed's loans was $14 billion, of which 40.17% is in AAA/AA/A bonds, 56.62% in BBB bonds, and 3.21% in BB bonds.

Figure 1 shows the distribution of bond par-value by sector as of December 31, 2020, with the sectors specified in the SMCCF disclosure. Consumer sectors received the most funds, whereas Insurance Financial, REITs, and Transportation sectors saw fewer bond purchases. The par-value was quite evenly distributed for the other sectors, which suggests that the SMCCF did not appear to target specific sectors.

We merge the SMCCF disclosures with the FISD data, which contains bond rating histories of publicly offered US bonds, as well as the issuing firms, offer dates, and maturity dates. We are able to match all firms on the SMCCF disclosures, and we assign ratings to

[8] The Fed also required that for broad market index bonds, the issuer cannot be an insured depository institution or its holding company. We exclude such institutions when we specify controls firms (e.g., banks or their holding companies).

Figure 1: Fraction of Bond Purchase by Sector



Notes. Figure 1 plots the par-value of bond purchases by sector as of December 31, 2020. The data is available in the January 2021 SMCCF disclosure.

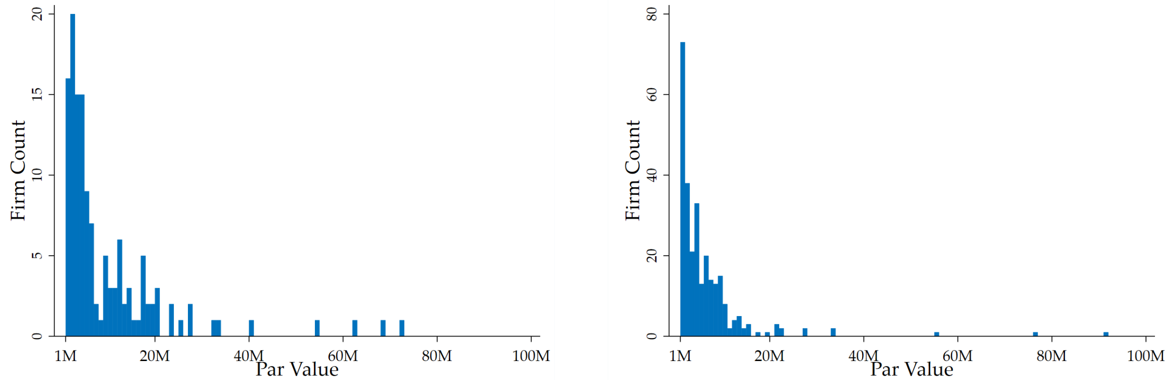
these firms at any point in time according to their bond ratings histories.

We characterize A (BBB) firms to be those rated AAA/AA/A (BBB+/BBB/BBB-) by S&P and Fitch, and those rated Aaa/Aa/A (Baa1/Baa2/Baa3) by Moody's. We note that the credit ratings for different bonds issued by the same firm are very consistent in our sample, with less than 5% of firms who have different ratings for their bonds under the same NRSRO. When the bond ratings for those issued by the same firm do differ in the same NRSRO, they would belong to the same A or BBB category. This implies that our characterization of firm credit ratings based on their bond ratings is consistent at each NRSRO.[9]

If the firms are rated by multiple agencies, the ratings need to be A (BBB) for at least two agencies, which allows us to obtain a time series of firm credit ratings. The firms need to be rated A (BBB) on March 22, 2020. We identify 183 unique A firms and 366 unique

[9]There are instances in which bonds issued by the same firm were rated, e.g., BBB+ and BBB at the same time under the same NRSRO. It is never the case that a bond issued by a firm was rated A while another one issued by the same firm was rated BBB under the same NRSRO.

Figure 2: SMCCF Bond Par Value Distribution



(a) A Firms (b) BBB Firms

Notes. Figure 2 plots the distribution of par-value of the SMCCF bond purchases at the firm level. The par-value is averaged from 2020m6 to 2020m12. A firms had a bond rating of at least A- and BBB firms had a bond rating of at least BBB- on March 22, 2020. Y-axis corresponds to the number of firms. X-axis corresponds to par-value. The minimum par-value was \$1 million and the maximum was \$91 million. The average par-value was \$9.8 million for A firms and \$6.2 million for BBB firms.

BBB firms.

Figure 2 shows the distribution of average bond holdings from 2020m6 to 2020m12 for A firms and BBB firms, respectively. The minimum par-value was \$1 million and the maximum was \$91 million. Many firms had a par-value of \$1 million, and most par-values were bunched between \$1 million and \$20 million, which arguably suggests that the Fed did not favor specific firms. The average par-value was \$9.8 million for A firms and \$6.2 million for BBB firms.

Next we combine the data with the BGT data, which contains the universe of US online vacancy postings. Our sample periods span 2019m1 to 2022m12. We exclude the firms whose vacancy postings were fewer than 10 in 2019 and fewer than 50 in the full sample period, which allows us to match 73% (133/183) of A firms and 76% (279/366) of BBB firms in the SMCCF disclosure. We refer the matched data as the FISD-BGT data.[10]

Figure 3 (a) shows the monthly vacancy postings growth for A firms and BBB firms,

[10]We argue that the BGT data is suitable for the current study because both treated and control firms are large in size, and they post vacancies online extensively (e.g., Hershbein and Kahn, 2018). Appendix Section A.1 contains details on how we merge the SMCCF data with the BGT data.

respectively, relative to their monthly average in 2019. The red dashed line corresponds to 2020m3 when the US entered a nationwide emergency. The first dash black line indicates the start of the SMCCF in 2020m6, whereas the second one corresponds to the end of the SMCCF in 2020m12.

Figure 3: Vacancy Growth and the Fraction of Actively-Posting Firms

(a) Vacancy Postings Growth

(b) Fraction of Actively-Posting Firms

Notes. Figure 3 (a) plots the monthly vacancy postings growth for A firms and BBB firms, normalized by the average monthly vacancy postings in 2019. The red dashed line corresponds to 2020m3 when the US entered a nationwide emergency. The first dash black line indicates the start of the SMCCF in 2020m6, whereas the second one corresponds to the end of the SMCCF in 2020m12. Figure 3 (b) plots the fraction of A firms and BBB firms in the matched FISD-BGT data that post vacancies in a given month.

The vacancy growth remained stable throughout 2019, and then it exhibited sharp declines for the BBB firms at the onsite of the COVID-19 pandemic. Subsequently, the vacancy growth of the A firms increased when the SMCCF started, which declined even before the end of the SMCCF in 2020m12. As the economy began to recover in 2021, both types of firms saw increases in their vacancy growth, with more postings than the average value in 2019.

Figure 3 (b) shows the fraction of firms who post vacancies in a month in our matched FISD-BGT data, referred to as the actively-posting firms.[11] The fraction of actively-posting BBB firms is about 5% higher than that of the A firms throughout the sample period, and both saw increases at the beginning of the SMCCF. The fraction started to decline before

[11]This means we exclude firms in the FISD who are not matched in the BGT data.

the SMCCF ended, which is similar to the trends in vacancy postings.

The analysis suggests interesting patterns: Both the number of vacancy postings and fraction of firms posting vacancies increased at the start of the SMCCF, which declined prior to the end of the program. These patterns could reflect changes in aggregate economic conditions, rather than suggesting causal effects of the SMCCF.

Finally, we merge the data with Compustat which contains information on firm fundamentals, including employment, asset, debt, etc. We match about 80% of the firms, which we refer to as the FISD-BGT-Compustat data.[12] Appendix Section A.4 lists the Compustat variables in the current study.

2.3 Empirical Methods

Our first empirical specification is the following Difference-in-Difference (DiD) regression:

$$\log(Vacancy)_{im} = \alpha + \sum_{\tau=-3}^{4,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_q + \epsilon_{im} \tag{1}$$

The outcome variable is log vacancy postings for firm i in month-year m. $\mathbb{I}_i^\tau$ is an indicator that the firm was treated τ periods away from the treatment period (2020h2), and we define one period to be half a year to reduce noises in vacancy postings.[13] We include firm fixed effects and quarter-year fixed effects, which absorb cross-firm differences in initial employment, asset-to-debt ratios, operating leverages, etc.[14] Therefore, we interpret the

[12]Specifically, we match 85% (113/133) of A firms and 81% (226/279) of BBB firms. For specific variables, e.g., employment, the number of observations could be smaller than the number of matched firms because of missing data in Compustat. Employment data is at an annual frequency, while the other firm characteristics are at a quarterly frequency.

[13]This implies the treatment period is from 2020m7 to 2020m12. $\mathbb{I}_i^0$ would be equal to 1 for treated firms in the second half of 2020, namely from 2020m7 to 2020m12, and $\mathbb{I}_i^1$ would be equal to 1 for treated firms in the first half of 2021, namely from 2021m1 to 2021m6, and so on. Appendix Section A.8 defines one period to be one quarter and shows the trajectories. We note that mechanically, the estimates using bi-annual frequency are the weighted averages of those using quarterly frequency.

[14]We use quarter-year fixed effects to be consistent with regressions in Section 4 which uses quarterly Compustat data. All results with monthly vacancies as the outcome variable are robust to using month-year fixed effects, which are available upon request.

coefficients as the effects of the SMCCF on vacancy postings after controlling for average differences in firm size. Equation (1) examines the effects of the SMCCF 3 periods before and 5 periods after the program, namely from 2019h1 to 2022h2. The regression uses the matched FISD-BGT data instead of the matched FISD-BGT-Compustat data, because we do not include time-varying firm fundamentals.

We are interested in

$$\overline{\beta} = \frac{1}{5}\sum_{\tau=0}^{4} \beta_{\tau} \tag{2}$$

Equation (2) is the average treatment effect of the SMCCF. Because the treatment indicators exhaust the sample period, we omit the period before the SMCCF (The first half of 2020), which effectively treats it as the base period. The standard error is clustered by firm.

We rely on the cutoffs of the SMCCF program to devise an identification strategy for Equation (1). Two main concerns related to the use of these cutoffs to assess the impact of SMCCF are noteworthy. First, the announcement of these facilities had a generalized effect on the entire bond market, with an additional differential effect on the short-term segment targeted by the Fed. A good identification strategy must be able to net out this effect. Second, a risk of using the bond maturity cutoff is that firms that tend to issue long-term debt and are less likely to be treated by the program may also recover with more difficulties from the COVID shock due to their own specific characteristics. A good identification strategy must be able to disentangle the benefits of SMCCF from the differential effects due the characteristics of non-treated firms.

Therefore, we adopt a primary identification of the causal effects of SMCCF based on the date cutoff of the ratings requirement.

Concretely, the treated firms are the those in the FISD-BGT data that were rated at least BBB- on March 22, 2020, but were subsequently downgraded to BB ratings in 2020, referred to as the "fallen angels." The control BB firms include those rated at least BB- on March 22, 2020, making them ineligible for the SMCCF. We also require that the control BB firms to maintain at least BB- ratings through 2020, which resembles the requirement in the SMCCF.

This includes firms that subsequently improved their ratings.[15]

Because the date cutoff is arguably arbitrary, the fallen angels should be similar to the control BB firms in factors that affect their bond ratings. Moreover, while remaining a technically necessary requirement, the bond maturity cutoff is less of a determinant of the treatment in this case. Specifically, both the fallen angels and control BB firms issue debts with a similar maturity profile. Therefore, they were borderline eligible or ineligible for the SMCCF because of the date cutoff, and the Fed arguably could not know with certainty which firms would have at least a BBB- rating on March 22, 2020. If the date cutoff were different, so would be the marginally eligible firms.[16]

Table 1 panel A suggests that the characteristics of the fallen angels and control BB firms are not significantly different prior to the SMCCF, which mitigates the concerns mentioned above and lends strength to our identification argument.[17] There are 21 fallen angels and 168 control BB firms in the matched FISD-BGT data.[18]

We extend the identification approach to a second set of comparison, in which we compare the treated BBB (A) firms with the control BBB (A) firms which were ineligible because of maturities longer than five years. Specifically, the characterization of the control firms' credit rating is the same as that for the treated firms, and the bond maturity of all bonds issued by the control firms needs to be longer than five years on January 1, 2021.[19] Our data includes 279 treated BBB firms and 133 treated A firms, as well as 101 control BBB firms and 55 control A firms. We use Equation (1) to compare the vacancies between the treated and control BBB (A) firms before and after the SMCCF.

We note that our identification in this case is less tight than that for the fallen angels

[15] Because we use the SMCCF disclosure, we can guarantee that our treated firms indeed received purchases while control firms never did, unlike earlier studies that used firms which were likely to be treated.

[16] Notable mentions of the fallen angels are Ford Motor Company and Nordstrom. A notable mention of the control BB firms, on the contrary, is Netflix, whose rating improved to BBB in 2021.

[17] Arguably, firms could not anticipate the announcement date of the SMCCF and manipulate their credit ratings shortly before the announcement.

[18] We match 62% (13/21) of the fallen angels and 84% (141/168) of the control BB firms in the FISD-BGT data with Compustat.

[19] We exclude insured depository institutions and their holding companies.

group. The treated BBB (A) firms tend to have a range of bonds with different remaining maturities, and they tend to issue bonds with an initial maturity of ten years. There are cases in which only a subset of the bonds issued by the treated firms were purchased by the SMCCF, because the other bonds had remaining maturities longer than five years. On the other hand, the control BBB (A) firms tend to issue bonds with an initial maturity of, e.g., thirty years, which makes them unlikely to be eligible for the SMCCF.[20] Such differences manifest themselves by observable characteristics, as the treated firms tend to post more vacancies, were larger in size, and had higher cash-to-asset ratios (Table 1 Panel A).[21]

To that end, we first note that even if the bond maturities are correlated with firms' characteristics, firm fixed effects would absorb any constant correlation between firm type and vacancy postings, as well as any initial difference in observable characteristics. Second, we control for a range of firm time-varying characteristics for robustness, and we also include a synthetic control regression, to be detailed below, to match on firm observable characteristics. Third, Appendix Section A.5 restricts the control firms to those who issued short-term bonds for additional robustness analysis. Although we cannot claim full causality for the results with BBB and A firms, we argue that we provide evidence and many robustness checks which fairly corroborate the plausibility of the identification for the second set of comparison as well. In any case, we believe these results are worth to be reported at least for completeness.

Our assignment of treatment at the firm level, rather than at the bond level, reflects the constraint that we cannot associate vacancy postings to specific bonds issued by a firm. However, we note that our identification strategy and mechanism analysis in Section 4 are consistent with firm-level treatment assignment. In addition, the literature shows that

[20]See Appendix Section A.5 for details.

[21]We note that the employment data is not available for some firms in the matched FISD-BGT data, and these firms could have different employment and vacancy postings. Specifically, we match 67% (68/101) of the control BBB firms and 45% (25/55) of the control A firms in the FISD-BGT data with Compustat. There are 16 BBB firms and 5 A firms that appear eligible according to FISD but were not treated by the Fed. The number is arguably small compared to the total number of treated firms. We show in Appendix Section A.2 that including them in a two-stage-least-square regression does not affect the results.

bond spreads of the bonds issued by the same firm tend to move together during the SMCCF, even if only a subset was eligible (e.g., Gilchrist et al., 2021; Boyarchenko et al., 2022).

We also note that our identification strategy allows us to estimate the overall effects of the SMCCF, but it is difficult to decompose the effects of various stages of the implementation. Specifically, we cannot estimate separately the effects of the initial announcement, the effects of the expansion of the SMCCF, the effects of holding the portfolio in 2021, etc., because of the data constraint and slow-adjusting nature of the labor market.

As discussed above, we address the difference in observable between the treated and control firms by using a synthetic control regression to match pre-treatment employment and vacancy postings. Specifically, we construct a synthetic control firm for each treated firm, and we require the fit to be better than 10% prior to the SMCCF.[22] We calculate the implied vacancy postings, and then we use the following regression to pool all the treated and synthetic control firms to estimate the average treatment effects:

$$\log(Vacancy)_{ih} = \alpha + \sum_{\tau=-3}^{4,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_h + \epsilon_{ih} \tag{3}$$

where we treat each synthetic control firm as a separate firm and cluster the standard errors at the firm level.

Table 1 Panel B shows that the treated BBB (A) firms and their synthetic control firms are almost identical in pre-treatment employment and vacancy postings, which results in 206 (78) treated BBB (A) firms and equal numbers of synthetic control firms. We use the synthetic control regression on the fallen angels as well, which reduces the sample to 13

[22]Concretely, we define one period to be half a year, and we aggregate monthly vacancies to the half-year frequency. And then, we calculate the average difference in log vacancies between the treated firm and its synthetic control prior to the SMCCF (2019h1 to 2020h1), and we require the average difference to be less than 10%, which essentially drops the very large treated firms without good synthetic controls. Table 1 shows that the synthetic control regression retains around 70% of the treated firms, but the average employment size decreased by over 85% for these firms. We also note that the lack of employment data for some control firms could contribute to the lack of good synthetic controls.

fallen angels. Because the sample size is small, we do not impose any fit requirement for the fallen angels and their synthetic controls.

Table 1: Summary Statistics and Synthetic Control Match

Panel A: Summary Statistics						
	Fallen Angels	BB	Treated BBB	Control BBB	Treated A	Control A
2019 Vacancies (1000s)	1.8	2.8	5.9	1.5	7.9	3.2
	(4.1)	(5.9)	(16.6)	(4.4)	(15.1)	(7.4)
2019 Employment (1000s)	28	21	45	16	99	13
	(53)	(40)	(80)	(33)	(232)	(20)
Cash-to-Asset Ratio	0.053	0.066	0.064	0.057	0.108	0.051
	(0.065)	(0.085)	(0.086)	(0.064)	(0.122)	(0.080)
Matched FISD-BGT	21	168	279	101	133	55
Matched FISD-BGT-Compustat	13	141	225	68	113	25
2019 Emp. Obs.	13	135	223	65	110	21
Cash-to-Asset Ratio Obs.	14	141	225	68	112	25

Panel B: Synthetic Control Summary Statistics						
	Fallen Angels	SC BB	Treated BBB	SC BBB	Treated A	SC A
Vacancies (1000s)	1.1	1.0	2.1	2.0	2.4	2.6
	(2.5)	(2.1)	(3.6)	(3.2)	(2.7)	(2.8)
2019 Employment (1000s)	5.3	5.2	6.4	6.4	7.1	7.1
	(2.3)	(2.3)	(1.7)	(1.7)	(1.2)	(1.2)
Obs.	13	13	206	206	78	78

Notes. Table 1 Panel A shows the vacancies (1000s), employment (1000s), and cash-to-asset ratio in 2019 for the treated and control firms. "Cash" include cash holdings and short-term investments. The numbers of matched FISD-BGT firms apply to vacancy postings. We use Compustat annual firm fundamentals data for employment and Compustat quarterly firm fundamentals data for the cash-to-asset ratio. Panel B shows the vacancies (1000s) postings prior to the SMCCF (2019h1-2020h1) and employment (1000s) in 2019 for the treated firms and their synthetic controls. We construct a synthetic control firm for each treated firm by matching pre-treatment log vacancies and 2019 employment. We choose one period to be half a year, and we require that the average difference in log vacancies between a treated firm and its synthetic control to be less than 10% prior to the SMCCF (2019h1-2020h1), which essentially drops the very large treated firms without good synthetic controls. We do not impose the requirement for the fallen angels.

The Fed launched other programs during the same period of the SMCCF, which could confound the effects. Of close relevance is the Primary Dealer Credit Facility (PDCF), which provided funding to primary dealers in the bond market. We note that the size of the PDCF ($0.5 billion) is much smaller than that of the SMCCF ($14 billion). In addition, the eligibility criteria differ across the two programs. Nonetheless, we address this issue by comparing the vacancy postings between any pair of control firms, e.g., the control

BB firms and control BBB firms. If these comparisons suggest similar vacancy postings, we argue that we cannot find evidence of other confounding factors which could bias the results based on firms' ratings.

Our second empirical specification is the following fuzzy DiD regression that estimates the causal response to an incremental change in the "dose" of the treatment D_i (de Chaisemartin and D'Haultfoeuille, 2020; Angrist and Imbens, 1995):

$$\log(Vacancy)_{im} = \alpha + \beta_{fd} * D_i * Post_m + \delta_i + Post_m + \epsilon_{im} \tag{4}$$

Namely, we separate the sample into pre- (2019m1-2020m6) and post-periods (2020m7-2022m12), and the firms into two groups to use the fuzzy DiD method by de Chaisemartin and D'Haultfoeuille (2018), which addresses the bias in regression weights when treatment doses vary across firms (Callaway et al., 2021). $\log(Vacancy)_{im}$ is the log vacancies for firm i in month-year m. Our group of firms include the fallen angels and the control BB firms whose treatment dose is 0. We characterize the treatment dose as the average par-value from 2020m7 to 2020m12 in $1 million increments, which means we are estimating the average marginal effect of an extra $1 million purchase of bonds on log vacancy postings. Equation (4) includes firm fixed effects and an indicator for post-treatment periods, and we use firm-clustered standard errors. We repeat Equation (4) for the treated versus control BBB (A) firms to see if the point estimates differ by the firms' potential credit constraints.

3 The Effects of the SMCCF on Labor Demand

We discuss separately the average treatment effects and causal response. For both discussions, we start from the fallen angels, and move to BBB and A firms. Table 3 shows the point estimates of the average treatment effects and causal responses.

3.1 Average Treatment Effects on Vacancy Postings

Fallen Angels Figure 4 shows that the change in vacancy postings of the fallen angels is statistically insignificant in the period of the SMCCF, which is equal to 7.3% (0.114), likely because most fallen angels experienced declines in credit ratings during the SMCCF.[23] The subsequent increase in vacancy postings is large, which shows that the effect increased to 13.8% (0.138) in the second period after the SMCCF (2021h1), and it continued to rise. The effect in the last period—namely, 2022h2—suggests that the vacancy postings of the fallen angels were 71.7% (0.254) higher than those of the control BB firms, which is much larger than that for the other treated firms. The average treatment effect is 42.1% (0.155), which is significant at 5%.

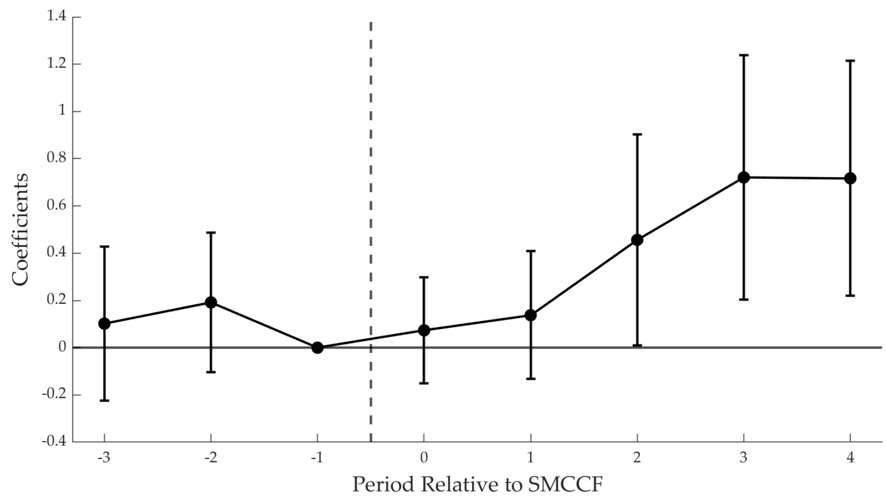


Figure 4: The Effects of the SMCCF on Log Vacancies: Fallen Angels

Notes. Figure 4 plots the coefficients from the DiD regression (Equation 1) for the fallen angels, which are firms in the SMCCF disclosure whose bond ratings were at least BBB- on march 22, 2020, and whose bond ratings were subsequently downgraded to BB+/BB/BB- in 2020. The control BB firms are those in the FISD whose bond ratings were at least BB- on March 22, 2020, and who maintained at least a BB- rating in 2020. We exclude insured depository institutions and their holding companies. We define one period to be half a year, with the sample spanning 2019h1-2022h2. The standard error is clustered at the firm level.

The effects did not become significant until the third period following the SMCCF (2021h2), which raises two questions: First, could the effects be driven by other confounds,

[23]14 of the 21 fallen angels changed credit ratings between June 1, 2020 and December 31, 2020, while the other 7 experienced ratings decline between March 23, 2020 and May 31, 2020.

given that we examine log vacancies two years following the SMCCF? Second, even if the results were not driven by confounds, how could the effects of the SMCCF on vacancy postings be delayed and long-lasting?

For the first questions, we note that if the results were driven by confounds, these confounds must be more likely to treat the fallen angels than the control BB firms. This would likely be the case if the fallen angels were BBB firms most of the time, whereas the control BB firms were usually BB firms, which would imply that the date cutoff is less relevant for determining treatment status, but the rating requirement is. And then, any confounds that would favor higher rated firms could drive the results in Figure 4.

To that end, we first note that the comparison later in the section between the control firms, e.g., control BB versus control A firms, reveals no evidence of other confounds (Figure 8). We further include three sharper control BB firm groups, with the idea that if the fallen angels and the sharper controls are indeed similar in factors that determine their bond ratings, then the arbitrary date cutoff should be more crucial for determining treatment status. As a result, other confounds would be less like to bias the estimates if the treatment status relies on which firms happened to maintain BBB ratings on March 22, 2020, rather than which firms were more likely to be high- or low-rating firms. In other words, the other confounds need to "correlate" with the arbitrary date cutoff, rather than firms' ratings, to be able to bias the results under tighter control firms.

Therefore, we characterize the following three sharper control firm groups among the control BB firms.

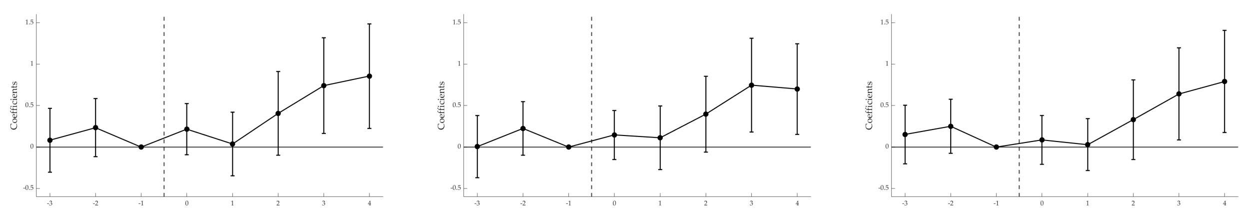
- Control BB firms whose bond rating were at least BBB-/Baa3 in one of the NRSROs on March 22, 2020, but were rated BB in the other NRSROs, which made them ineligible for the SMCCF. These firms were very close to being eligible, and we refer to them as "disagreeing control BB firms." There are 21 disagreeing control BB firms.

- Control BB firms whose bond rating were at least BBB-/Baa3 in 2019, but were downgraded to BB between January 1, 2020 and March 22, 2020. If the date cutoff had been earlier, these firms would become eligible, and we refer to them as "early-downgrade control BB firms." There are 22 such firms.

- Control BB firms whose bond ratings were at least BBB-/Baa3 by the end of 2021, which is the mid-point of the post-treatment periods. Because the effects started to increase in 2021h2, if there were confounds, they should be arguably likely to occur around that time. And then, because these control BB firms improved to BBB ratings, the confounds would be less likely to favor the fallen angels over these firms, at least in terms of bond ratings. Further, if the date cutoff had been after March 22, 2020, these firms would be likely to receive treatment.[24] We refer to them as "late-upgrade control BB firms," and there are 28 such firms.

Table A.4 shows that the pre-treatment characteristics between the fallen angels and these firms are similar. We use the baseline regression to compare the fallen angels with these firms, and plot the coefficients in Figure 5, which shows that the point estimates are most identical to those in Figure 4 with larger standard errors.

Figure 5: The Effects of the SMCCF on Log Vacancies: Sharp Control BB Firms



(a) Disagreeing Firms (b) Early Downgraders (c) Late Upgraders

Notes. Figure 5 plots the coefficients from the DiD regression (Equation 1) for the fallen angels and three sharp control BB firm groups. The disagreeing firms had at least BBB-/Baa3 ratings in one of the NRSROs on March 22, 2020, but were rated BB in the other NRSROs. The early-downgraders are firms with BBB ratings in 2019, and were downgraded to BB between January 1, 2020 and March 22, 2020. The late-upgraders are firms with at least BBB-/Baa3 ratings by the end of 2021.

Table 2 Columns (1) to (3) show that the average treatment effects differ by at most 4 percentage points or 10% (0.04/0.42) from that in the baseline (Table 3 Column 1). All three comparisons result in point estimates that are significant at 5%. Moreover, Figure A.3

[24] A firm could improve to a BBB rating in 2020 and maintain the rating in 2021, e.g., Lennar Corp.

compares the vacancy postings between the three sharper control groups, which suggests that they do not differ in vacancy postings and there is no evidence of other confounds. Therefore, we conclude that the results are robust to using the sharper control BB firms, which makes other confounds less likely to bias the results.[25]

We note that we do not rule out the possibility that the SMCCF had broader impacts on the *aggregate economy*, as Appendix Section A.7 shows that the vacancy postings of control firms were also increasing after 2021. However, our identification does not allow us to separate the effects of the SMCCF on the aggregate economy from other concurrent interventions. In other words, if the SMCCF had an impact on the aggregate economy, the effects would be netted out by our sharper control firms.

Table 2: The Effects of the SMCCF on the Vacancy Postings of Fallen Angels: Sharp Controls

	(1)	(2)	(3)
$\overline{\beta}$	0.4507	0.4201	0.3756
	(0.1854)	(0.1748)	(0.1793)
N	2,784	2,928	2,880
Disagreeing Firms	Y		
Early-Downgraders		Y	
Late-Upgraders			Y

Notes. Table 2 shows the average treatment effects (Equation 2) of the SMCCF on log vacancies of the fallen angels versus three sharp control BB firm groups. The disagreeing firms had at least BBB-/Baa3 ratings in one of the NRSROs on March 22, 2020, but were rated BB in the other NRSROs. The early-downgraders are firms with BBB ratings in 2019, and were downgraded to BB between January 1, 2020 and March 22, 2020. The late-upgraders are firms with at least BBB-/Baa3 ratings by the end of 2021. The standard errors are clustered at the firm level.

Next, we discuss potential explanations of the delayed effects on vacancy postings, to which we attribute two factors: the long-lasting effects of the SMCCF on firms' credit supply and the slow adjustment of the labor market.

The SMCCF continued to hold the bonds until 2021h2, which implies that the liquidity

[25]We prefer the baseline characterization of the control BB firms for two reasons: First, the number of control firms is larger, which results in similar yet more precise point estimates. Second, the sharper control groups risk picking specific type of control firms, which could narrow the interpretation of the estimates. Indeed, there are numerous ways of "sharpening" the control firms, and we aim to provide three examples to show that the results are robust, with the understanding that it is not possible to exhaust the options.

provision did not immediately stop after the Fed ceased bond purchase. In particular, the effects on the bond spread of eligible bonds extended well beyond the initial announcement of the SMCCF and into 2021 (Boyarchenko et al., 2022), which reflects that the market trusted the Fed's ability to deliver on its promise to supply credit to eligible firms and do "whatever it takes" (Gilchrist et al., 2021).[26]

In addition, credit frictions could be correlated over time, which means that firms who receive temporary credit could persistently outperform those who do not. For example, financial institutions might have less uncertainty over firms' productivity when firms operate actively (Straub and Ulbricht, 2021).

The slow adjustment of labor demand could pertain more to the fallen angels, whose credit ratings were falling in 2020 by construction. Indeed, we show later in the section that the BBB and A firms displayed faster changes in their vacancy postings (Figure 6). The credit provision to the fallen angels could take longer than that to firms with higher ratings, as Boyarchenko et al. (2022) document that the probability of new bond issuance for the former remained elevated after the SMCCF was operational whereas the latter increased issuance much earlier, which highlights the slower dissemination of issuance opportunities to riskier borrowers. Further, we show in Section 4 that the market value of the fallen angels started to recover in 2021h2, which could contribute to the delayed transmission from credit provision to its labor demand.

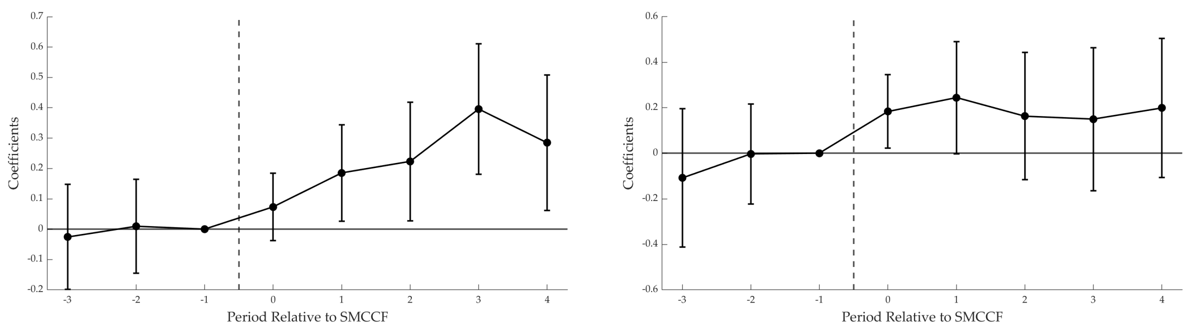
In this sense, our analysis suggests that unconventional monetary policy may share the similar trait with conventional monetary policy which is shown to have delayed and persistent effects on employment (e.g., Christiano et al., 1999). Further, the literature on the labor market effects of credit provision has also shown that it is not unusual to see long-lasting effects on labor market outcomes (e.g., Chodorow-Reich, 2014; Popov and Rocholl, 2018). While analyzing the channels through which the persistence occurs is

[26]Another possibility is that the treatment effects would have been larger if the Fed had maintained the portfolio longer, but we do not have a counter-factual of what would have happened if the program had lasted longer.

beyond the scope of the current study, we note that our results are consistent with the notion that it takes time to issue new bonds and to make hiring decisions.

BBB and A Firms Figure 6 (a) shows that the treated BBB firms saw a statistically insignificant 7.3% (0.057) increase in vacancy postings in the period of the SMCCF, but the effect quickly turned significant in the second period (2021h1), with the point estimates increasing over time and reaching as much as 39.6% (0.109) in 2022h1. The coefficient decreased in the 2022h2, when the growth rate of aggregate vacancy postings decelerated, but it remained large and significant.[27] On average, the treated BBB firms had 23.2% (0.080) more vacancy postings than the control BBB firms from 2020m7 to 2022m12, which is significant at 5%. Prior to the SMCCF, the BBB firms had almost identical trends in vacancy postings.

Figure 6: The Effects of the SMCCF on Log Vacancies: BBB and A Firms



(a) BBB Firms (b) A Firms

Notes. Figure 6 plots the coefficients from the DiD regression (Equation 1) for the BBB and A firms. The treated BBB (A) firms are those on the SMCCF disclosure whose bond ratings were at least BBB- (A-) on March 22, 2020. The control BBB (A) firms are those in the FISD whose bond ratings were at least BBB- (A-) on March 22, 2020, with bond maturities longer than 5 years on January 1, 2021, which made them ineligible for the SMCCF. We exclude insured depository institutions and their holding companies. We define one period to be half a year, with the sample spanning 2019h1-2022h2. The standard error is clustered at the firm level.

On the other hand, Figure 6 (b) shows that the treated A firms saw a significant 18.4% (0.083) increase in vacancy postings immediately following the SMCCF, which lasted temporarily for the first two periods, namely one year following the SMCCF. The point

[27]See, e.g., Job Openings and Labor Turnover (JOLTS) release for the decline in vacancy postings in 2022h2: https://www.bls.gov/news.release/pdf/jolts.pdf.

estimates became statistically insignificant subsequently, with the average treatment effect equal to 18.8% (0.113), which is significant at 10%. While the treated and control A firms differed in employment, they did not differ in the pre-trends of vacancy postings after controlling for the fixed effects.

Table 3: The Effects of the SMCCF on Log Vacancies

	Panel A: Fallen Angels						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\beta}$	0.4210	0.4112	0.4868	0.8933	-0.2489	0.2298	
	(0.1549)	(0.1530)	(0.3006)	(0.4868)	(0.2176)	(0.1621)	
β_{fd}							0.0708
							(0.0269)
N	13,920	13,920	208	1,680	1,968	6,864	13,920
	Panel B: BBB Firms						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\beta}$	0.2324	0.2237	0.1745	0.3869	0.5454	0.0314	
	(0.0796)	(0.0796)	(0.0469)	(0.1682)	(0.1479)	(0.1291)	
β_{fd}							0.0389
							(0.0147)
N	22,656	22,656	3,296	2,400	4,224	9,936	22,656
	Panel C: A Firms						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\beta}$	0.1882	0.2038	0.1793	0.0417	0.6212	0.2786	
	(0.1134)	(0.1171)	(0.0686)	(0.2760)	(0.2799)	(0.3236)	
β_{fd}							0.0267
							(0.0149)
N	12,144	12,144	1,248	1,056	1,632	5,712	12,144
Firm Control		Y					
Stacked SC			Y				
Most Affected Ind.				Y			
Mod. Affected Ind.					Y		
Least Affected Ind.						Y	
Fuzzy DiD							Y

Notes. Table 3 shows the average treatment effects (Equation 2) of the SMCCF on log vacancies. Column (1) shows the results from the baseline regression (Equation 1), which uses the matched FISD-BGT data. Column (2) adds firm annual log employment, quarterly debt-to-asset ratio, and quarterly cash-to-asset ratio, which uses the matched FISD-BGT-Compustat data, and we use indicators for missing variables. Appendix Section A.4 contains details on the Compustat variables. Column (3) shows the results from the synthetic control regression (Equation 3). Columns (4) to (6) show the results by industry, which categorize 15 industries in Cajner et al. (2020) into three even groups based on the initial employment decline during the COVID-19 pandemic. Column (7) shows the results of the fuzzy DiD regression (Equation 4), and the treatment dose is the average par-value from 2020m7 to 2020m12 in $1 million increment. The standard errors are clustered at the firm level.

The point estimates of the average treatment effect decreases with firms' credit ratings, which coincides with the intuition that the effect of the SMCCF could be more significant for more credit-constrained firms.

Table 3 Column (2) shows the results when we control for log annual employment, cash-to-asset ratio, and debt-to-asset ratio, which suggest that our baseline results are robust to including firm-level time-varying characteristics that partially address the difference between the treated and control BBB (A) firms.[28]

Synthetic Control Regression Figure 7 shows the results of the synthetic control regression, which suggest that the qualitative results are similar to those of the baseline.[29] The fallen angels and treated BBB firms still saw the effects growing over time, while the treated A firms saw a large immediate effect. Table 3 Column (3) shows that the point estimates of the average treatment effects are significant at 5% for the treated BBB and A firms. The average treatment effect is statistically insignificant for the fallen angels, but we note that the number of treated firms is smaller than that of the baseline. In addition, Appendix Section A.10 shows that the result for the fallen angels is significant when we match more pre-treatment firm characteristics.[30]

To summarize, there are strong positive effects of the SMCCF on the vacancy postings of the fallen angels, and the SMCCF is also associated with increases in vacancy postings of the treated BBB and A firms. The effects could be increasing in the tightness of firms' credit constraint.

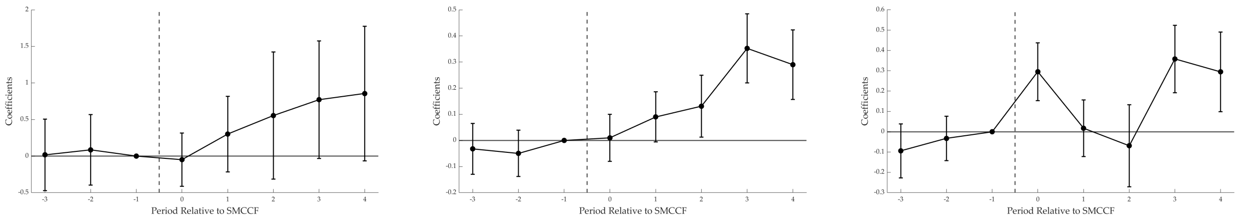
Comparing Control Firms Next, we turn to the comparison between the control firms, whose diverging vacancy postings could be evidence for confounding factors. However, we do not find such evidence, because Figure 8 shows that, except for one period, their vacancy

[28]"Debt" include debt in current liabilities and long-term debt. We prefer the baseline regression because firm-level time varying characteristics could be endogenous to vacancy postings (e.g., employment) and the SMCCF (see Section 4). We include indicators for missing observations. Appendix Section A.9 shows the results of robustness analysis, which includes other firm fundamentals in the regression.

[29]Appendix Section A.10 considers using more pre-treatment firm characteristics to construct synthetic controls, which gives similar results.

[30]Appendix Section A.5 shows that the results for the treated BBB firms are robust to using only control firms who issued short-term bonds. The results for the treated A firms are not robust to reducing the control firms, but we note that we lose 80% of the control A firms.

Figure 7: The Effects of the SMCCF: Synthetic Control Regression

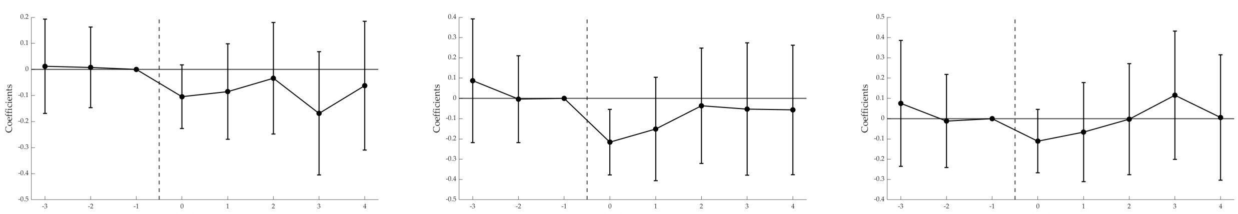


(a) Fallen Angels (b) BBB Firms (c) A Firms

Notes. Figure 7 plots the coefficients of the synthetic control regression (Equation 3). We construct a synthetic control firm for each treated firm by matching pre-treatment log vacancies and employment. We require the difference in the average pre-treatment log vacancy between the treated firm and its synthetic control to be less than 10% for the treated A and BBB firms, which essentially drops the very large treated firms without good synthetic controls. We do not impose the requirement for the fallen angels. We treat each synthetic control firm as a separate firm and cluster the standard errors at the firm level. We define one period to be half a year, with the sample spanning 2019h1-2022h2.

postings remained similar throughout the sample. As a result, the average treatment effects are statistically insignificant for all three comparisons.

Figure 8: Vacancy Dynamics: Control Firms



(a) BB vs BBB (b) BB vs A (c) BBB vs A

Notes. Figure 8 plots the coefficients of comparing the vacancy postings of any pair of the control groups using Equation (1). For example, Figure 8 (a) compares the vacancy postings between the control BB firms and control BBB firms. The control BB firms are those in the FISD whose bond ratings were at least BB- on March 22, 2020, and who maintained at least a BB- rating in 2020. The control BBB (A) firms are those in the FISD whose bond ratings were at least BBB- (A-) on March 22, 2020, with bond maturities longer than 5 years on January 1, 2021. We exclude insured depository institutions and their holding companies. We define one period to be half a year, with the sample spanning 2019h1-2022h2. The standard error is clustered at the firm level.

The Effects by Industry The COVID-19 pandemic had different impact across industries. For example, Finance and Insurance industry saw an initial decline of 1.2% in employment, while Arts, Entertainment, and Recreation industry had a 50.7% decline in employment (Cajner et al., 2020). In addition, reasons for the employment decline vary by industries (Forsythe et al., 2022). Therefore, industries might have different responses of vacancy postings to the SMCCF, which could amplify industry inequality in the employment response during the pandemic, if industries with the largest increase in vacancy postings are the least affected ones.

To examine this issue, we separate the 15 NAICS two-digit industries in Cajner et al. (2020) into three groups based on the employment decline at the onset of the COVID-19 pandemic. The most affected 5 industries are Arts, Accommodation, Retail Trade, Other services, and Transportation. The modestly affected ones are Real Estate, Information, Wholesale Trade, Administrative, and Healthcare. The least affected ones are Educational Services, Construction, Manufacturing, Professional Services, and Finance. For each group, we estimate the effects of the SMCCF for A firms, BBB firms, and fallen angels.[31]

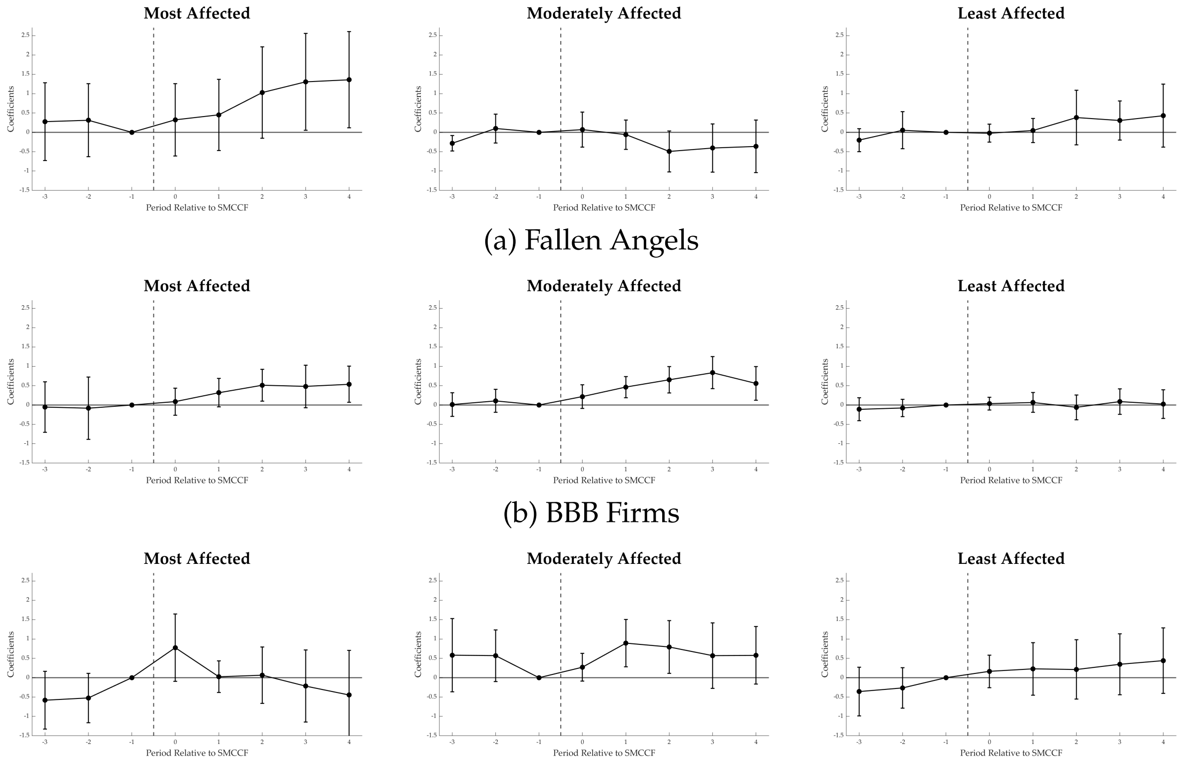
Figure 9 shows that the more affected industries had the largest and most significant point estimates in vacancies postings, which is robust for all three types of firms. Specifically, the most and moderately affected industries saw larger vacancy posting increases than the least affected ones, and the former drives all the effects for the fallen angels (Figure 9 a), which contrasts the results in Beraja et al. (2019) who show that Quantitative Easing (QE) during the Great Recession amplified regional inequalities in consumption and employment. While the SMCCF does not appear to target the more affected industries, we argue that it worked better for those industries, which is similar to the results by bond ratings because firms that were potentially more affected by the pandemic had the largest responses.

3.2 Causal Responses

We examine the causal response, which is the average marginal effect of the SMCCF. Specifically, we calculate the average par-value—i.e., bond holdings—from 2020m7 to 2020m12, and we normalize the average par-value to be in increments of $1 million, which means that the estimated coefficients are the percent increase in vacancy postings following

[31]NAICS industry information for each firm is available in the FISD data.

Figure 9: The Effects of the SMCCF by Industry



(a) Fallen Angels

(b) BBB Firms

(c) A Firms

Notes. Figure 9 plots the estimates of Equation (1) by restricting the sample to subgroups of industries. We separate the 15 NAICS two-digit industries in Cajner et al. (2020) into three groups based on the employment decline at the beginning of the pandemic. The most affected 5 industries are Arts, Accommodation, Retail Trade, Other Services, and Transportation. The modestly affected are Real Estate, Information, Wholesale Trade, Administrative, and Health Care industries. The least affected are Educational Services, Construction, Manufacturing, Professional Services, and Finance industries. We estimate the effects of the SMCCF on vacancy postings for the fallen angels, BBB, and A firms, separately for each industry group. For example, the right figure in Equation (1) (a) compares the vacancy postings between the fallen angels and control BB firms in the most affected industries. We take the log of vacancy postings and include firm fixed effects and time fixed effects. We define one period to be half a year, with the sample spanning 2019h1-2022h2. The standard error is clustered at the firm level.

an extra \$1 million bond purchases by the SMCCF.

We use Equation (4) on the treated and control firms, which utilizes variation in "treatment intensity." The result suggests that an extra \$1 million bond purchase increased vacancy postings by 7.1% (0.027) for the fallen angels, and is associated with a 3.9% (0.015) and 2.7% (0.015) increase for the BBB and A firms, respectively. The effects are significant at 5% for the fallen angels and BBB firms and 10% for A firms, which imply that the causal response could be increasing in firms' credit constraint.

The implied increases in the number of vacancy postings for every $1 million bond purchase are 128 for the fallen angels, 230 for BBB firms, and 213 for A firms, which means one extra vacancy posting is associated with approximately $5000 bond purchase. The percent effect is smaller than that of small business loans on employment, but the level effect is much larger.[32] Thus, asset purchasing programs tailored towards large firms could have substantial real effects on employment.[33]

3.3 The Effects of the SMCCF on the Quality of Labor Demand

The analysis so far suggests that the SMCCF increased the quantity of labor demand. Appendix Sections A.12 and A.13 examine changes in the quality of labor demand by focusing on the skill content and posted salaries of vacancies, which shows no significant change in either. Therefore, while the pandemic could, e.g., replace onsite jobs with remote ones, we conclude that the SMCCF did not change the skill content or posted salaries of vacancies.

4 The Effects of the SMCCF on Borrowings, Market Value, and Liquidity

We examine whether the treated firms increased borrowings or faced lower liquidity, which sheds light on the mechanism of the SMCCF. Specifically, the literature on the effects of the SMCCF has documented that it reduced bond spreads of the treated firms for extended periods of time, which could allow firms to adjust in the labor market (e.g., Boyarchenko

[32] Brown and Earle (2017) estimate that an $1 million loan to small business would increase employment by 3 to 3.5 in small businesses, amounting to an 15% increase.

[33] We show further evidence that the purchases of the SMCCF could matter in Appendix Section A.11, and we note that Boyarchenko et al. (2022) show that the SMCCF decreased bond spreads of eligible bonds during the purchases, which suggests that the purchases could reveal more information and validates our interpretation of the causal response.

et al., 2022). Further, the aim of the SMCCF, according to the Fed's disclosures, was to support credit to large employers. Firms' borrowings and liquidity would reflect whether such decreases in bond spreads transmitted to real effects on firms' balance sheets.

We measure firm-level borrowings using the debt-to-asset ratio, with quarterly data available in Compustat, and, therefore, our matched FISD-BGT-Compustat data. Table 4 shows the average treatment effects, whereas we relegate the details of how we construct the data and omitted figures of the robustness analysis to Appendix Section A.15.[34]

Our empirical specification is

$$\left(\frac{Debt}{Asset}\right)_{iq} = \alpha + \sum_{\tau=-3}^{4,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_q + \epsilon_{iq} \tag{5}$$

where $\left(\frac{Debt}{Asset}\right)_{iq}$ is quarterly debt-to-asset ratio for firm i. As in Equation (1), we define one period to be half a year for the treatment indicator, so that $\mathbb{I}_i^\tau$ is equal to 1 if firm i was treated τ period from the treatment period (2020h1). We include firm fixed effects and quarter-year fixed effects.[35]

Figure 10 shows that both the fallen angels and treated BBB firms immediately experienced increases in the borrowings, with the estimates significant at 5%, which is consistent with D'Amico et al. (2020) who show that the issuance of investment-grade bonds increased after the SMCCF announcement. The increase in borrowings persisted for two periods (one year), after which the treated and control firms began to converge in their debt-to-asset ratios. Therefore, the SMCCF could allow these firms who were arguably more credit constrained to temporarily increase their borrowings.[36] On the other hand, the treated A firms experienced negative point estimates in the debt-to-asset ratio, who experienced large increases in market value (Figure 12 c) and might pay down pre-existing debt. The point

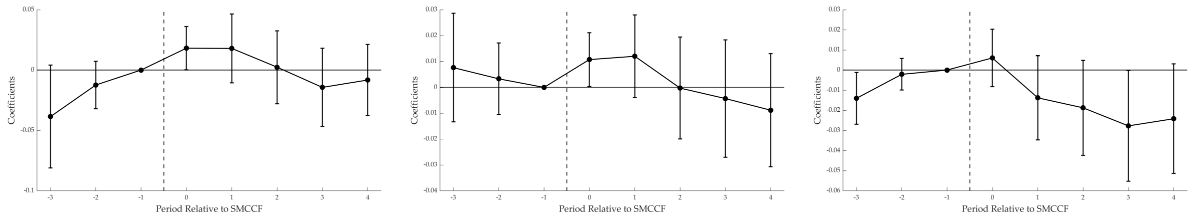
[34]We include all matched FISD-BGT-Compustat firms for results in this section. Appendix Section A.15 shows the effects when we exclude firms in Utility industry (NAICS2 22), which have similar results.

[35]Table A.8 shows that the number of treated and control firms for the variables in Section 4.

[36]We emphasize that the results pertain to the comparison between the fallen angels and control BB firms. Darmouni and Siani (2022) show that increased borrowings might not apply to high-yield bond issuers generally.

estimates of the average treatment effects are statistically insignificant (Table 4 Column 1).

Figure 10: The Effects of the SMCCF on Firms' Borrowing



(a) Fallen Angels (b) BBB Firms (c) A Firms

Notes. Figure 10 plots the coefficients of the DiD regression in Equation (1), using the debt-to-asset ratio as the outcome variable. Figure 10 (a) compares the fallen angels and control BB firms. Figure 10 (b) compares the treated and control BBB firms. Figure 10 (c) compares the treated and control A firms. Figure 10 uses the matched FISD-BGT-Compustat data. We define one period to be half a year, with the sample spanning 2019h1-2022h2. Table A.8 shows that the number of treated and control firms. The standard error is clustered at the firm level.

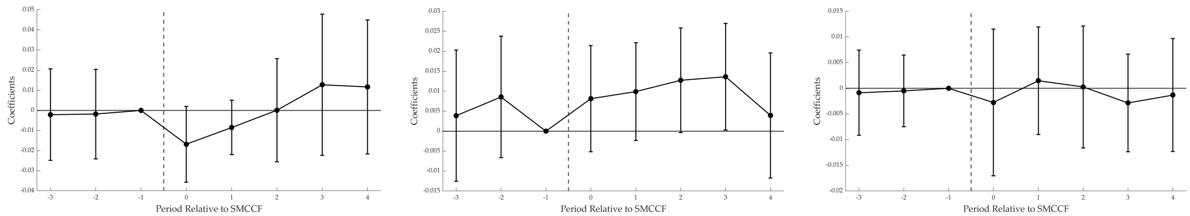
For robustness, we repeat the analysis but exclude firms in Pharmaceutical and Medicine Manufacturing industry (NAICS 3254), which received various funding during the COVID-19 pandemic, and those funding could confound the effects of the SMCCF.[37] In addition, the results on firms' borrowings could be more sensitive to outliers because of a smaller sample size. Table 4 Column (2) suggests that the point estimates of the average treatment effects are similar.

We further examine the changes in firms' expense-to-asset ratio following the SMCCF using Equation (5), which measures responses in firms' expenditure, and we measure expense as firms' total revenue minus income before extraordinary items. Figure 11 suggests that the fallen angels saw decreases in expenditure at the beginning of the SMCCF, which grew almost linearly subsequently. The treated BBB firms saw increases in their expenditure, with the point estimate of the average treatment effect to be 0.0097 (0.0062) (Table 4 Panel B Column 3). The treated A firms experienced no change in their expense-to-asset ratio. Excluding firms in Pharmaceutical and Medicine Manufacturing industry gives similar results (Column 4).

The decline in bond spread should translate to an increase in firm's market value,

[37] Notable mentions are AbbVie and Pfizer. The former is a treated BBB firm and the latter is a treated A firm.

Figure 11: The Effects of the SMCCF on Firms' Expenditure



(a) Fallen Angels (b) BBB Firms (c) A Firms

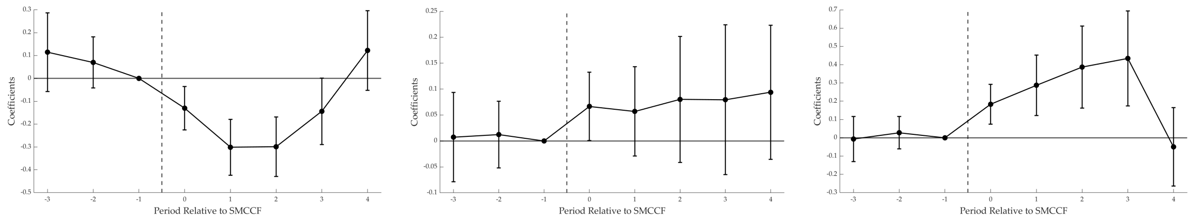
Notes. Figure 11 plots the coefficients of the DiD regression in Equation (1), using expense-to-asset ratio as the outcome variable. We measure expense as firms' total revenue minus income before extraordinary items. Figure 11 (a) compares the fallen angels and control BB firms. Figure 11 (b) compares the treated and control BBB firms. Figure 10 (c) compares the treated and control A firms. Figure 11 uses the matched FISD-BGT-Compustat data. We define one period to be half a year, with the sample spanning 2019h1-2022h2. Table A.8 shows that the number of treated and control firms. The standard error is clustered at the firm level.

because the investors discount firms' future profits at a lower rate. We examine changes in firms' market-value-to-asset ratio with Equation (5).[38] Figure 12 shows that the SMCCF did not prevent the decline in market value for fallen angels, whose credit ratings were downgraded during the program. However, their credit ratings recovered after the second half of 2020, which increased almost linearly. Therefore, we argue that the initial decrease in fallen angels' market value reflects the market perception of the decline in their bond ratings, rather than a negative impact of the SMCCF. On the other hand, the treated BBB saw an immediate increase in the market value, so did the treated A firms. Table 4 Column (5) shows that the average increase in market value is 7.3% (0.043) for BBB firms and 24.9% (0.085) for A firms, respectively, which are robust to excluding firms in Pharmaceutical and Medicine Manufacturing industry (Column 6).

However, increases in borrowings and expenditure could lead to a lower liquidity, especially if firms faced negative idiosyncratic shocks. We examine the impact of the SMCCF on liquidity using three measures. Our preferred measure for liquidity is the cash-to-asset ratio, with "cash" including cash holdings and short-term investments, which strikes a balance between accuracy and sample size. The other two measures are the cash-holdings-to-asset ratio and KZ-index. The former omits short-term investments, and

[38] Appendix Section A.14 examines changes in log market value and finds similar results.

Figure 12: The Effects of the SMCCF on Firms' Market Value



(a) Fallen Angels (b) BBB Firms (c) A Firms

Notes. Figure 12 plots the coefficients of the DiD regression in Equation (1), using market-value-to-asset ratio as the outcome variable. Figure 12 (a) compares the fallen angels and control BB firms. Figure 12 (b) compares the treated and control BBB firms. Figure 12 (c) compares the treated and control A firms. Figure 12 uses the matched FISD-BGT-Compustat data. We define one period to be half a year, with the sample spanning 2019h1-2022h2. Table A.8 shows that the number of treated and control firms. The standard error is clustered at the firm level.

therefore, is narrower in scope. The latter is a comprehensive measure of firms' credit constraint, which combines various balance sheet items to gauge firms' access to funds (Kaplan and Zingales, 1997; Lamont et al., 2001), with the disadvantage of having fewer observations.[39]

We replace the debt-to-asset ratio in Equation (5) with the measures of liquidity and show the average treatment effects in Table 4 Columns (7) to (9). Figure 13 plots the estimates for cash-to-asset ratio, which suggests that the fallen angels and treated BBB firms did not appear to be more liquid-constrained following the temporary increase in borrowings and expenditure, and the point estimates of the average treatment effects are statistically insignificant for all three measures. The treated A firms' cash-to-asset ratio displays a declining trend, but the point estimate of the average treatment effect is not significant at 5%. The decline is driven by a decrease in cash holdings (Table 4 Panel A Column 6), which could imply that the treated A firms used cash to pay down their debt because of a similar downward trend in their debt-to-asset ratio (Figure 10 a).

Therefore, we argue that the SMCCF could allow the treated firms—especially those who were potentially more constrained—to increase borrowings and expenditure without being more liquid constrained. The market also perceived the treated firms to provide

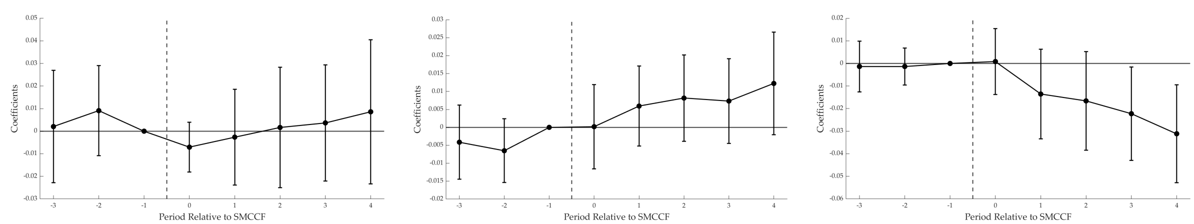
[39] A higher KZ-index implies that the firm is more credit constrained.

Table 4: The Effects of the SMCCF on Borrowings and Liquidity

	Panel A: Fallen Angels								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Debt-Asset		Expense-Asset		Market-Value-Asset			Liquidity	
$\overline{\beta}$	0.0007	0.0037	-0.0002	-0.0001	-0.1483	-0.1483	0.0008	0.0015	0.3899
	(0.0110)	(0.0124)	(0.0102)	(0.0102)	(0.0523)	(0.0523)	(0.0110)	(0.0105)	(0.9517)
N	2,283	2,267	2,142	2,127	2,077	2,077	2,162	2,147	997
	Panel B: BBB Firms								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{\beta}$	0.0019	0.0020	0.0097	0.0097	0.0730	0.0727	0.0068	0.0062	-1.6780
	(0.0081)	(0.0081)	(0.0062)	(0.0062)	(0.0434)	(0.0434)	(0.0050)	(0.0046)	(3.0388)
N	3,681	3,621	4,260	4,200	4,045	3,985	4,273	4,258	1,838
	Panel C: A Firms								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\overline{\beta}$	-0.0156	-0.0159	-0.0010	-0.0016	0.2486	0.2626	-0.0165	-0.0219	-1.7879
	(0.0107)	(0.0108)	(0.0048)	(0.0049)	(0.0851)	(0.0872)	(0.0089)	(0.0101)	(1.8880)
N	1,861	1,746	1,940	1,825	1,509	1,416	1,955	1,940	629
No Pharma.		Y		Y		Y			

Notes. Table 4 shows the effects of the SMCCF on firms' debt-to-asset ratio (Columns 1 and 2), expense-to-asset ratio (Columns 3 and 4), market-value-to-asset ratio (Columns 5 and 6), and liquidity (Columns 5 to 7), which use the regression Equation (5) and the matched FISD-BGT-Compustat data. "Debt" includes current debt and long-term debt, and "expense" includes total revenue minus income before extraordinary items. We exclude firms in Pharmaceutical and Medicine Manufacturing industry (NAICS 3254) in Columns (2), (4), and (6). The three measures of liquidity from Columns (7) to (9) are the cash-to-asset ratio, cash-holding-to-asset ratio, and KZ-index, respectively. Appendix Section A.15 shows the construction of the KZ-index. We define one period to be half a year, with the sample spanning 2019h1-2022h2. Table A.8 shows that the number of treated and control firms. The standard error is clustered at the firm level.

Figure 13: The Effects of the SMCCF on Firms' Liquidity



(a) Fallen Angels (b) BBB Firms (c) A Firms

Notes. Figure 13 plots the coefficients the DiD regression in Equation (5), using the cash-to-asset ratio as the outcome variable. "Cash" includes cash holdings and short-term investments. Figure 13 (a) compares the fallen angels and control BB firms. Figure 13 (b) compares the treated and control BBB firms. Figure 13 (c) compares the treated and control A firms. We define one period to be half a year, with the sample spanning 2019h1-2022h2. Table A.8 shows that the number of treated and control firms. The standard error is clustered at the firm level.

safer assets, which increased their market value and further relaxed their credit constraints. In that sense, the SMCCF indeed provided liquidity to the firms through the bond market, which led to increases in labor demand.

5 Conclusion

We estimate the effects of the SMCCF on firms' vacancy postings, which suggests large potential gains in employment, with the effects increasing in the credit constraint firms face. The causal response suggests that approximately every $5,000 bond purchase implies one more vacancy. Treated firms saw increases in borrowings, expenditure, and market value without being more liquidity constrained.

The SMCCF is unprecedented both in terms of its size and scale, that is, the range of firm bonds that are eligible. Its large real effects on the labor demand open up questions about whether the Fed should intervene in future circumstances.

We hypothesize that the gain of the intervention could be smaller under persistent productivity shocks, because if firms are always good or bad, a temporary ease of credit constraint cannot incentivize them to post more vacancies. Therefore, whether the SMCCF could have large gains during the Great Recession or future events—namely the external validity of the program—is both a theoretical and an empirical question. We leave the examination of unconventional monetary policy on firms' labor demand under persistent productivity shocks to future research.

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Online Appendices

A Data Construction

A.1 Merging the FISD with the BGT Data

We first merge the SMCCF disclosures with the FISD data using bond CUSIP, and we match all firms in the SMCCF disclosures. We assign credit ratings to these treated firms according to what we describe in Section 2.

We describe how we match the firms in the FISD data and those in the BGT data in detail. Specifically, we manually link the two dataset by firm names, because the FISD data and the BGT data do not share common identifiers. We first calculate firm-level vacancy postings for 2019 and for the full sample period (2019m1 to 2022m12) for each firm in the BGT data. Our rules for matching the two dataset are the following:

1. Firms in the BGT data need to satisfy at least one of the two conditions: i) post more than 10 vacancies in 2019; and ii) post more than 50 vacancies in the full sample period. This mainly aims to filter out the firm names that are typos, and firms that rarely use online platforms for recruiting.

2. We first merge firms that have the same name in the FISD data and the BGT data. For example, "3M CO" in the FISD data is matched with "3M Company" in the BGT data. And then, we apply the method in, e.g., Author et al. (2020) to search the firm name in the FISD data in google, and we make sure the name in the BGT data appear in the first five entries.

3. For holding companies in the FISD data, we search for the name in front of "Holdings". For example, if the firm name is "BAE Systems Holdings Inc", we search for "BAE Systems" in the BGT data, where we find an exact match with 11,283 vacancy postings

in 2019. We do not consider subsidiaries of the holding companies. We verify the match using the method in Author et al. (2020).

4. For firms without exact matches, we use the phrase that identifies the firm. For example, the firm "BP Capital Markets America Inc" in the FISD data does not have an exact match in the BGT data. We search for the phrase "BP Capital" and find a firm with "BP Capital Management" in the BGT data. And then, we use the method in Author et al. (2020) to make sure that they point to the same firm. We do not include BP Capital in our final dataset, because its vacancy postings is 1 in 2019 and 4 in total.

The procedure allows us to match 279 out of 366 BBB firms and 133 out of 183 A firms in the FISD data. Table A.1 Panel A shows that the matched firms and unmatched firms have similar parvalue and left-over maturity, which suggests that the matching outcome might not correlate the assignment of treatment. On the other hand, by design, the matched firms post more vacancies than the unmatched firms. Table A.1 Panel B shows that the matched firms are also larger than unmatched ones, but the difference is not as large as those in Table 1. Further, the matched and unmatched firms do not have significant difference in their debt-to-asset ratio, cash-to-asset ratio, and market-value-to-asset ratio. We hence argue that the matching allows us to better select the firms whose vacancies can be measured by online vacancy postings, instead of biasing the results on labor demand by dropping the firms whose labor demand could decrease.

A.2 Selecting the Control Firms

We describe how we select the control firms in the FISD data in detail. We use the FISD data to obtain information on firms' bond rating histories and bond maturity. For each firm, we categorize it as a control according to the following procedure:

1. For control BB firms, we require that their bond ratings were at least BB- on March

Table A.1: Summary Statistics: Matched and Unmatched Firms

	Panel A: Treatment Assignment	
	Matched Firms	Unmatched Firms
Parvalue ($ Million)	7.4	8.3
	(10.4)	(11.7)
Maturity (Year)	7.6	7.7
	(2.3)	(2.6)
Obs.	412	164
	Panel B: Characteristics in 2019	
	Matched Firms	Unmatched Firms
Emp. (1000s)	63	30
	(150)	(80)
N	333	59
Cash-to-Asset	0.078	0.059
	(0.101)	(0.087)
N	337	64
Debt-to-Asset	0.354	0.347
	(0.154)	(0.150)
N	324	57
Market-Value-to-Asset	1.57	1.24
	(1.39)	(1.21)
N	303	47

22, 2020, which maintained that way through 2020. Their bond ratings could be subsequently upgraded or downgraded after 2021, but we exclude the ones whose ratings fell below B-. We do not have any control BB firms whose ratings were upgraded to A.

2. Control BBB (A) firms are those whose ratings were rated BBB- (A-) by at least one of three credit agencies prior to March 22, 2020. If they were rated by multiple agencies, the ratings needed to be BBB- (A-) for at least two agencies. We exclude depository institutions and their holding firms and subsidiaries. Control firms cannot appear on the SMCCF disclosure.

3. The most recent rating of the firm bond is after January 1, 2017. This means we exclude firms who did not have credit history within about three years of the SMCCF, which mostly filter firms whose most recent ratings were prior to 2010.

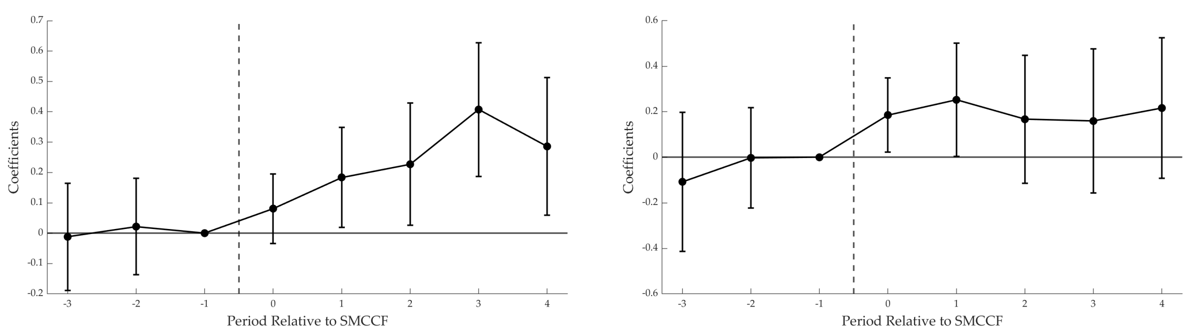
4. The firm's bonds have maturities longer than 5 years on January 1, 2021, which needs to hold for all bonds issued by the firm.

5. After identifying the control firms, we merge them with the BGT data using the same procedure as in Section A.1.

The procedure allows us to match 168 control BB firms, 101 control BBB firms, and 55 control A firms. There are 5 A firms and 16 BBB firms that appears eligible for the SMCCF according to the FISD data, referred to as the missing firms. We exclude these firms in Section 2, and we note that they present a small fraction of the treated firms. Further, our analysis using the date cutoff is not subject to the potential selection issue, because the control BB firms need not satisfy any maturity requirement.

For robustness, we present results by instrumenting the actual treatment status with eligibility. In particular, we regress, e.g., BBB firms' treatment status on their eligibility in the first stage, which implies that we include the missing BBB firms that appeared eligible. In the second stage, we use the predicted treatment status as the instrumental variable. We are able to match 7 missing BBB firms and 1 missing A firm with the BGT data, subject to the matching rule in Section A.1. Figure A.1 shows that the effects barely change compared to those in Section 2.

Figure A.1: The Effects of the SMCCF: Adding Missing Firms



(a) BBB Firms

(b) A Firms

A.3 Matching with the Compustat Data

Appendix Section A.1 and Section A.2 give the matched FISD-BGT data, which we use to match with the Compustat data. We do not use the CRSP-Compustat data because our baseline regression does not require firm characteristics, and because we would like to maximize the number of control firms.

We match the FISD-BGT data with Compustat data using both firm names and CUSIP as follows:

- We use firm names in the FISD data to match with those in the Compustat data.
- We first merge firms that have the same name in the FISD data and the Compustat data. For example, "3M CO" in the FISD data is matched with "3M CO" in the Compustat data. And then, we apply the method in, e.g., Author et al. (2020) to search the firm name in the FISD data in google, and we make sure the name in the BGT data appear in the first five entries.
- For holding companies in the FISD data, we search for the name in front of "Holdings". For example, if the firm name is "BAE Systems Holdings Inc", we search for "BAE Systems" in the Compustat data. We do not consider subsidiaries of the holding companies. We verify the match using the method in Author et al. (2020).
- For firms with CUSIPs, we make sure that the first six digits are identical in both the FISD and Compustat data. We use the method in Author et al. (2020) to make sure that firms with different CUSIPs across the two data are the same one.

The matching method allows us to match over 80% of the treated firms and about 50% to 80% of the control firms. In particular, we match 84% of the control BB firms to compare with the fallen angels, which is arguable our sharpest identification.

A.4 List of Compustat Variables

Table A.2 lists the Compustat variables in the current study. All variables are at a quarterly frequency, except for employment, which is at an annual frequency.

Table A.2: List of Compustat Variables

Variable Name	Compustat Variable
Asset	atq
Current Asset	actq
Cash	cheq
Cash Holdings	chq
Current Debt	dlcq
Long-term Debt	dlttq
Market Value	mkvaltq
Total Property	ppegtq
Dividends	dvpq
Income Before Extraordinary Items	ibq
Depreciation and Amortization	dpq
Total Shareholder's Equity	teqq
Book Value of Common Equity	ceqq
Deferred Tax Asset	txdbcaq+txdbaq
Revenue	revtq
Employment	emp

A.5 Bond Maturities and Ratings Within and Across Firms

We note that firms usually issue various bonds, and the maturities of these bonds also vary. We know the bond maturities of treated firms from the SMCCF disclosure, but we cannot know the bond maturities of control firms with certainty. To that end, we assign the bond maturity that is closest to January 1, 2026 to each control firm. And then, we calculate the left-over maturities as the years between the average maturity and March 22, 2020.

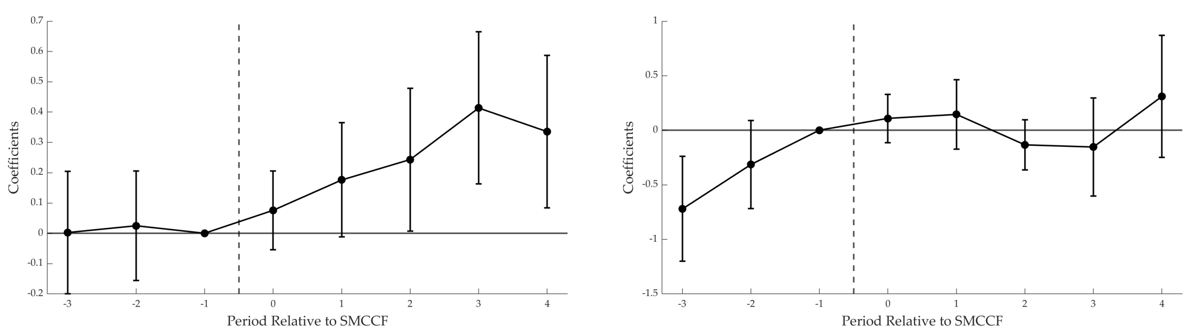
Table A.3 shows that the average maturities of treated BBB and A firms are shorter than those of control BBB and A firms, which is partly by design of the program, and partly because most of the control firms issued bonds with long maturities to begin with. For example, 38 out of 101 control BBB firms have an initial bond maturity of more than 10 years, while 42 out of 55 control A firms do. Conditionally on the maturity longer than 10 years, the average maturity is about 30 years. While the comparison raises concern that the Fed could target firms that issue short-term bonds, we note that our comparison between the fallen angels and BB firms does not rely on bond maturities.

Table A.3: Firm Average Bond Maturity

	Treated BBB	Control BBB	Treated A	Control A
Ave. Maturity (Year)	3.60	12.32	3.55	14.96
	(1.09)	(8.13)	(1.07)	(7.62)
N	279	101	133	55

Despite the difference, Section 3 shows that our empirical results when comparing the treated and control BBB (A) firms are robust to a range of specifications, including adding firm time-varying characteristics and using the synthetic control regression. We show an additional robustness exercise in this section by using only the control firms with short-term bonds, which are the firms whose bond maturity at issuance is shorter than or equal to 10 years. The restriction leaves us with 63 control BBB firms and 13 control A firms.

Figure A.2: The Evolution of Vacancy Postings: Using Controls with Short-Term Bonds



(a) BBB Firms

(b) A Firms

Figure A.2 shows that the treated BBB saw robustness estimates, which are almost identical to those in the baseline (Figure 6 b). On the other hand, the treated A firms showed significant pre-trend for one period, and the coefficients are insignificant after the SMCCF. The result could reflect that the treated and control A firms are the least comparable, but it could also be because there are only 13 control A firms in Figure A.2 (b).

Moreover, we anticipate the effects of the SMCCF to be the least significant for the treated A firms.

A.6 Sharper Control BB Firms for the Fallen Angels

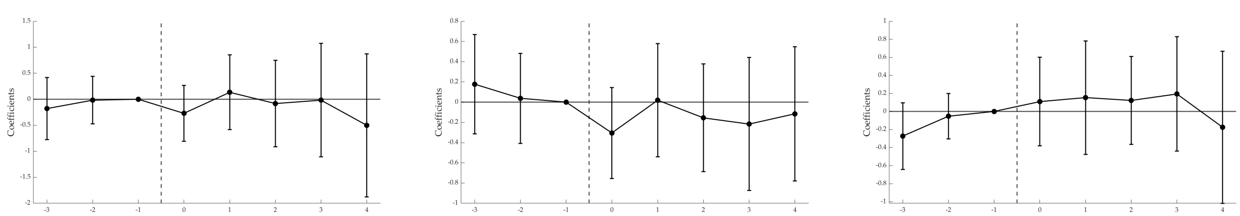
As Section 3.1 shows, we include three sharper control BB firm groups for the fallen angels. Table A.4 presents the summary statistics of the fallen angels and these firms, which shows that they do not differ in any of the observables in 2019.

Table A.4: Summary Statistics: Sharper Control BB Firms

	Fallen Angels	Disagreeing Firm	Early Downgrader	Late Upgrader
2019 Vacancies (1000s)	1.8	1.5	1.4	2.5
	(4.1)	(2.2)	(1.8)	(5.2)
2019 Employment (1000s)	28	20	26	32
	(53)	(18)	(63)	(63)
Cash-to-Asset Ratio	0.053	0.084	0.034	0.102
	(0.065)	(0.149)	(0.032)	(0.133)
Matched FISD-BGT	21	21	22	28
Matched FISD-BGT-Compustat	13	18	20	25
2019 Emp. Obs.	13	17	19	24
Cash-to-Asset Ratio Obs.	13	18	20	25

We further compare the vacancy postings between any pair of the sharper control BB firm groups. For each comparison, we exclude the firms which are in both groups. Figure A.3 suggests that they do not differ in vacancy postings, and therefore, there is no evidence of other confounds.

Figure A.3: The Effects of the SMCCF on Log Vacancies: Sharp Control BB Firms



(a) Disagreeing Firms vs Early Downgraders

(b) Disagreeing Firms vs Late Upgraders

(c) Late Upgraders vs Early Downgraders

A.7 Vacancy Postings Trajectories of Control Firms

We plot the vacancy growth of the control firms as we do in Figure 3.

Figure A.4: Vacancy Growth of Control Firms

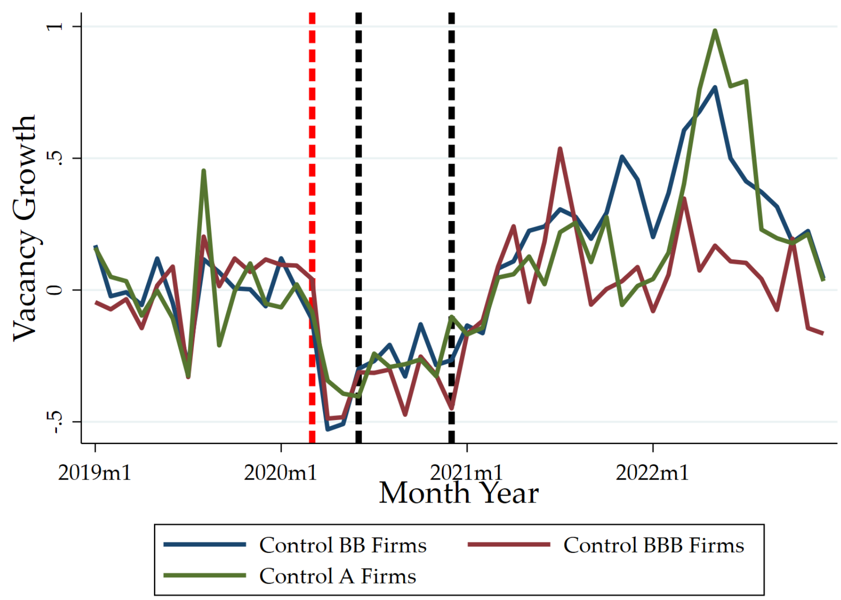


Figure A.4 shows that all control firms display increases in vacancy postings after 2021, which could indicate that the SMCCF had broader impacts on the aggregate economy. However, we note that we cannot separate such effects from other concurrent intervention during the COVID-19 pandemic.

A.8 Regressions with Quarterly Coefficients

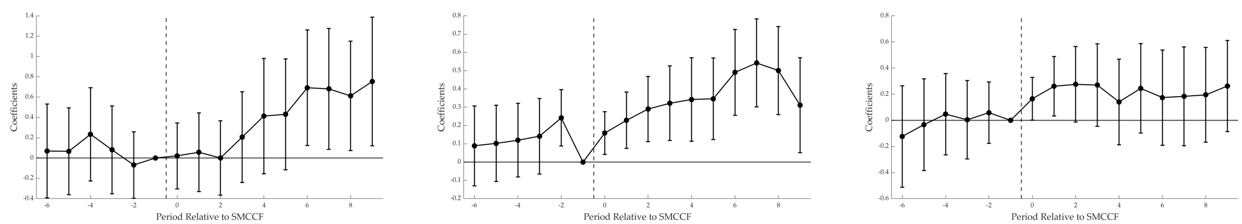
Our baseline regression Equation (1) specifies the treatment indicators at the bi-annual frequency, mainly to filter out volatility in vacancy postings. However, because the vacancy postings data is monthly, we could in principal specify the indicators to be at any frequency lower than monthly. We show here the results using quarterly coefficients from the following regression:

$$\log(Vacancy)_{im} = \alpha + \sum_{\tau=-6}^{9,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_q + \epsilon_{im} \tag{A.1}$$

where $\mathbb{I}_i^\tau$ is an indicator that the firm was treated τ quarters away from the treatment period (2020q3). By construction, the bi-annual estimates in the baseline would be the weighted averages of the quarterly estimates in Equation (A.1), with the weights determined by the data. Monthly coefficients are available upon request, but we note that they are noisy and do not help with the interpretation of the effects of the SMCCF on vacancy postings.

Figure A.5 shows the coefficients for the fallen angels, BBB, and A firms. Compared to the dynamics in the baseline (Figure 4 and Figure 6), the quarterly coefficients display very similar patterns, which suggest delayed effects for the fallen angels and immediate effects for the BBB and A firms.

Figure A.5: The Effects of the SMCCF on Log Vacancies: Quarterly Coefficients



(a) Fallen Angels (b) BBB Firms (c) A Firms

A.9 Robustness Analysis of Adding More Firm-Level Characteristics

We augment the baseline regression with more firm-level time-varying controls in this section. Specifically, in addition to log annual employment, quarterly cash-to-asset ratio, and debt-to-asset ratio, we add the following variables one by one Table 3 Column (2):

1. Cash-flow-to-property ratio: (Income before extraordinary items + Depreciation and amortization)/Total property, plants and equipment

2. Q: (Market value + Total shareholder's equity - Book value of common equity - Deferred tax asset)/Total shareholder's equity

3. Dividend-to-property ratio: Dividends/Total property, plants and equipment

4. Cash-holdings-to-property ratio: Cash holdings/Total property, plants and equipment

5. Expense-to-asset ratio: (Revenue - Income before extraordinary items)/Total asset

We add indicators for missing observations to keep the sample size constant. Table A.5 shows the results, which are consistent with those in Table 3.

Table A.5: The Effects of the SMCCF on Labor Demand

		Panel A: Fallen Angels			
	(1)	(2)	(3)	(4)	(5)
$\overline{\beta}$	0.4143	0.4183	0.4204	0.4192	0.4196
	(0.1518)	(0.1518)	(0.1514)	(0.1512)	(0.1513)
N	13,920	13,920	13,920	13,920	13,920
		Panel B: BBB Firms			
	(1)	(2)	(3)	(4)	(5)
$\overline{\beta}$	0.2262	0.2213	0.2231	0.2231	0.2203
	(0.0797)	(0.0795)	(0.0797)	(0.0797)	(0.0800)
N	22,656	22,656	22,656	22,656	22,656
		Panel C: A Firms			
	(1)	(2)	(3)	(4)	(5)
$\overline{\beta}$	0.2050	0.1935	0.1921	0.1928	0.1933
	(0.1172)	(0.1175)	(0.1176)	(0.1175)	(0.1176)
N	12,144	12,144	12,144	12,144	12,144
Cash-Flow-to-Property	Y	Y	Y	Y	Y
Q		Y	Y	Y	Y
Dividend-to-Property			Y	Y	Y
Cash-Holdings-to-Property				Y	Y
Expense-to-Asset					Y

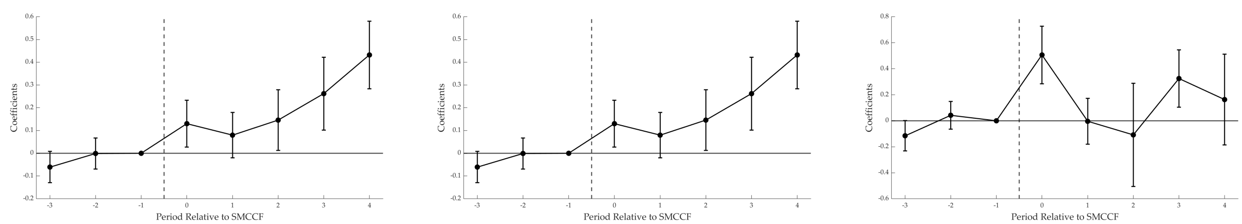
A.10 Synthetic Control Construction: Robustness

In Section 2, we construct synthetic controls by matching pre-treatment employment and vacancy postings. Here we consider matching more firm-level characteristics.

In addition to vacancy postings and employment, we include the cash-to-asset ratio and debt-to-asset ratio. We have 9 fallen angels, 155 treated BBB firms, and 33 treated A firms. As in Section 2, we require the difference in the average pre-treatment vacancy postings between the treated and synthetic control firm to be within 10% which does not apply to synthetic controls for the fallen angels.

Figure A.6 plots the coefficients, which shows that the results are similar. The average treatment effects are significant at 5% for the fallen angels and BBB firms, which are equal to 0.5592 (0.2486) and 0.2100 (0.0519), respectively. The point estimate of the average treatment effect is significant at 10% for A firms, which is equal to 0.1764 (0.1067). Therefore, we conclude that the results of the synthetic control regression are robust to matching more pre-treatment firm characteristics.

Figure A.6: Synthetic Control Regression by Matching More Variables



(a) Fallen Angels (b) BBB Firms (c) A Firms

A.11 Do Actual Purchases of the SMCCF Matter?

While the size of the SMCCF is $14 billion, it is less than 1% of the total investment grade corporate bond outstanding as of December 2019, which was $6 trillion. This raises questions about whether the effects of the SMCCF are consistent with its size, and whether the actual purchases matter.

We first note that the question applies to the study on the effects of the SMCCF on the financial market as well, which show that the announcement of the SMCCF immediately decreased bond spread and stabilized the bond market (e.g., D'Amico et al., 2020). The announcement was important because the Fed did not explicit communicate the size of the program, and the market viewed the Fed as lender of last resort (O'Hara and Zhou, 2021), and trusted the Fed's ability to deliver on its promise to stabilize the corporate bond market and do "whatever it takes" (Gilchrist et al., 2021). Our results in Section 4 are consistent with this interpretation, which suggests that the market value of treated BBB and A firms immediately increased following the SMCCF.

This means that the ex post size of the SMCCF is more likely to reflect that the Fed deemed the amount to be sufficient for stabilizing the corporate bond market. Specifically, the Fed initially collateralized \$50 billion for the SMCCF and \$25 billion for the PMCCF, and the former accounted for 3% of total investment grade corporate bonds with a maturity of five years or less (Berndt et al., 2017; Çelik et al., 2020). Therefore, the actual purchases could reveal extra information, because the market did not know for sure which firms would be treated at the announcement. This intuition is consistent with Boyarchenko et al. (2022), who show that the SMCCF decreased bond spreads of eligible bonds during the actual purchases.

In addition, we show suggestive evidence that the actual purchases could matter for labor demand by two methods. First, we decompose Equation (4) to be

$$\log(Vacancy)_{im} = \alpha + \beta * \mathbb{I}_{D_i=\$1 \text{ million}} * Post_m + \widetilde{\beta}_{fd} \widetilde{D}_i * Post_m + \delta_i + Post_m + \epsilon_{im} \quad \text{(A.2)}$$

where $\mathbb{I}_{D_i=\$1 \text{ million}}$ is an indicator that the par-value is \$1 million, and $\widetilde{D}_i$ are the par-value in excess of \$1 million in \$1 million increments.[40] Therefore, Equation (A.2) decomposes the causal effects into a part implied by the first \$1 million purchase and an additional part. We expect $\widetilde{\beta}_{fd}$ to be 0 if the amount of purchase does not matter, which is equivalent to the notion that giving every firm \$1 million would result in the same treatment effects.

The results suggest that the causal effects $\widetilde{\beta}_{fd}$ are larger, with the estimates equal to 9.1% (0.036), 4.6% (0.018), and 3.0% (0.017) for the fallen angels, BBB, and A firms, respectively.

Second, we use a permutation exercise. For each comparison, e.g., fallen angels and

[40] For example, if the par-value of a firm is \$1.5 million, $\widetilde{D}_i$ would be 0.5.

control BB firms, we take the distribution of par-value of the treated firms as given, and we run 100 permutations which assign the par-value randomly among treated firms. For each permutation, we estimate the causal response using Equation (4). If the par-value does not matter, we should not expect the baseline results to be systematically at the left or right tail of the permutation results.

To see this, suppose there are two treated firms, Apple and Walmart, whose treatment effects are 2% and 4%, respectively, regardless of their par-values. Further suppose that the par-values are \$2 million for Apple and \$3 million for Walmart. The estimated causal response would be between 1% and 1.3% for every \$1 million bond purchase. If instead the par-values are \$3 million for Apple and \$2 million for Walmart, the estimated causal response would be smaller than 1%, because the treatment effects are fixed.

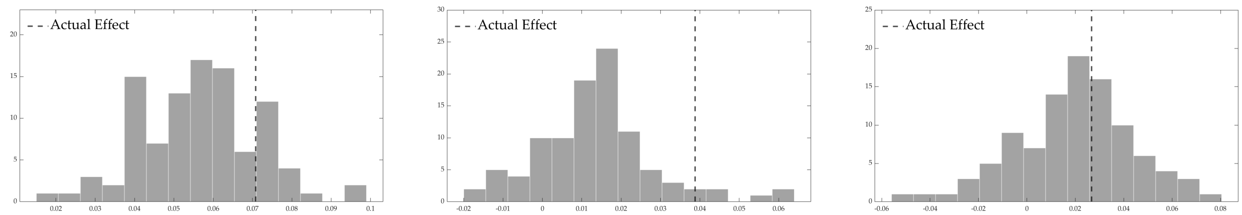
Therefore, conditioning on the treatment effects being orthogonal to actual purchases, the effect of any treatment assignment would draw from the same distribution, and we should not expect what actually happened in the SMCCF to be different. In other word, the effect of the SMCCF would be similar to a toss of a fair coin, and we should not expect to always observe heads or tails.

Figure A.7 plots the distribution of permutation results, which suggest that the baseline results are consistently at the right tail. Specifically, the baseline estimates are greater than 80%, 95%, and 63% of the permutation results for fallen angels, BBB, and A firms. In addition, 72%, 81%, and 55% of the permutation estimates are statistically insignificant for fallen angels, BBB, and A firms. We argue that the evidence suggests that the actual purchases could matter.

A.12 The Effects of the SMCCF on the Skill Content of Vacancies

Because the pandemic induced major changes in the way firms operate (e.g., Bloom et al., 2022), we investigate whether the SMCCF changed the content of labor demand, namely the type of vacancies firms posted. For example, while the treated firms posted more

Figure A.7: The Baseline Results and the Permutation Results



(a) Fallen Angels (b) BBB Firms (c) A Firms

vacancies, these vacancies could be concentrated on jobs with high rates of turnovers, or they could reflect efforts to reorganize firms' labor force.

We examine one aspect of such changes, which is the skill content of vacancy postings. We construct a skill index by occupation, and we aggregate the skill index at the firm level. If the treated firms demanded mainly, e.g., low-skill workers whose turnover rate was high, the skill index would capture the difference compared to the control firms.

Specifically, we follow Lise and Postel-Vinay (2020) and calculate the skill requirements of each SOC-Code occupation by three dimensions: Cognitive, Manual, and Inter-personal. The skill requirements are normalized to be within the $[0, 1]$ interval, and we weight each skill by its productivity which is estimated in Lise and Postel-Vinay (2020). This process leads to a single skill index for each SOC-Code occupation.

For example, Chief Executives (SOC 11-1011.00) requires 0.66 cognitive skills, 0.44 manual skills, and 0.82 inter-personal skills. We calculate the skill index for Chief Executives by:

$$0.66 * 1 + 0.44 * 0.191 + 0.82 * 0.065 = 0.80$$

where we normalize the productivity to be multiples of the productivity of cognitive skills. We merge the occupation skill index with our FISD-BGT data, and we compute the skill index for each firm by taking the unweighted average of the firm's vacancies in a month.

Table A.6 shows the summary statistics of skill indices in 2019. The numbers of observations differ from those in the baseline regression on vacancies (Table 1) because we could not construct the skill index for some occupations. Nonetheless, the results suggest that the treated and control firms have similar skill indices in 2019.

Table A.6: Summary Statistics of Skill Indices

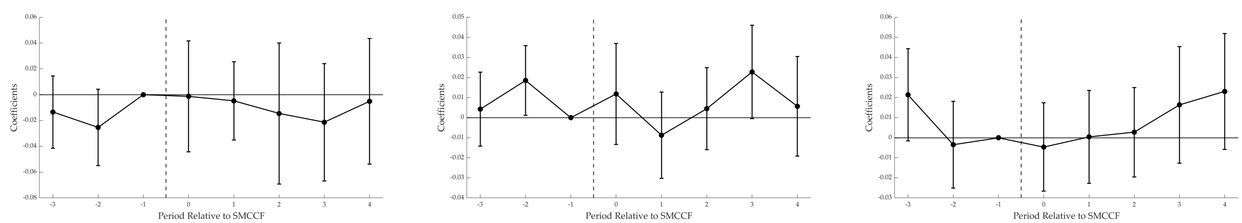
	Fallen Angels	BB	Treated BBB	Control BBB	Treated A	Control A
Skill Index in 2019	0.619	0.631	0.641	0.629	0.650	0.642
	(0.116)	(0.093)	(0.092)	(0.089)	(0.085)	(0.072)
N	19	166	273	93	133	54

The empirical specification is

$$\log(Skill)_{im} = \alpha + \sum_{\tau=-3}^{4,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_q + \epsilon_{im} \tag{A.3}$$

where we replace log vacancies in Equation (1) by the log skill index. We continue to compare the same treated and control firms as those in the baseline.

Figure A.8: The Effects of the SMCCF on the Skill Index



(a) Fallen Angels (b) BBB Firms (c) A Firms

Notes. Figure A.8 plots the coefficients of Equation (A.3), and we calculate the skill index for each occupation and aggregate it for each firm. The fallen angels are the treated BBB firms on march 22, 2020 who were subsequently downgraded to BB in 2020. The control BB firms are those in the FISD whose bond ratings were at least BB- on March 22, 2020, and who maintained at least a BB- rating in 2020. The treated BBB (A) firms are those on the SMCCF disclosure whose bond ratings were at least BBB- (A-) on March 22, 2020. The control BBB (A) firms are those in the FISD whose bond ratings were at least BBB- (A-) on March 22, 2020, with bond maturities longer than 5 years on January 1, 2021, which made them ineligible for the SMCCF. We exclude insured depository institutions and their holding companies. We define one period to be half a year, with the sample spanning 2019h1-2022h2. The standard error is clustered at the firm level.

Figure A.8 shows little evidence that the skill content of vacancies changed at the firm level. Interestingly, the skill index of treated A firms displayed increasing trends following the SMCCF, but the point estimates are statistically insignificant. Therefore, while the pandemic could, e.g., replace onsite jobs with remote ones, we conclude that the SMCCF did not change the skill content of vacancies.

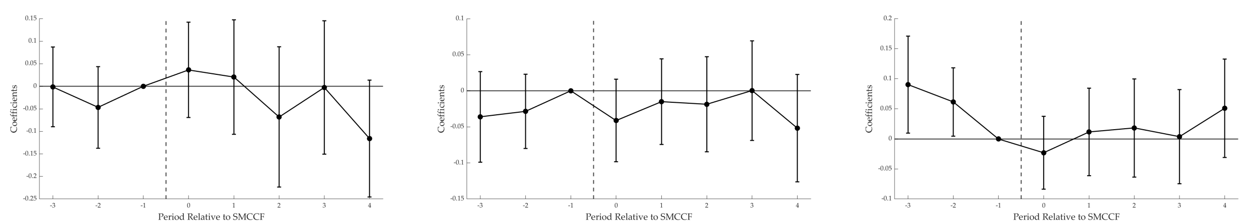
A.13 The Effects of the SMCCF on Posted Salaries

The BGT data has information on posted salaries for a subset of vacancies, which is another measure of the content of labor demand. We construct the average posted salary for each firm in a given month by taking the unweighted average of all its vacancies with posted salary. And then, we use the following regression for the fallen angels, treated BBB, and A firms:

$$\log(Salary)_{im} = \alpha + \sum_{\tau=-3}^{4,\tau\neq-1} \beta_\tau \mathbb{I}_i^\tau + \delta_i + \lambda_q + \epsilon_{im}$$

Figure A.9 plots the coefficients and Table A.7 shows the average treatment effects. There is little evidence of significant change in posted salaries, but Figure A.9 (c) suggests that the treated A firms have significant pre-trends, which could imply that these firms are not comparable to the control A firms with respect to the content of labor demand.

Figure A.9: The Effects of the SMCCF on Posted Salaries



(a) Fallen Angels (b) BBB Firms (c) A Firms

Table A.7: The Effects of the SMCCF on Posted Salaries

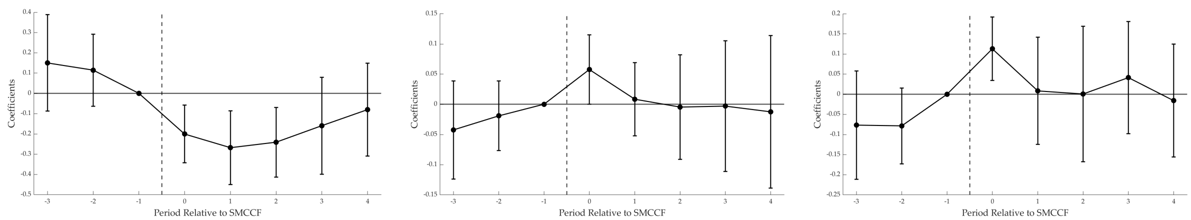
	(1) Fallen Angels	(2) BBB Firms	(3) A Firms
$\overline{\beta}$	-0.0259	-0.0253	0.0123
	(0.0563)	(0.0279)	(0.0321)
N	7,747	14,488	8,214

We note that only a subset of firms have information on posted salaries, which leads to a 50% smaller sample than that of vacancies. Further, the results using skill indices suggest no significant pre-trend, and the sample size is larger because almost every vacancy has information on occupation.

A.14 The Effects of the SMCCF on Log Market Value

We examine the change in firms' log market value following the SMCCF, and we use Equation (5) as the regression specification. Figure A.10 suggests that fallen angels experienced declines in their log market value following the SMCCF, likely because the market take into account their downgrading.

Figure A.10: The Effects of the SMCCF on Firms' Market Value



(a) Fallen Angels (b) BBB Firms (c) A Firms

Both the treated BBB and A firms saw immediate increases in the log market value following the SMCCF, which is consistent with the results in Section 4. Overall, we argue that the results are consistent with those in Section 4.

A.15 The Effects of the SMCCF on Borrowings and Liquidity: Robustness

A.15.1 Summary Statistics of Firm Characteristics

Table A.8 shows the summary statistics of the variables in Section 4 and this section. All variables are 2019 quarterly averages. Both the fallen angels and treated BBB firms are comparable to their controls in the observables, but the treated A firms differ more significantly from their controls.

Table A.8: Summary Statistics of Firm Characteristics in 2019

	Fallen Angels	BB	Treated BBB	Control BBB	Treated A	Control A
Debt-to-Asset	0.401	0.436	0.374	0.352	0.315	0.298
	(0.131)	(0.168)	(0.144)	(0.154)	(0.165)	(0.144)
N	9	140	213	65	111	25
Expense-to-Asset	0.150	0.185	0.156	0.135	0.156	0.073
	(0.167)	(0.129)	(0.156)	(0.101)	(0.172)	(0.046)
N	13	140	225	67	112	24
Cash-Holdings-to-Asset	0.045	0.054	0.052	0.049	0.074	0.033
	(0.059)	(0.054)	(0.067)	(0.060)	(0.083)	(0.052)
N	13	140	225	67	112	24
KZ-Index	2.62	2.41	3.16	2.24	8.21	1.39
	(1.27)	(5.58)	(15.24)	(1.26)	(30.77)	(1.58)
N	8	110	173	40	69	8

A.15.2 Construction of the KZ-Index

The construction of the KZ-index follows Kaplan and Zingales (1997) and Straub and Ulbricht (2021). Specifically,

$$kz_{it} = -1.001909 \times \frac{\text{cashflow}_{it}}{k_{it}} + 0.2826389 \times Q_{it} + 3.139193 \times \frac{\text{debt}_{it}}{\text{total capital}_{it}} - 39.3678 \times \frac{\text{dividends}_{it}}{k_{it}} - 1.314759 \times \frac{\text{cash}_{it}}{k_{it}}$$

cashflow_{it} is the sum of "income before extraordinary items" and "depreciation and amortization". Q_{it} is ("market capitalization" + "total shareholder's equity" - "book value of common equity" - "deferred tax assets")/"total shareholder's equity". debt_{it} is "long-term debt" + "debt in current liabilities". $\text{total capital}_{it}$ is "long-term debt" + "debt in current liabilities" + "stockholders equity". k_{it} is "total property, plants, and equipment". All items refer to Compustat variable names.

A.15.3 Robustness

We show the results of the SMCCF on borrowings and liquidity, and we exclude firms in Utility industry (NAICS2 22). Table A.9 shows that our results in Section 4 are robust. Plots of coefficients are omitted and available upon request.

Table A.9: The Effects of the SMCCF on Borrowings and Liquidity: Excluding Utility Industry

	Panel A: Fallen Angels						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Debt-Asset		Expense-Asset			Liquidity	
$\overline{\beta}$	-0.0125	-0.0120	0.0001	0.0002	0.0006	0.0013	0.7761
	(0.0200)	(0.0200)	(0.0129)	(0.0129)	(0.0136)	(0.0129)	(0.9025)
N	1,844	1,829	1,997	1,982	2,017	2,002	884
	Panel A: BBB Firms						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\beta}$	-0.0017	-0.0017	0.0121	0.0122	0.0086	0.0071	-2.0668
	(0.0085)	(0.0085)	(0.0067)	(0.0068)	(0.0055)	(0.0052)	(3.7553)
N	3,199	3,139	3,778	3,718	3,791	3,776	1,545
	Panel C: A Firms						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\overline{\beta}$	-0.0135	-0.0141	0.0019	0.0011	-0.0372	-0.0453	-1.7087
	(0.0213)	(0.0214)	(0.0095)	(0.0096)	(0.0160)	(0.0190)	(2.2047)
N	1,471	1,356	1,550	1,435	1,565	1,550	539
No Pharma.		Y		Y			