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Abstract

This paper studies the firm-level short-term impact of one of the world's largest credit guarantee programs recently implemented in Türkiye. Using a combination of firm-level administrative databases of the tax registry, credit registry, and the credit guarantee fund (CGF) registry, we analyze the characteristics of the CGF-supported firms and the program's impact on their employment, sales, and credit default probability. We find that the CGF program on average had a positive impact on the performance of treated firms. The CGF-supported firms were able to increase their employment by 17 percent and sales by 70 percent while these firms reduced their credit default probability by 0.6 percentage point relative to their matched-control group. Evaluating our estimation results at variable averages shows that every 1 million TL credit generated via the CGF program preserved 2.7 extra employment and stimulated about 3 million TL in sales. We also observe an overall increase in firm indebtedness, which may adversely affect firms' long-term financial health. Moreover, our findings reveal that the program impact is heterogeneous across firm size and sector groups. Using this heterogeneity, we perform counter-factual policy exercises indicating that redesigning the program with such priorities can bring substantial efficiency gains.

JEL Classifications: G21, G3, L25

Keywords: Credit Guarantee Schemes; SME Lending; Impact Analysis

ملخص

تدرس هذه الورقة التأثير قصير الأجل على الشركات لأحد أكبر برامج ضمان الائتمان/القروض في العالم التي تم تنفيذها مؤخرا في تركيا. فباستخدام مجموعة من قواعد البيانات الإدارية على مستوى الشركات للسجل الضريبي وسجل الائتمان/القروض وسجل صندوق ضمان الائتمان(CGF) ، نقوم بتحليل خصائص الشركات المدعومة من صندوق ضمان الائتمان (CGF) وتأثير البرنامج على التوظيف والمبيعات واحتمال التخلف عن سداد القروض. وقد جدنا أن برنامج صندوق ضمان الائتمان (CGF)في المتوسط كان له تأثير إيجابي على أداء الشركات الخاضعة للبحث. وتمكنت الشركات المدعومة من صندوق ضمان الائتمان من زيادة توظيفها بنسبة 17 في المائة وزيادة مبيعاتها بنسبة 70 في المائة، في حين خفضت هذه الشركات احتمالية عجزها عن سداد الائتمان بنسبة 0.6 نقطة مئوية مقارنة بمجموعة التحكم. يظهر تقييم نتائج تقديرنا بمتوسطات متغيرة أن كل 1 مليون ليرة تركية تم إنشاؤها عبر برنامج صندوق ضمان الائتمان (CGF) حافظت على 2.7 وظيفة إضافية وحققت حوالي 3 ملايين ليرة تركية في المبيعات. كما نلاحظ زيادة إجمالية في مديونية الشركات، مما قد يؤثر سلبا على الصحة المالية للشركات على المدى الطويل. علاوة على ذلك، تكشف النتائج التي توصلنا إليها أن تأثير البرنامج غير متجانس عبر الشركات ومجموعات القطاع من الأحجام المختلفة. وباستخدام هذا التباين، نقوم بإعداد سياسيات تجريبية بناء على الواقع تشير إلى أن إعادة تصميم البرنامج بمثل هذه الأولويات يمكن أن يحقق مكاسب كبيرة في الكفاءة.

1 Introduction

Improving credit access to firms with resource shortages is a difficult policy question that is usually raised for small and medium-sized enterprises (SMEs). As bank debt remains the primary source of external finance for most SMEs in many countries, particularly emerging ones, most public policy initiatives have consequently centered on bank lending. Traditional banking practices, by generally placing strong reliance on hard information (e.g., reliable financial statements) and collateral capacity in risk assessment, limit SMEs' credit access. With a holding power to improve collateral capacity, public guarantee schemes have recently emerged as a popular policy tool in many developed and developing countries. In this paper, we use a combination of firm-level administrative databases of the tax registry, credit registry, and credit guarantee fund (CGF) registry to study Türkiye's 2017 CGF program. More specifically, we first analyze the characteristics of the CGF-supported firms and then study the program's impact on various firm performance indicators in the short run. Türkiye's CGF program implemented in 2017 was a unique experience. With roughly 7.6 percent GDP share credit stimulus coverage, which was roughly double the size of the second-largest guarantee program implemented in Japan in the same year (4 percent of the GDP), Türkiye's CGF program stood out as the largest guarantee program implemented globally in the same year.

Türkiye's domestic credit markets had been experiencing a tightening since the shrinking in global liquidity in 2013, which further toughened with the increase in domestic uncertainty due to the geopolitical developments in 2016. The credit growth was recorded to be negative along with the lowest GDP growth experienced in 2016 for the first time since the Global Financial Crisis (GFC) in 2009. To bring back the economy in 2017, the Turkish government implemented one of the world's largest credit guarantee programs that reached almost 20 percent of its total existing firm credit stock as of 2016. In this paper, we use novel administrative databases to analyze the firm-level impact of this massive CGF program. We first analyze the differences between the CGF-supported and non-supported firms' characteristics, including sector, size, and ex-ante risk distributions. We then build on this background to match the CGF-supported firms (the treatment group) with their closest pairs (the control group) via coarsened and exact matching (CEM) methodology. Given the richness of our data, we select the control firms based on revenue size, asset, capital and debt structures, ex-ante riskiness, industry, and year. This level of detailedness of our data is rather rare in similar studies, which is essential to construct a reliable control group that will mostly determine the identification quality of the program impact. Using matched pairs, we then employ a Difference-in-Differences (DiD) framework to provide an in-depth evaluation of the firm-level impact of the CGF program on the ex-post performance of the CGF-supported firms in terms of employment, sales, and credit default probability.

We find that the CGF program created a significant redistribution of credits in 2017 toward smaller-sized firms (e.g., micro and SMEs) and particularly benefited wholesale & trade, manufacturing, and construction industries. In terms of their ex-ante risk attributes, we did not find any significant divergence between the CGF-supported and non-supported firms. This is to say that we do not observe any statistically significant tendency toward allocating more CGF resources to risky firms given the government guarantees (i.e., moral hazard problem). More specifically, our findings show that the CGF program had a substantial positive impact on firm performance in the post-program years. According to the results, the CGF-supported firms on average preserved 17 percent more employment, generated 70 percent more sales, and experienced 0.6 percentage point less credit default than their matched pairs in 2018. Evaluating these estimates at their sample averages implies that an extra 1 million TL loan generated via the CGF program preserved roughly 2.75 more employment, generated about 3 million more sales, and reduced the average credit default probability by nearly 6.5 percent in 2018. These findings are robust to various checks, including additional controls and sub-sample considerations. Our findings also document that the program impact is heterogeneous across firm size and sector groups. In particular, the program's positive impact on medium-sized firms is much larger than on other size groups. On the sectoral heterogeneity, the CGF program is more effective in preserving employment in labor-intensive industries (e.g., service) and more effective in generating sales in sectors that serve more the domestic economy (e.g., wholesale & trade). The manufacturing sector shows an intermediate case, where the employment and sales impact of the program is comparable. Our counter-factual analysis shows that substantial efficiency gains are possible by redesigning the program based on the program's size and sectoral impact heterogeneity.

We also provide further estimations on the program's impact on various firm asset types and liabilities. The results indicate that the program's positive impact on long-term assets (e.g., intangible assets such as R&D) appears to be weaker compared to short-term assets (e.g., inventories). This is perhaps expected given the original purpose for expanding the CGF program in 2017 was to mitigate the temporary negative impact of the geopolitical developments of 2016. In that regard, the program seems to be successful in reversing the domestic economy's negative trend by empowering firm performance through large liquidity injection. However, considering its weaker support for firms' long-term growth perspectives, the CGF program may be complemented by other government programs aiming to support productive capital, including investment subsidies and incentives. An increase in overall firm indebtedness due to the CGF program is also evident from our results, which may adversely affect firm credit default probabilities in the long term. This is especially the case for micro firms. Our results show that the CGF-supported micro firms experienced an increase in their credit default probability in 2018. Monitoring firms' indebtedness and ensuring appropriate debt management practices through mentoring services can significantly mitigate long-term credit default risks.

Over the last two decades, credit guarantee schemes (CGS) are being expanded in size and volume in many countries (OECD, 2019). Therefore, the economic impact of credit guarantee programs has been examined in a variety of theoretical and empirical studies; however, no consensus exists among researchers. One strand of theoretical literature suggests that credit guarantee programs may reduce credit rationing under asymmetric information à la Stiglitz and Weiss (1981) and result in funding profitable projects that would not be realized without government intervention (Mankiw, 1986; Gale, 1990, 1991). Another strand in the theoretical literature suggests that government intervention may increase information problems and worsen credit conditions (Chaney and Thakor, 1985; Aghion and Bolton, 1997). However, the literature on firm-level credit guarantee scheme evaluation is brief and to the point. In pioneer papers, Instrumental Variable (IV) and DiD methods are often used. For example, Kang and Heshmati (2008) used IV and OLS methods for Korea's KOTEC program, one of the largest CGS globally, and found that the scheme partially improved loan availability and employment level of the firms. Zecchini and Ventura (2009) applied DiD to credit guarantee program data from Italy and confirmed that such a program leads to higher leverage and lower debt costs for firms. In France, Lelarge et al. (2010) assessed the SOFARIS program's impact using OLS and DiD methods, confirming the program's positive effects on firm growth, external finance availability as well as negative effects on interest payments in the newly created firms.

In the last decade, other causal inference methods such as Propensity Score Matching (PSM), CEM, and Regression Discontinuity Design (RDD) are integrated into existing methods. In that respect, Hancock et al. (2007) employed state-level US data for the period of 1990-2010 and found that Small Business Administration (SBA) loans had a positive impact on employment, but the impact on firms' default probability was moderate. Hancock et al. (2007) also found that SBA programs helped stabilize the economy by offsetting the slowdown in business and the financial sector's capital pressures. Uesugi et al. (2010) applied the PSM method to Japanese credit guarantee programs and emphasized progress in credit availability. Uesugi et al. (2010) also showed that banks' financial structure is important in liquidity persistence. Ono et al. (2013) used PSM and found that although Japan's Emergency Credit Guarantee Program significantly improved credit availability for SMEs, the program had no significant impact on investment, employment, or profitability. De Blasio et al. (2014) used RDD techniques for Italy and found that the Fondo di Grazia program's loans had no impact on investment and interest rate charged by the banks and a mixed impact on sales. Moreover, their results suggested that the program decreased the loan repayment likelihood of eligible firms. Using firm-level data drawn from fiscal receipts over the years 1992–1999, Bach (2014) estimated the effect of eligibility for the CODEVI program, France's loan guarantee program, on bank finance availability with a DiD approach. Bach (2014) found that the program substantially increases debt financing without substitution between subsidized and unsubsidized finance while returns on subsidized debt are significantly above its market cost. He also found that the program did not cause a surge in default risk.

Brown and Earle (2017) analyzed linked databases on all SBA loans and lenders and on all U.S. employers to estimate the impact of access to finance on firm-level employment growth. They employed PSM methodology and used fixed effects and IVs-based regressions. They showed that, on average, 3-3.5 jobs were created for each million-dollar loan supplied via the SBA program. Their results also suggested that estimated impacts were stronger for younger and larger firms. Using the same SBA program data, a recent study (Bachas et al., 2021) also showed that the program was effective in increasing the loan supply for SMEs which is particularly key for the credit access of many young firms. The paper also highlighted the fact that many of today's global giants, such as Apple, Nike, and Intel, once upon a time have utilized the

SBA program in their early stages. More recently, Bertoni et al. (2019a) used PSM and IV-2SLS to study a sample of 512 entrepreneurial ventures that received a government-sponsored participative loan from a Spanish government agency between 2005 and 2011. Bertoni et al. (2019a) found evidence that government-sponsored participative loans significantly boosted the beneficiaries' employment and sales. Similarly, using CEM and PSM, Bertoni et al. (2019b) investigated the economic effects of guaranteed loans granted under the EU programs MAP and CIP implemented in Italy, the Benelux, and the Nordic countries from 2002 to 2016. The researchers found guaranteed loans positively affect the growth in assets, sales, employment, and the share of intangible assets. Using the PSM estimator and the DiD regressions on a sample of 38,000 Italian SMEs in the period 2007-2009, Caselli et al. (2019) showed that the magnitude of the effect varies across firm sizes and sectors, where micro-and small-sized firms benefit more from the support of Italy's Central Guarantee Fund.

The Turkish public credit guarantee experience has two distinct features, which makes it a rare one compared to other country experiences. First, the program size was extensive, rather than a focused credit program for SMEs, as implemented in many other countries. Secondly, it was used as a fiscal-response measure to alleviate the negative impact of an aggregate shock on the domestic economy, while most of the other programs were implemented during normal times. These distinct features make the Turkish case exceptionally an interesting and important one to think about the effectiveness of public guarantees as a fiscal-response measure during aggregate shocks, which we have limited studies on. For instance, during the recent pandemic crises, public credit guarantees were widely used in many countries as a fiscal-response measure, amounting to multi-trillion US$ in size (IMF, 2020). Our findings are particularly relevant to think about their effectiveness while delivering important policy lessons for improving their impact.

The remainder of this paper is organized as follows. Section 2 presents the evolution of the Turkish CGF experience. Section 3 briefly describes our data. Section 4 displays the main differences between the CGF-supported and non-supported firms and discusses the construction of our ex-ante risk assessment model. Section 5 presents the impact analysis, including the details of our identification strategy and the main estimation results. Section 6 includes the size and sector breakdown of the main results along with a counter-factual policy discussion. Section 7 shows extended results on various firm outcomes. Section 8 provides several robustness checks and finally, Section 9 presents the conclusions.

2 Institutional Background

Türkiye's CGF was established in 1991 as a state-funded program with the primary mandate of improving credit access conditions for SMEs. The CGF operates as a joint-stock company, shareholders of which include chambers, non-government organizations, banks, and public agencies.[1] The CGF issues guarantees via bank loans either through its equity or through the Treasury

[1]CGF is exempt from corporate tax and value-added tax in its transactions for providing loan guarantees.

support funds. In doing so, the CGF provides a guarantee for borrowers, aiming to improve borrowers' collateral quality and to reduce the damage on lenders in the case of default. In other words, CGF acts as a guarantor for credit-constrained firms that face difficulty in obtaining loans due to insufficient collateral. With the CGF guarantees, firms, particularly SMEs, can better access credit at a lower cost and longer maturities. The low-risk nature of CGF-backed loans also brings certain benefits for the loan issuing banks, allowing them to share their credit risk and strengthen their regulatory capital. The risk weight[2] for the CGF-backed loans is usually close to zero or at least lower than non-CGF-backed loans, which supports the issuing banks' capital adequacy ratio. In what follows, we discuss the CGF program's development and its recent policy context in Türkiye.

The tightening in global liquidity following the Fed taper tantrum policy in 2013 sharpened the decline in credit growth, particularly in FX, in the Turkish domestic credit market (Figure 1). In addition to this global tightening, Türkiye experienced a severe geopolitical shock in 2016. The shock increased domestic uncertainty and further tightened the domestic credit conditions (CBRT, 2016). Real credit growth was recorded to be negative in 2016 for the first time since the GFC in 2009. The negative credit growth was apparent in both FX and TL credits in 2016. Given the high reliance of Turkish industries on credit finance (Akcigit et al., 2020), the annual real GDP growth recorded the lowest rate in 2016 since the GFC, although it remained positive. Many firms experienced an instant slowdown in business, while the financial sector's credit issuance appetite was rather low. To restore expectations and avoid a potential risk of a sudden stop in the economy, the Turkish government provided significant liquidity to the markets via the CGF program by multi-doubling its size in 2017. With the implementation of the CGF program in 2017, we observe an instant reversal in TL credit growth, while FX's negative trend continued.[3] Moreover, the real GDP growth in 2017 bounced back to 7.5 percent.

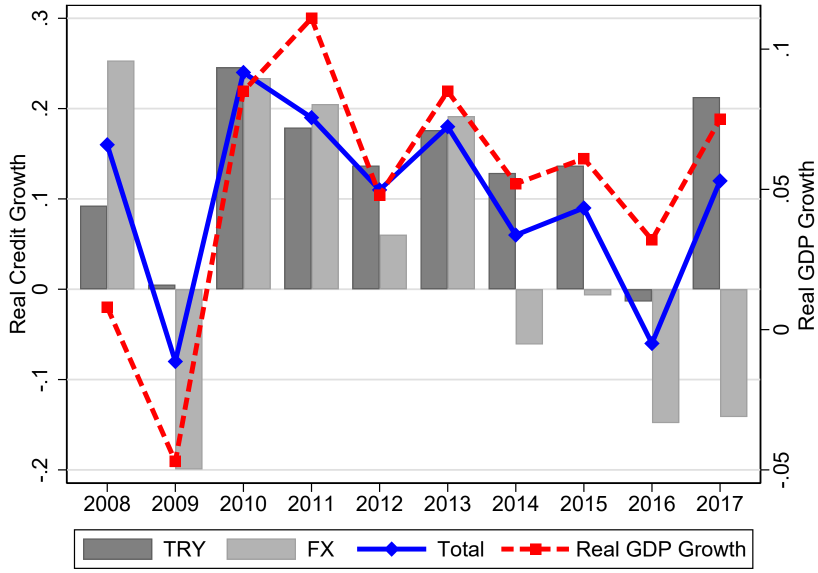
Until the end of 2016, CGF had mostly run on a small scale and issued credit guarantees only from its limited equity. In December 2016, the Turkish Treasury signed the first protocol with the CGF to increase its guarantee capacity up to the first 20 billion TL, which was then further upgraded to 250 billion TL in March 2017 with additional protocols.[4] Smaller scale packages continued to be implemented in the following years; however, the 2017 package has been the biggest guarantee program not only in the history of Türkiye but also in the world. Figure 2

[2]The risk weights are determined by the Banking Regulation and Supervision Agency (BRSA) of Türkiye.

[3]Most of the CGF backed loans were issued in TL (i.e., the share of CGF-backed TL loans in 2017 was about 85 percent and the remaining 15 percent was denominated in FX). The CGF program seems to be successful in reversing the negative trend in especially TL credit growth. However, high volatility in TL during these years would also add to the negative growth in FX credits and hence, might have contributed to the instant increase in TL credit growth.

[4]With the new protocols, some of the tighter conditions in the earlier protocols were also removed. For instance, the condition that the beneficiary firms must not have outstanding non-performing loans (NPLs) in the regulation was also relaxed in this package. Credits in Türkiye are classified into five groups, where the first two groups are performing loans, and the last three groups are non-performing loans with at least 90 days and more overdue loan payments. The new regulation allowed only the firms with 3*rd* and 4*th* group NPLs to apply for the CGF program, while the last group would still not be allowed to benefit from the program. The details of the current NPL definitions in Türkiye can be found in decree numbered 29750 in the Official Gazette dated 22/06/2016, and the details of the CGF program regarding the NPL classification can be found in decree numbered 9969 in the Official Gazette dated 10/03/2017.

Figure 1: Real Annual Credit Growth Contribution by Credit Denomination and Real GDP Growth



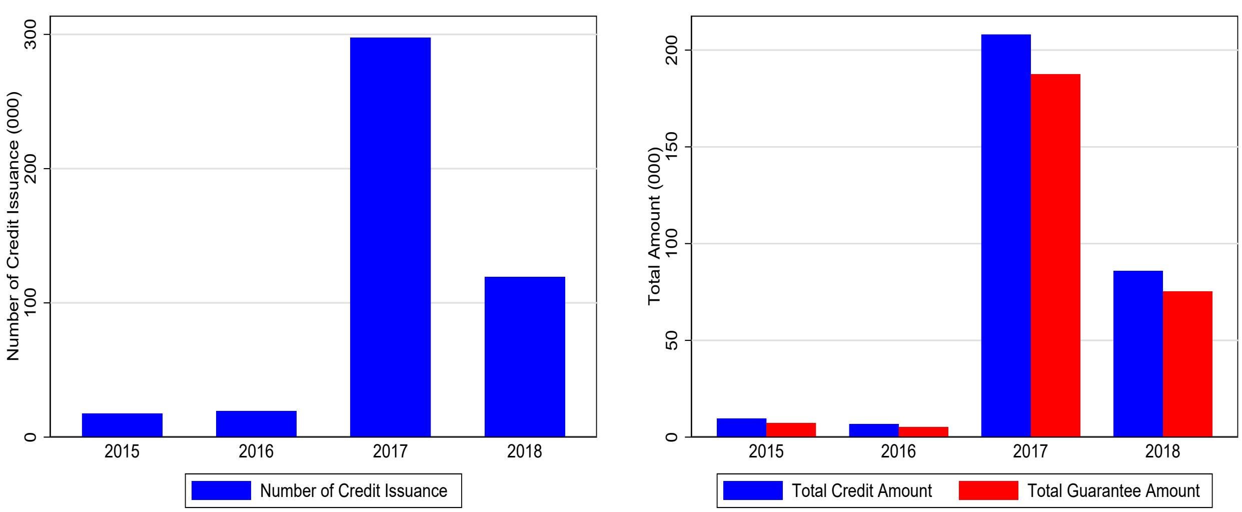
Source: Authors' calculation from the CR and Turkish Statistical Institute (TSI) databases.
Notes: The figure shows the real annual credit growth contribution by credit denomination and real GDP growth over the last decade.

summarizes the official numbers for the CGF program in number of credit issuance tiny before 2017, the program expanded significantly in 2017. The CGF program of 2018 was also important, but it was not comparable to the program's size in 2017. Hence, the current study focuses on the evaluation of the CGF program in 2017.

Figure 2: Size of Credit Guarantee Fund

(a) Number of Firms

(b) Total Amount (TL)



Source: CGF Activity Report in 2018.
Notes: The number of credits issued represents the total number of credit issuance, including multiple credits by any firm.

The CGF expanded its operational capacity in 2017 by using two separate streams of assessment procedures for guarantee issuance: the portfolio guarantee system (PGS), and the portfolio limit system (PLS). Under the PGS, the SME group guarantee limit was 12 million TL, and the group limit for large firms was 50 million TL.[5] The PLS, on the other hand, was designed specifically for large firms where the group limit was 250 million TL. Under the PGS, banks followed their internal credit risk assessment[6] and the CGF authorities did not make an additional risk assessment, while under the PLS, the CGF authority also undertook its risk assessment in order to make a final decision on the guarantee application. Moreover, the CGF followed a different guarantee coverage for different firms, based on their size and export status. The guarantee coverage in the 2017 program was 90% for SME loans, 85% for large firm loans, and 100% for exporter loans. Details of the 2017 CGF program are summarized in Table 1.[7]

Table 1: Main characteristics of the CGF program in 2017

Characteristics	**PGS**	**PLS**
Total Guarantee Limits	12 million TL for SMEs 50 million TL for large firms	200 million TL for large firms
Risk Assessment	Based on banks' internal risk assessment	In addition to banks' internal assessment, CGF also conducts its risk assessment
Assessment Duration	Final assessment completed in 2 days	No duration limit on assessment
Maturity	For working capital loans: maximum 5 years, with a grace period of maximum 1 year. For investment loans: maximum 10 years, with a grace period of maximum 3 year.	
Guarantee Coverage	For SMEs 90% , for large firms 85% and for exporters 100%, of the total loan amount	

Source: CGF.

The moral hazard problem is a potential challenge for guarantee programs in general (Boot and Thakor, 1994; Aghion and Bolton, 1997). In order to avoid moral hazard problems, the CGF program of 2017 imposed an additional limit on each issuing bank's non-performing loan (NPL) rate of its CGF portfolio. This is to say that the Turkish Treasury will pay off the non-performing CGF balance based on the guaranteed schedule as long as the issuing bank's CGF portfolio NPL rate remains below 7 percent. If a bank's NPL rate of its CGF portfolio exceeds 7%, then the bank has to bear the remaining credit risk fully. Regarding the fee and commission expenses, the issuing bank demands a one-off guarantee commission from the beneficiary firm at a rate of 0.03% of the guarantee amount for each guarantee payment at the time of a letter of guarantee requested. Moreover, the bank cannot charge any additional fees other than the costs to be paid for procedures to be performed by third parties (e.g., appraisal, insurance, etc.) and the one-off guarantee commission to be paid to the CGF.

[5] Limits were imposed on the company holdings or groups, not on individual firms. Basically, there was one global limit for the group company, and the total lending to firms within the same group could not exceed the global limit.

[6] Banks in Türkiye follow Basel requirements in terms of their risk assessment methodology that must also be approved by the regulatory agency, BRSA.

[7] For a more detailed discussion on the CGF program design, see CBRT (2017).

3 Data

We utilize several administrative databases that are made available to the CBRT by the relevant government bodies. These are the Firm Tax Registry (FTR) of the Treasury and Finance Ministry, Credit Registry (CR) of the Banks Association of Türkiye, and the Credit Guarantee Fund (CGF) database. FTR contains yearly balance sheets and income statements for virtually all Turkish firms, both private and state-owned, from 2006 until 2018–the most recent year available. We only focus on the non-financial private legal entities (e.g., incorporated businesses) in the FTR, where we exclude the finance and public sectors and the unincorporated business (i.e., sole-proprietorship or partnership businesses). CR records all credit institutions' exposures to Turkish firms monthly, providing detailed information on all firm-bank credit relations. The CGF database records all firm-level credit information in 2017 at a monthly frequency. We discuss further details of each data set below.

3.1 Tax Registry

We use balance sheets and income statements of only the non-financial private legal entities in the analysis, given that most unincorporated businesses only report simplified tax records.[8] The raw administrative data were initially revised by the Turkish Statistical Institute (TSI), especially with respect to firm sector classifications to ensure the quality of sector identifications. The TSI also provided firm-level employment data that originated from the social security records. Moreover, legal entities cover most SMEs and all the large firms, and some of the micro firms. Among legal entities, we exclude firms that reported incomplete or incoherent data from the analysis, such as observations with negative fixed assets, negative current assets, negative total assets, and negative net sales. We also impose a one percent winsorizing on each of these variables at a given year and NACE Rev-2 digit sector level in the analysis.

3.2 Credit Registry

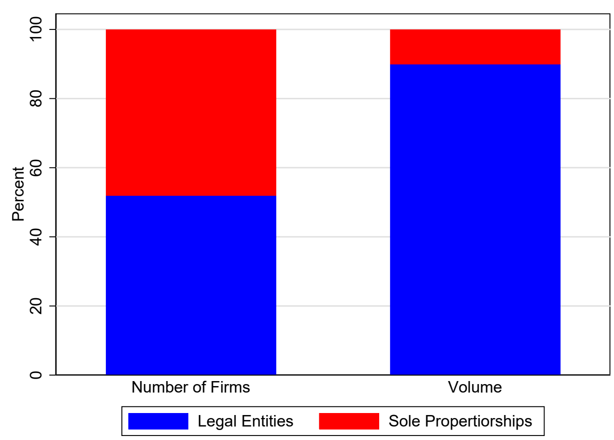
Credit Registry provides further details of all firm-bank credit relations, including type, maturity, and currency denomination of all the credit relations, as well as, lending institution branch level information. We use credit registry in the analysis mainly for two purposes: first, we obtain non-CGF firm-bank credit relations in 2017 and 2018, and also, the credit distributions in other years outside 2017. Second, we utilize the CR database to develop a risk-scoring tool to measure firm riskiness. The critical variable we compiled from the CR database is the default event – i.e., defined as the existence of 90 days overdue loan payment (e.g., non-performing loans (NPL)) for each firm in a given year. We also use several other characteristics of firm-bank credit relations, such as the age of credit relation, the number of bank relations, and credit default history in estimating risk scoring.

[8] The vast majority of unincorporated businesses operate under simplified tax regimes and thus, are not obliged to report regular balance sheets and income statements for tax purposes.

3.3 Credit Guarantee Fund Registry

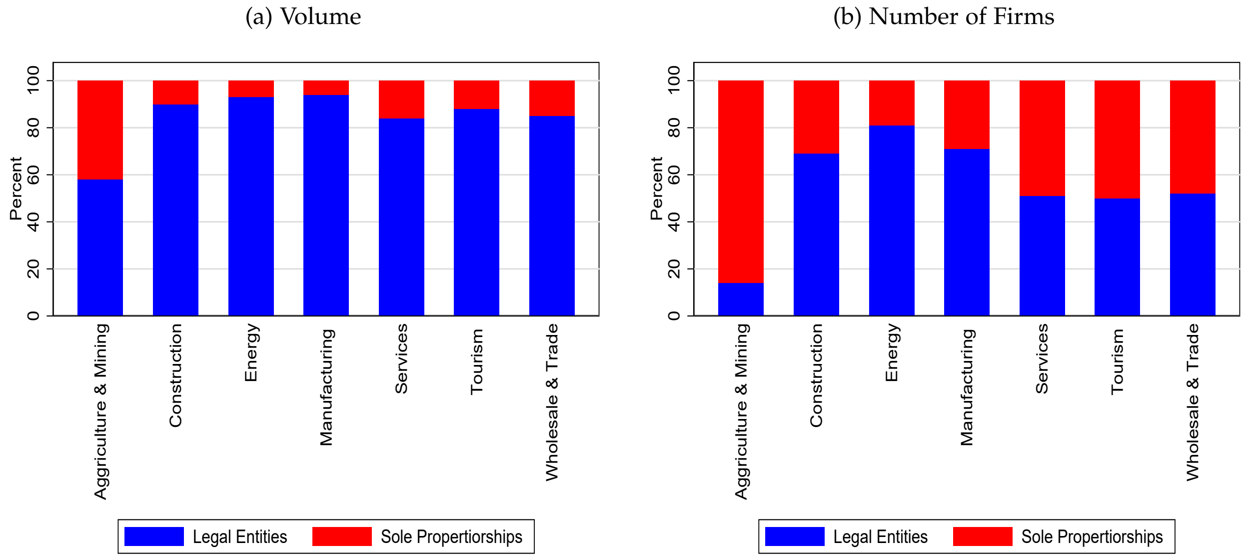
The CGF registry contains information on all the firm-bank level guaranteed credit transactions, including loan size, maturity, bearing interest rate, location, and guarantee level issued under the CGF program. We specifically use the information on the beneficiary firm, loan amount, and issuance date from the CGF database in the analysis. About half of the firms that benefited from the CGF program in 2017 were unincorporated businesses, although their volume is only about 10.2 percent of the CGF-backed loans in 2017 (Figure 3), which is similar to their average share in total firm credits (10 percent according to the credit registry) in 2017. The vast majority of the CGF back loans were issued to legal entities by volume which correspond to 90 percent of the program. A further breakdown of these figures by sector is presented in Figure 4. The figure shows that the share of unincorporated businesses in terms of volume is less than 16 percent in all sectors, except in agriculture & mining. This is mainly because most of the firms, especially in agriculture, are family businesses owned by farmers. Our coverage of this sector by volume is about 58 percent. Moreover, more than 70 percent of the CGF-supported firms in the construction, energy, and manufacturing sectors are legal entities and, thus, covered in the analysis. The share of the CGF-supported legal entities in the service, tourism, and wholesale & trade sectors is above 50 percent. Our sample coverage of the CGF-supported firms in the agriculture & mining sector is only 15 percent.

Figure 3: CGF Credits by Firm Type



Source: Authors' calculation from the CGF database.

Figure 4: CGF Credit Distribution by Firm Type and Sector



Source: Authors' calculation from the CGF and FTR databases.

Overall, we focus on legal entities in the study, which implies that our sample covers about 52 percent of the CGF-supported firms and 88 percent of the CGF-backed loans in 2017.

4 How Different are the CGF-Supported Firms?

We first provide a descriptive analysis of the distributional comparisons of the CGF-supported firms to those not supported under the CGF program (non-CGF firms). In particular, we show distributions of the CGF and non-CGF loans by firm size, sector, and risk groups. To establish ex-ante risk scores, we also develop a risk scoring model following the relevant literature.

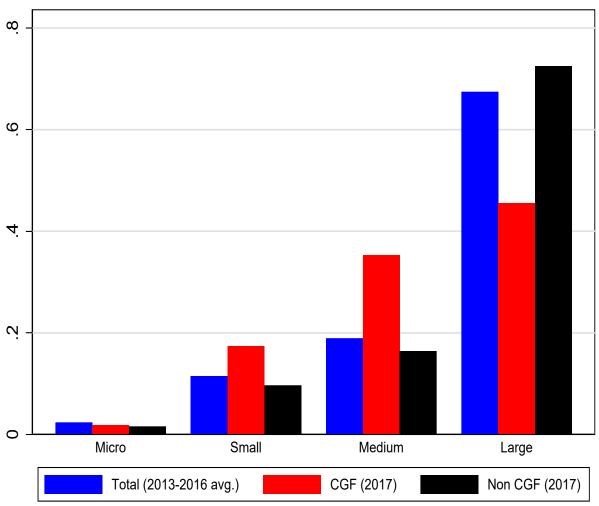
4.1 Size and Sector Distributions

We present and discuss the size and sector distributions of our final CGF data in this section. To make comparisons, in Figure 5, we also present the same distributions for average total lending between 2013 and 2016 and non-CGF loans in 2017, as benchmarks. More specifically, Panel (a) of the figure displays the size distributions, and Panel (b) shows the sector distributions. The CGF program seems to increase credit access of micro, small and medium-sized firms, given that the CGF credit shares of these size groups were much higher than the presented benchmarks. Moreover, large firms received a smaller share of CGF-backed loans relative to their benchmark shares. Their share of the CGF-backed loans in 2017 (45 percent) was much smaller compare to their share of non-CGF loans in 2017 (75 percent) and the share of credits in earlier periods (on average higher than 70 percent). The CGF program clearly achieved a redistribution of credits from large firms toward SMEs.

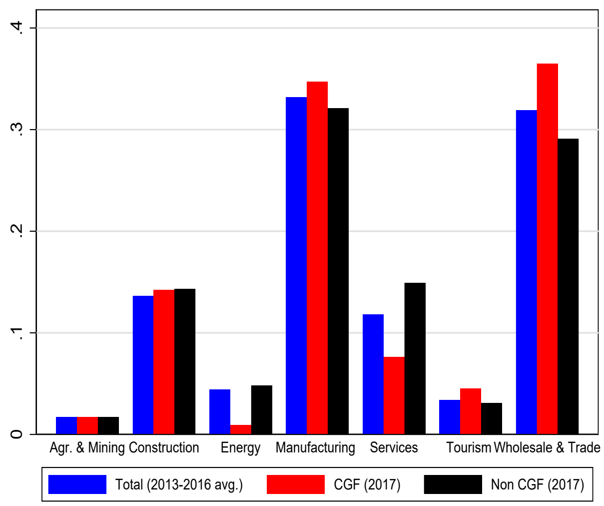
Figure 5b also displays the sectoral distributions of the CGF-backed loans and relevant benchmarks. The CGF-backed loan shares of the manufacturing, tourism, and wholesale & trade sectors appear to be higher than their shares from non-CGF loans in 2017 and from loans issued in the pre-CGF period (between 2013 and 2016). In contrast, the services and energy sectors obtained much smaller shares from the CGF program than the benchmarks.[9] The remaining two sectors, agriculture & mining and construction sectors, received similar shares from the CGF program to their general benchmarks. Overall, the CGF program seems to induce a moderate credit redistribution toward manufacturing, tourism, and wholesale & trade sectors.

Figure 5: Sample Loan Distributions

(a) Loan Distribution by Firm Size



(b) Loan Distribution by Sector

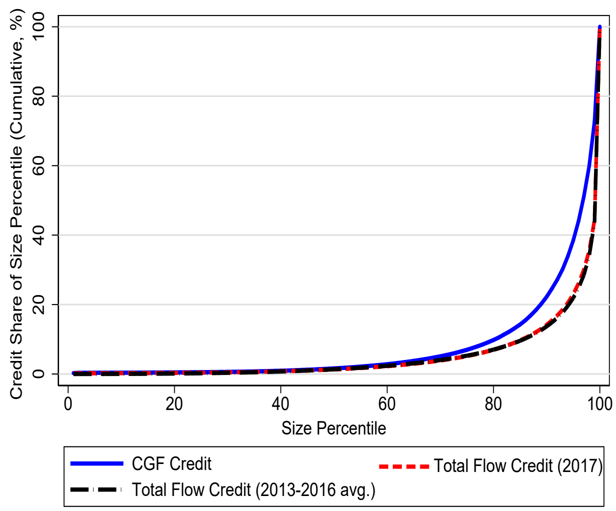


Source: Authors' calculation from the CGF and CR databases.
Notes: Each column in (a) shows the share of credit (CGF and Non CGF) given to each size group, excluding the non-matched CGF-supported firms. Each column in (b) shows the share of credit (CGF or Non CGF) given to each sector. Agr. & Mining represents the agriculture & mining sectors.

Figure 6 presents credit concentration by firm size percentiles, where the firm size is measured by total assets. As before, we also present the same distributions for average total lending between 2013 and 2016, and non-CGF loans in 2017 in the same figure as benchmarks. The figure shows that the CGF-backed loan distribution is more skewed toward relatively smaller size firms, which implies granting greater credit access to micro and SMEs.

[9] This is perhaps because firms in the energy sector tend to demand more FX loans than TL, while the CGF program mainly provided TL liquidity. According to the Credit Registry, as of December 2016, roughly 90 percent of the energy sector's outstanding credit balance is in FX.

Figure 6: Credit Concentration by Firm Size



Source: Authors' calculation from the CGF, FTR, and CR databases.
Notes: Panel (a) presents the cumulative distribution of credit share with respect to the firm size based on the total asset. Panels (b) and (c) show the credit share of each size percentile for small (below 50^{th} percentile) and large firms (above 79^{th} percentile), respectively.

4.2 Ex-Ante Risk Distributions

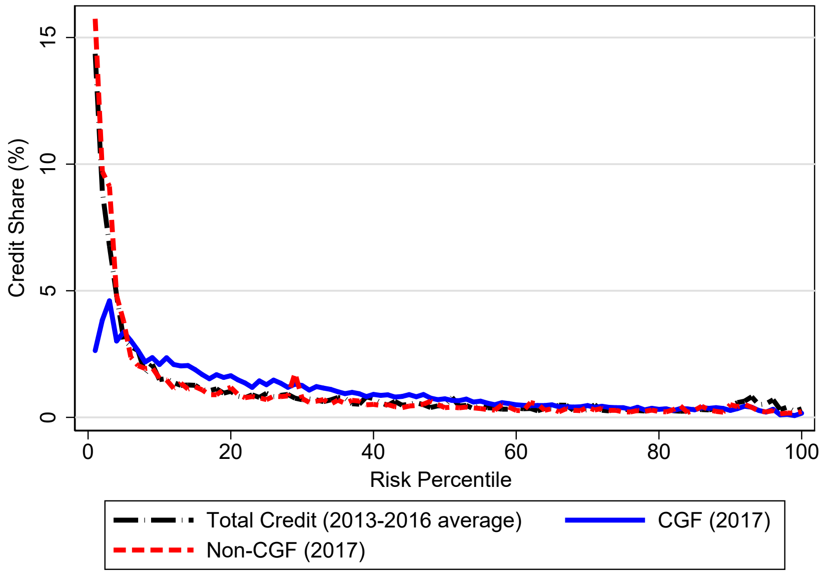
As briefly discussed above, the moral hazard problem is a potential challenge for guarantee programs in general (Boot and Thakor, 1994; Aghion and Bolton, 1997), where the participating lending institutions may also consider issuing credits to risky borrowers given the state guarantees. CGF programs generally include various check-and-balance conditions, as done in the Turkish case, which included certain credit worthies and payback capacity of borrowers, as well as NPL limits on the lending institution's CGF-backed loan portfolio. However, it is still worth investigating how sufficiently these conditions ensure the CGF credit portfolio risk remains at acceptable levels. Given our data's richness, we first develop a scoring tool to assess ex-ante firm credit default riskiness. Using these scores, we then present ex-ante credit default risk distributions for the CGF-supported and non-supported firms in 2017.

The risk-scoring tool follows the related credit risk-scoring literature (e.g., Antunes et al., 2016 and Martinho and Antunes, 2012), where we employ a simple logit model to estimate the ex-ante probability of default (PD). The default event is defined as past-due payment of more than 90 days on any credit obligation in a given year, which coincides with the Basel II default definition. We first construct firm-level financial history data from the CR database to estimate the default probabilities, containing a panel of firms with credit default and credit relation history between 2006 and 2016. We also construct a second-panel data set on firm characteristics and a set of performance indicators using FTR for the same period. We then match the two data sets using firms' tax identifiers. To capture ex-ante risk scores, we regress firm default status in $t+1$ over financial history and non-financial firm characteristics (e.g., several balance sheet ratios such as leverage, liquidity, etc.) in t. The model predicts firm risk scores in $t+2$ (that is unknown at time $t + 1$) by applying the estimated coefficients to firm controls in $t + 1$.[10] Our purpose of focusing on ex-ante risk scores – rather than directly looking at firm default status in 2017 – is to account for the creditors' perspective. With this approach, we can also control for creditor (mis)behaviors, such as a lending–tendency toward more risky firms under the CGF program given the state guarantees.

After predicting risk scores for firms in our sample, we divide scores into percentiles, from the lowest to the highest, to show the total amount of credit issued to firms in each risk-percentile group. When firms are ranked according to the risk groups, we observe that the credit distributions of 2017 do not show a significant difference either between the CGF and the non-CGF loans, or compared to previous years, namely the 2013-2016 average, in terms of ex-ante credit riskiness (Figure 7). The only difference between the CGF loans and the rest seems to be the coverage of around-zero risky firms, which tend to be the largest firms in the economy. Given the CGF program's lower coverage of large firms, it has a relatively broader coverage of firms in the second-lowest decile (i.e., from the 10^{th} to 20^{th} percentiles). Moreover, there appears to be a clear negative relationship between risk score percentiles and credit share that would be expected in a regular risk management framework. Considering these results, we conclude that creditors have no prior systematic selection, such as pushing relatively riskier firms among the legal entities to be under the CGF program.

[10] This is a classical approach in firm scoring that is also used by many financial institutions in accordance with Basel requirements. The main point of ex-ante risk scoring comes from the fact that, for instance, banks did not have firm balance sheets for 2017 when firms applied for the CGF program that year. Therefore, banks had to run their risk models with default events in 2016 on firm characteristics in 2015, and then, with these predicted coefficients and the balance sheet information of 2016, banks can assign risk scores to firms for 2017. Further details of our risk scoring methodology, including data, variable selection, estimation, and performance evaluation, are presented in the Appendix A.

Figure 7: Credit Risk Distribution



Source: Authors' calculations from the CR, FTR databases, and estimated PDs.
Notes: The figure presents the credit risk distribution by credit type. Flow credits are calculated by consolidating the bank-firm-level new loans on a monthly basis for each year by using the CR database.

5 Impact Analysis

In the second part of the analysis, we estimate a conditional difference-in-differences model whereby we first match each treated firm with a control firm. As the CGF provision was not a random process, but rather subject to several layers of screening by the credit-issuing banks and the CGF regulations, implementing the estimation without matching would produce bias results. In what follows, we first explain the details of our matching methodology and then present our estimation strategy. We conclude the section with a detailed discussion of our estimation results.

5.1 Matching: Establishing a Control Group

Following the initial cleaning, our sample of legal firms, receiving loans via the CGF program (the treatment group), reduces to 86,000 observations in 2017. Given that we have access to the entire population of legal firms that existed in the same years, we have a large sample for selecting our control group. In the matching, we require both treatment (the CGF-supported) and control (non-supported) firms to exist in both years, 2016 and 2015.[11] We conduct one-to-one matching using the coarsened exact matching methodology of Iacus et al. (2012) with no replacement. The matching is implemented based on observable firm characteristics, including total assets, tangible assets, financial debt (i.e., outstanding credit balance), and total sales in 2016 and 2015. Additionally, we also employ predicted risk scores, developed in Section 4.2, in the

[11] In an alternative sample (henceforth *Sample 2*), we also included firms that existed only in 2016, not in 2015.

matching to control for firms' ex-ante riskiness in 2016. The main sectors are preserved in the matching.[12] In each variable, we employ 10 groups.[13] We present the summary statistics before and after matching in Tables 2 and 3, and the balancing test results for the variables used in the matching are shown in Table 4.

Table 2: Summary Statistics (Treatment Firms and the Rest) Before Matching

	2015-2016				2017-2018			
	CGF		Rest		CGF		Rest	
Variables	N	Mean	N	Mean	N	Mean	N	Mean
Total Assets	169,762	14.65	1,009,954	12.93	168,369	15.06	903,411	13.15
Total Sales	169,762	14.36	1,009,954	10.24	168,369	14.85	903,411	10.42
Tangible Assets	169,762	12.55	1,009,954	9.54	168,369	13.03	903,411	10.03
Financial Debt	169,762	10.62	1,009,954	3.85	168,369	12.43	903,411	4.06
Risk Scores	169,375	0.06	1,004,858	0.12	167,906	0.10	898,080	0.17
Employment	169,762	2.39	1,009,954	1.38	168,369	2.46	903,411	1.37
Inventory	169,762	11.94	1,009,954	7.95	168,369	12.49	903,411	8.30
Liquid Assets	169,762	10.92	1,009,954	9.43	168,369	11.20	903,411	9.47
Land & Buildings	169,762	5.04	1,009,954	2.22	168,369	5.76	903,411	2.54
Machinery & Equipment	169,762	5.48	1,009,954	3.11	168,369	5.99	903,411	3.40
Vehicles	169,762	9.98	1,009,954	5.61	168,369	10.39	903,411	5.95
Default	169,762	0.00	1,009,954	0.05	168,369	0.04	903,411	0.06

Notes: N denotes the number of firms. The mean values (in TL for monetary variables) in the table are annual averages. All variables except risk scores and default are in logarithmic form. Default is one for firms with non-performing loans and zero otherwise.

Tables 2 and 3 show summary statistics of the key variables before and after the matching, respectively. Table 2 shows that the CGF-supported firms are relatively larger in assets, sales, and employment. Their financial debt (i.e., outstanding credits) is larger with relatively lower risk scores. However, after matching, most differences significantly reduce, Table 3. Asset size, sales, employment, credit balance, and default probability are merely the same in the matched sample in the pre-2017 years. Expectedly, we observe differences between the two groups in 2017 and 2018 that will be further explored in the following section.

[12]Main sectors include agriculture & mining, construction, energy, manufacturing, services, tourism, and wholesale & trade.

[13]With the exceptions of predicted risk score (default probability) that is employed with five groups and total sales that is employed with 20 groups in 2016 and 10 groups in 2015. This differentiation in the number of groups is just for improving the matching quality.

Table 3: Summary Statistics (Treatment Firms and the Rest) After Matching

Variables	2015-2016				2017-2018			
	CGF		Rest		CGF		Rest	
	N	Mean	N	Mean	N	Mean	N	Mean
Total Assets	127,500	14.46	127,500	14.49	126,504	14.84	121,921	14.62
Total Sales	127,500	14.26	127,500	14.26	126,504	14.66	121,921	14.06
Tangible Assets	127,500	12.46	127,500	12.49	126,504	12.88	121,921	12.62
Financial Debt	127,500	9.98	127,500	9.89	126,504	11.91	121,921	9.20
Risk Scores	127,338	0.05	127,334	0.05	126,182	0.10	121,479	0.11
Employment	127,500	2.32	127,500	2.32	126,504	2.38	121,921	2.21
Inventory	127,500	11.63	127,500	11.23	126,504	12.15	121,921	11.31
Liquid Assets	127,500	10.78	127,500	10.91	126,504	11.04	121,921	10.91
Land & Buildings	127,500	4.61	127,500	4.50	126,504	5.26	121,921	4.78
Machinery & Equipment	127,500	5.24	127,500	5.40	126,504	5.71	121,921	5.60
Vehicles	127,500	9.94	127,500	9.51	126,504	10.28	121,921	9.52
Default	127,500	0.00	127,500	0.02	126,504	0.03	121,921	0.06

Notes: N denotes the number of firms. The mean values (in TL for monetary variables) in the table are annual averages. All variables except risk scores and default are in logarithmic form. Default is one for firms with non-performing loans and zero otherwise.

According to Table 4, the initial bias between the treatment and the control groups is significantly reduced by our matching. In particular, we either obtain statistically insignificant mean difference test results for the difference between the CGF-supported (treatment) and non-supported (control) firms, or the test statistics dramatically declined along with an above 97 percent reduction in the percentage bias. In the base sample, we have ended up with 63,750 matches.[14] In addition to the variables used in the matching, we also report balancing test results for two other main variables that were not employed in the matching; total liabilities and employment.[15] After the matching, we also observe a significant reduction in the bias for these variables.

[14]In the alternative sample, *Sample 2*, where we also included firms that only existed in 2016, our sample reached to 67,446 matches.

[15]In the matching, we used financial debt and total sales instead of total liabilities and employment.

Table 4: Matching Performances: Balancing Tests for Treatment Firms and Matched Control Firms

Covariates		N		Mean		Percentage bias reduction	*T* test	
		Treated	Control	Treated	Control		*t*-statistics	p-value
Total Assets in 2016	Unmatched	84,881	504,977	14.80	12.95		-205.82	0.00
	Matched	63,750	63,750	14.59	14.59	99.80	0.42	0.67
Total Sales in 2016	Unmatched	84,881	504,977	14.62	10.26		-220.12	0.00
	Matched	63,750	63,750	14.45	14.43	99.45	-1.91	0.06
Tangible Assets in 2016	Unmatched	84,881	504,977	12.78	9.63		-188.20	0.00
	Matched	63,750	63,750	12.65	12.65	99.89	0.24	0.81
Financial Debt in 2016	Unmatched	84,881	504,977	11.05	3.86		-346.95	0.00
	Matched	63,750	63,750	10.32	10.18	98.11	-4.39	0.00
Risk Scores in 2016	Unmatched	84,692	502,315	0.06	0.12		88.61	0.00
	Matched	63,701	63,701	0.05	0.06	96.72	4.94	0.00
Total Assets in 2015	Unmatched	84,881	504,977	14.51	12.90		-204.06	0.00
	Matched	63,750	63,750	14.34	14.39	96.98	5.31	0.00
Total Sales in 2015	Unmatched	84,881	504,977	14.10	10.21		-195.19	0.00
	Matched	63,750	63,750	14.08	14.09	99.58	1.04	0.30
Tangible Assets in 2015	Unmatched	84,881	504,977	12.32	9.44		-168.12	0.00
	Matched	63,750	63,750	12.28	12.32	98.31	2.84	0.00
Financial Debt in 2015	Unmatched	84,881	504,977	10.18	3.84		-302.87	0.00
	Matched	63,750	63,750	9.64	9.60	99.31	-1.34	0.18
Out of Sample Tests:								
Total Liabilities in 2016	Unmatched	84,881	504,977	14.35	12.13		-196.68	0.00
	Matched	63,750	63,750	14.09	14.10	99.52	1.01	0.31
Employment in 2016	Unmatched	84,881	504,977	2.44	1.37		-242.80	0.00
	Matched	63,750	63,750	2.35	2.32	97.33	-4.05	0.00

Notes: N denotes the number of firms. All variables except risk score (PD) are in logarithmic form.

For further inference, we also present full distributions of total assets (a stock variable) and total sales (a flow variable) for the treatment and control groups in 2016 with samples before and after the matching in Figure 8. As an outside-matching criteria variable, we also present the same distributions for total liabilities. The distributions visually emphasize the quality of our matching, where the pairs almost entirely overlap.[16] Distributions of the variables before and after the matching in only one year do not provide much information for the trends outside the years used in the matching. We, therefore, display the trends for total assets, total sales, and total liabilities in the panels of Figure 9 in the years between 2006 and 2018.[17] After the matching, our treatment and control groups, on average, follow similar trends until the CGF program implemented in 2016.

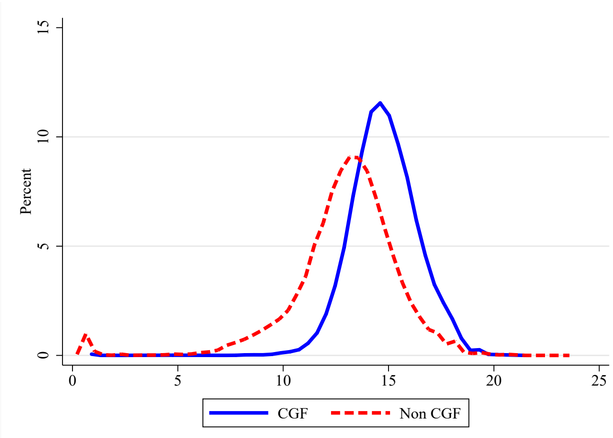
[16]Distributions of all other variables, used in the matching, present a similar picture and hence, are not reported here. They are nevertheless available upon request.

[17]Trends of all other variables, used in the matching, present a similar picture and hence, not reported here. They are nevertheless available upon request.

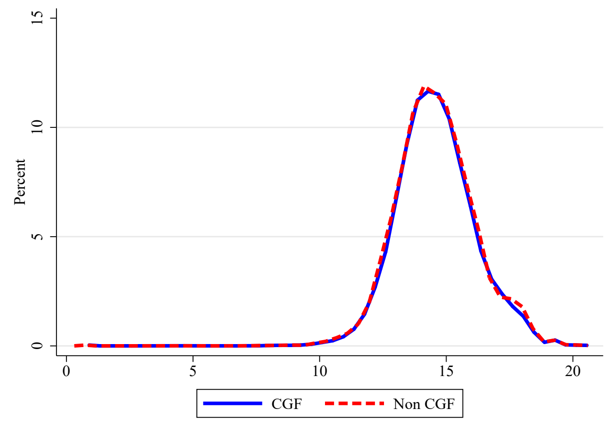
Figure 8: Matching Performance: Distributions

Log Total Assets

(a) Before Matching

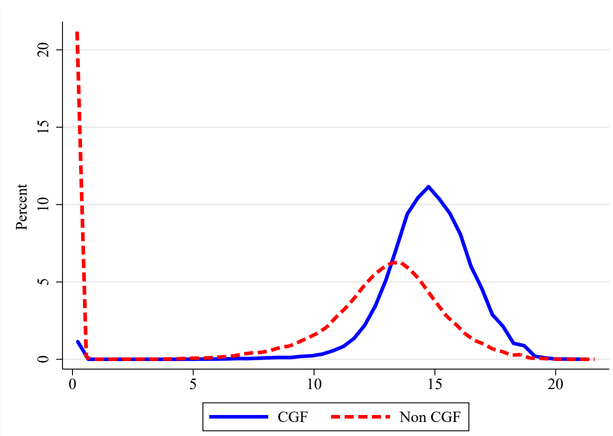


(b) After Matching

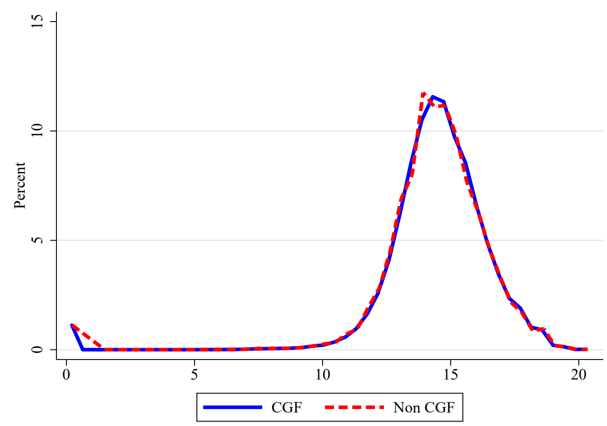


Log Total Sales

(a) Before Matching

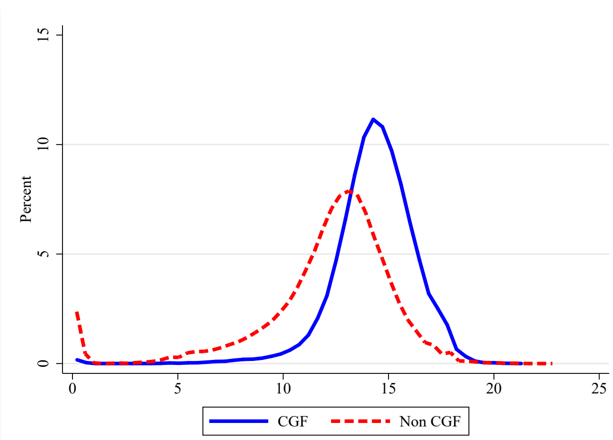


(b) After Matching

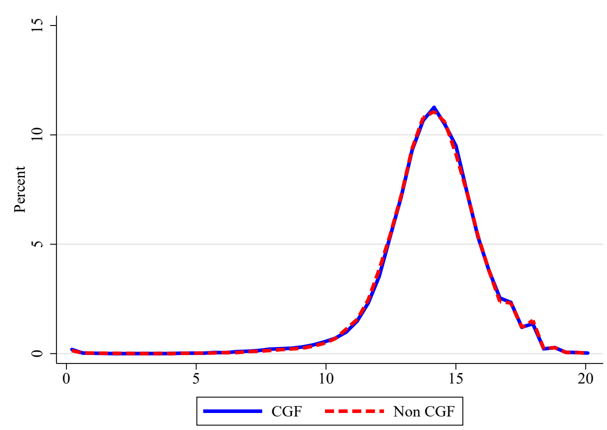


Log Total Liabilities

(a) Before Matching



(b) After Matching

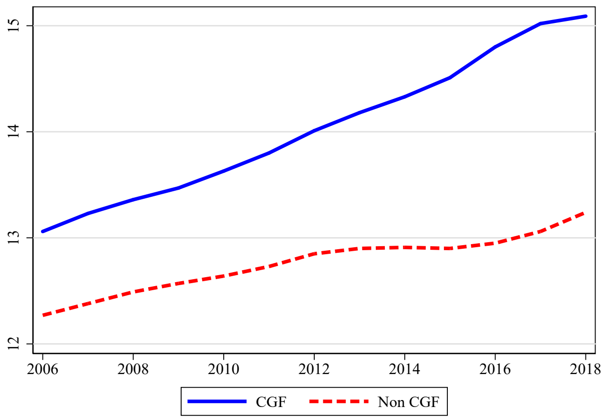


Source: Authors' calculation from the CGF and FTR databases. The sample is from 2016.

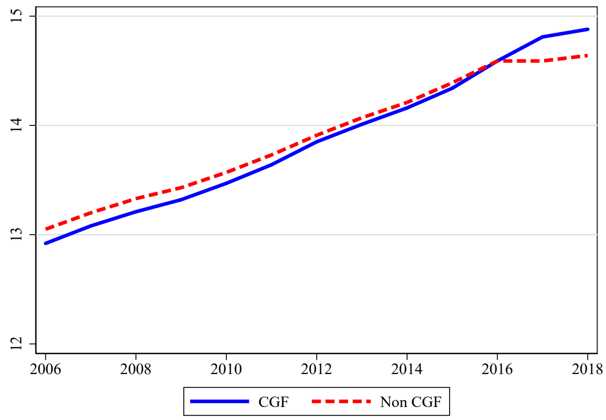
Figure 9: Matching Performance: Trends

Log Total Assets

(a) Before Matching

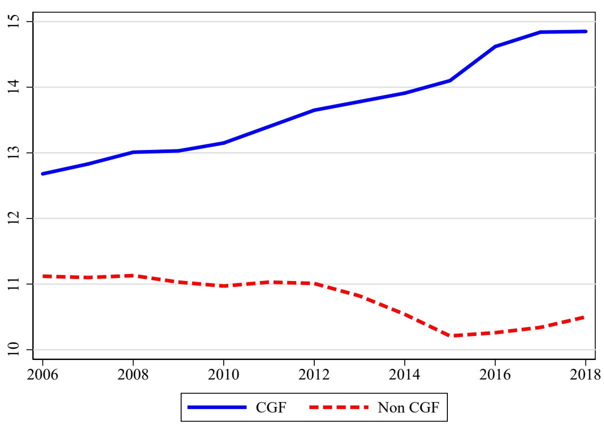


(b) After Matching

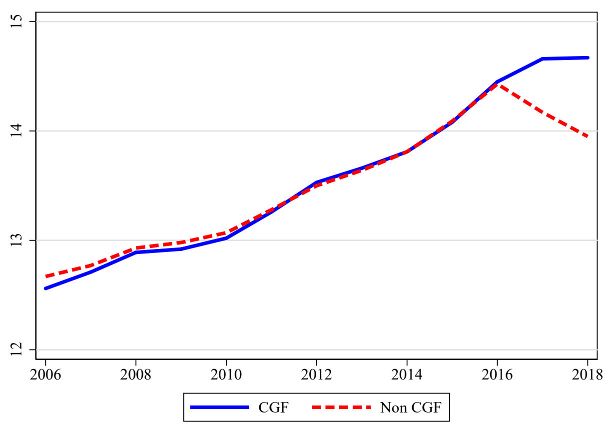


Log Total Sales

(a) Before Matching

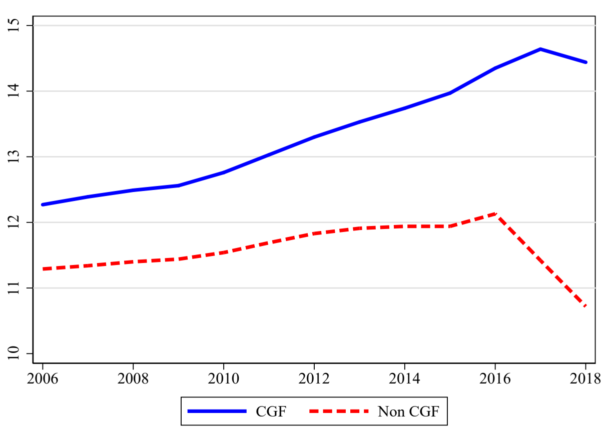


(b) After Matching

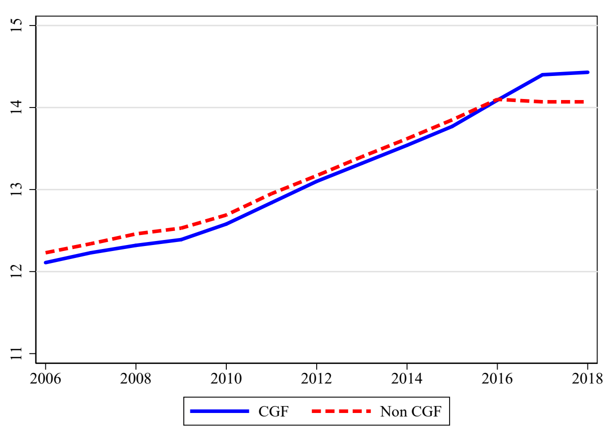


Log Total Liabilities

(a) Before Matching



(b) After Matching



Source: Authors' calculation from the CGF and FTR databases.

5.2 Estimation: Difference-in-Differences Analysis

Using the matched sample, we estimate the following regression equation:

$$y_{it} = \alpha treat_i * post_t + \beta post_t + d_t + pair_i + sector_i * d_t + region_i * d_t + e_{it} \quad (1)$$

where the subscript i denotes firm and t denotes year. The outcome of interest, y_{it}, covers various firm performance measures, including employment, sales, and credit default. All the dependent variables are in log levels, except the credit default which is a binary variable (i.e., one for firms with 90 days overdue credit payment; otherwise, zero). We implement two different timing specifications: very short run and short run. The very short-term results account for the program's impact only in 2017, which is presumably less than one year. As some significant portion of the CGF-guaranteed loans were issued in the first four months of 2017, the program is expected to have some initial impact in the first year.[18] The short-term results show the program's impact in a relatively long time horizon, from the control year, 2016, to 2018. The implied impact of the program in 2018 would thereby account for the program impact in roughly one and half year time horizon. More specifically, in the first specification, $post_t$, the post-policy variable is one for 2017; otherwise, it is zero for the control years 2016 and 2015. In the second specification, $post_t$ is equal to one for 2018 and zero for 2016, where we employ only the two years in the specification to capture the program's effect in a longer time horizon.

In both specifications, the treatment variable ($treat_i$) takes the value of one if the firm received CGF-backed loan in 2017, otherwise zero. $pair_i$ is a fixed effect identifying each matched pair, treated firm, and its matched control. In an alternative specification, we control for firm fixed effects instead of pair fixed effects, in case our comprehensive matching methodology leaves out some non-random time-invariant variation between the treatment and control groups. We also control for time dummies and their interactions with industry and province to account for time-varying common sectoral or provincial-level shifts (e.g., demand shifts) in all specifications. The parameter α is our coefficient of interest, which shows the impact of receiving CGF-backed loan in 2017 on the firm performance in 2017 and/or in 2018 relative to the control group. In addition to the binary treatment, we also estimate the model with continuous treatment, whereby the treatment is changed from a binary (i.e., zero/one) variable to a continuous one. In a nutshell, the binary treatment is multiplied by the CGF-backed loan amount (in logs) in the respective years. More specifically, in the first specification (i.e., very short run), the continuous treatment is the CGF-backed loan amount received in 2017. However, in the second specification (i.e., short run), the continuous treatment is the sum of the CGF-backed loans received in 2017 and the additional loans in 2018.

During the CGF program years, regular credit operations outside the program continued. This implies that some firms have also received other loans besides the CGF program, given that

[18] See Appendix A for further details on the monthly distributions of the program.

the program has balance limits and relatively lower coverage of certain credit types.[19] To account for this, we test the robustness of our main estimates to controlling for non-CGF loans received in respective years. Excluding this control may overstate the CGF program's impact, as both loan types will provide support for firm activities and thus, would be expected to affect firm performance.

In principle, firms may utilize their CGF backed loans in 2017, while some firms may continue to use their approved credit line (with CGF support) or apply for new credit in 2018, as the CGF program continued to run in 2018. However, given the aim of this paper is to evaluate the impact of the largest CGF program, which was implemented in 2017, we only keep the firms receiving CGF backed loans for the first time in 2017 and may continue to use their credit lines or apply for a new one in 2018. In other words, we exclude firms that receive CGF support for the first time in 2018. Moreover, our main sample requires firms to survive in the post-treatment years, as exiting firms do not report financial documents, and thus, drop out of the sample. However, we relax this condition by imputing zeros to exiting firms' performance indicators in the robustness section. Secondly, in the credit default estimations, we exclude firms (and their matched pairs) with outstanding NPL balance before receiving CGF support. Dropping these firms from the credit default estimation sample ensures that the matched firms have similar ex-ante risk profiles and no default history before the treatment.

5.3 Results: Difference-in-Differences Analysis

Our estimation results are displayed in Tables 5 and 6. Each table has two panels: the very short-term (Panel A) and the short-term (Panel B) impact of the program. Results in each panel are reported for employment, total sales, and firm credit default. The binary and continuous treatment results are presented in separate tables.

Columns (1) – (3) of Tables 5 and 6 present the results for the impact of the program on firm employment. According to the results, the CGF-supported firms, on average, preserved more employment than their pairs in the treatment years. This effect is statistically significant and consistent across different specifications. According to the baseline estimates in Column (1), the CGF supported firms preserved 15.8 percent more employment in the very short run relative to their pairs (Panel A), while the magnitude of this effect slightly increases to 17.3 percent (Panel B) in the short run. Controlling for non-CGF loans in the same years (Column (2) of both panels) reduces the magnitude of the CGF effect only marginally, while the statistical significance and economic importance remain strong. In Column (3) of both panels, we present the results with firm fixed effects (instead of pair fixed effects). Results remain consistent with only a marginal reduction in magnitude.

[19] For instance, the CGF program had lending limits, see Table 1, and also, lower coverage of FX denominated credits, see Footnote 3.

Table 5: The CGF Program's Effect on Firm Performance: Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Very Short-Run									
POSTxCGF	0.15782***	0.14416***	0.14071***	0.49114***	0.44944***	0.42702***	-0.03063***	-0.03026***	-0.02965***
	(0.00290)	(0.00286)	(0.00295)	(0.01082)	(0.01051)	(0.01170)	(0.00089)	(0.00089)	(0.00088)
CGF	-0.01321***	-0.04457***		0.00605***	-0.08968***		-0.00005	0.00095***	
	(0.00382)	(0.00390)		(0.00175)	(0.00280)		(0.00004)	(0.00009)	
Non CGF credit		0.02311***	0.02871***		0.07056***	0.10920***		-0.00073***	-0.00186***
		(0.00049)	(0.00042)		(0.00147)	(0.00203)		(0.00006)	(0.00008)
Observations	372,330	372,330	372,330	372,330	372,330	372,330	361,416	361,416	361,416
R-squared	0.80192	0.80488	0.94015	0.71577	0.72250	0.75970	0.19199	0.19259	0.35528
Panel B: Short-Run									
POSTxCGF	0.17306***	0.15239***	0.14660***	0.70930***	0.64126***	0.60465***	-0.00640***	-0.00591***	-0.00336**
	(0.00382)	(0.00378)	(0.00376)	(0.01521)	(0.01456)	(0.01521)	(0.00133)	(0.00133)	(0.00132)
CGF	0.00871**	-0.03298***		0.02112***	-0.11613***		-0.00018*	0.00090***	
	(0.00412)	(0.00429)		(0.00201)	(0.00422)		(0.00010)	(0.00022)	
Non CGF credit		0.02700***	0.03452***		0.08886***	0.13644***		-0.00069***	-0.00427***
		(0.00069)	(0.00073)		(0.00225)	(0.00357)		(0.00013)	(0.00021)
Observations	235,800	235,800	235,800	235,800	235,800	235,800	230,272	230,272	230,272
R-squared	0.78492	0.78791	0.93536	0.63349	0.64053	0.75828	0.27773	0.27785	0.51901

*Notes: The table presents the regression results for the CGF program's effect on firm performance in a binary setting. Each panel is a separate regression. Each column presents a regression of column heading on the variables listed in each panel. Columns 3-6-9 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors are in parentheses. All dependent variables except Default are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Very Short-Run" covers the impact of the program only in 2017, while "Short-Run" covers the impact of the program in 2018.*

Although the binary treatment results provide an overall picture of the program impact, they say little about the relationship between the CGF-backed loan amount and firm employment. We explore this dimension in the first three columns of Table 6, where the treatment is now continuous. According to the very short run results, a one percent increase in CGF loans preserved 0.012 percent more employment. The same exercise in the short run, Panel (B), produces only a slightly higher impact, a 0.013 percent increase in employment. As before, controlling for the non-CGF loans and firm fixed effects does not change the main conclusion.

Table 6: The CGF Program's Effect on Firm Performance: Continuous Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Very Short-Run									
POSTxCGF	0.01193***	0.01119***	0.01100***	0.03671***	0.03446***	0.03327***	-0.00229***	-0.00227***	-0.00224***
	(0.00022)	(0.00022)	(0.00023)	(0.00082)	(0.00080)	(0.00088)	(0.00007)	(0.00007)	(0.00007)
CGF	-0.00094***	-0.00334***		0.00058***	-0.00675***		-0.00002***	0.00006***	
	(0.00030)	(0.00031)		(0.00014)	(0.00021)		(0.00000)	(0.00001)	
Non CGF credit		0.02319***	0.02895***		0.07101***	0.10995***		-0.00077***	-0.00192***
		(0.00049)	(0.00042)		(0.00146)	(0.00203)		(0.00006)	(0.00008)
Observations	372,330	372,330	372,330	372,330	372,330	372,330	361,416	361,416	361,416
R-squared	0.80192	0.80492	0.94019	0.71569	0.72256	0.75979	0.19184	0.19252	0.35525
Panel B: Short-Run									
POSTxCGF	0.01299***	0.01159***	0.01119***	0.05390***	0.04926***	0.04675***	-0.00032***	-0.00029***	-0.00012
	(0.00029)	(0.00029)	(0.00029)	(0.00113)	(0.00109)	(0.00113)	(0.00010)	(0.00010)	(0.00010)
CGF	0.00085***	-0.00228***		0.00140***	-0.00896***		-0.00007***	0.00001	
	(0.00032)	(0.00033)		(0.00017)	(0.00032)		(0.00001)	(0.00002)	
Non CGF credit		0.02696***	0.03473***		0.08937***	0.13720***		-0.00073***	-0.00430***
		(0.00069)	(0.00073)		(0.00224)	(0.00357)		(0.00013)	(0.00021)
Observations	235,800	235,800	235,800	235,800	235,800	235,800	230,272	230,272	230,272
R-squared	0.78497	0.78797	0.93539	0.63354	0.64073	0.75845	0.27766	0.27779	0.51899

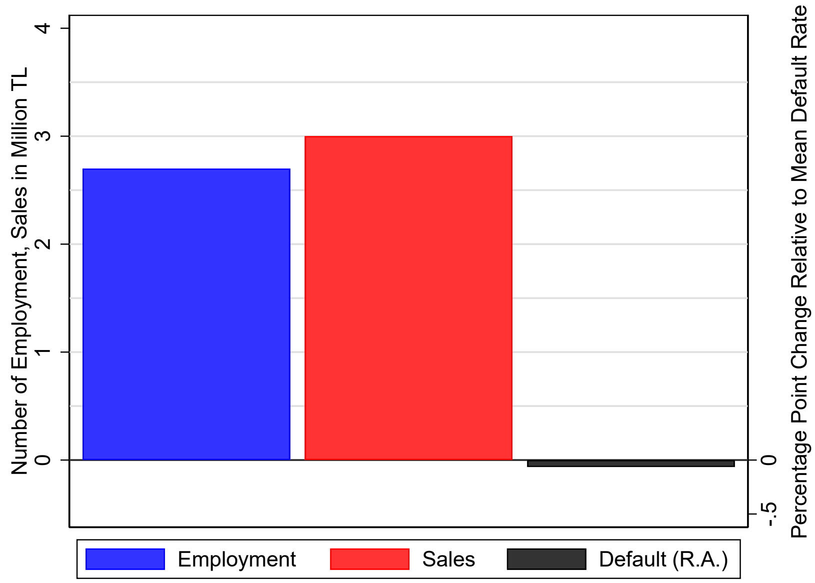
*Notes: The table presents the regression results for the CGF program's effect on firm performance in a continuous setting. Columns 3-6-9 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors in parentheses. All dependent variables except Default are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Very Short-Run" covers the impact of the program only in 2017, while "Short-Run" covers the impact of the program in 2018.*

Columns (4) – (6) of Tables 5 and 6 present the results for the impact of the program on firm sales. The results show that the CGF-supported firms significantly increased their sales relative to their pairs. According to the binary treatment results, displayed in the respective columns of Table 5, the CGF-supported firms on average increased their sales by 49 percent in the very short run and 71 percent in the short run. The continuous treatment results, presented in Table 6, imply a one percent increase in CGF loan support stimulated sales for 0.037 percent in the very short run and 0.054 percent in the short run. These results remain robust to controlling for non-CGF loans, as well as employing firm fixed effects instead of pair fixed effects.

Columns (7) – (9) of Tables 5 and 6 show the estimates for the impact of the program on firm credit default probability. The CGF program appears to reduce a firm's credit default probability in the very short run, while the magnitude of the reduction fades in the short run. More specifically, firms that are supported by the CGF program experienced a 3 percentage point less credit default in the very short run relative to the control group. In the short run, the impact reduces to 0.6 percentage point less credit default. Our results with continuous treatment show that a one percent increase in CGF-backed loans leads to a 0.3 percentage point reduction in firm default probability in the very short run and a 0.03 percentage point reduction in the short run. Controlling for non-CGF loans or exploiting firm fixed effects only marginally changes the magnitude of the estimates, while the results remain qualitatively the same.

So far, the discussion provides a technical overview of the program impact, where evaluating the estimates at some reference values can bring a more intuitive understanding of the impact. All the reference mean values used in the evaluation are presented in Appendix B. For instance, evaluating the short run employment impact of the CGF program with binary treatment, 17.3 percent more employment (in the baseline specification), at the mean employment in 2016 (i.e., 29.4 employees) implies an average increase in employment for 5.1 workers in 2018. Considering the average total CGF-backed loans per firm being around 1.9 million TL (i.e., loans received in 2017 and additionally in 2018), the implied monetary value for extra employment is roughly 370 thousand TL. Evaluation of the continues treatment estimates yield almost identical results for employment. Following the same approach and using baseline estimates from binary treatment, we present the average impact of a 1 million TL loan issued under the CGF program on employment, sales, and credit default probability in Figure 10. According to the figure, an extra 1 million TL loan generated via the CGF program on average preserved 2.7 employment, generates 3 million in sales, and leads to a 6.5 percent decrease in average credit default probability in 2018.

Figure 10: Average Monetary Impact of CGF-Supported Loans (per 1 million TL of CGF loan)



Source: Authors' calculations.
Notes: The figures present the average monetary impacts of receiving 1 million TL of CGF loan.

6 Breakdown of the Effect by Size and Sector Groups

In this section, we split our sample into size and sector groups to re-estimate our main specifications with different sub-samples. The firm size groups[20] are four, namely, micro, small, medium, and large, and the aggregate sectors are wholesale & trade, manufacturing, services, construction, tourism, energy, and agriculture & mining.

6.1 Estimations by Firm Size Groups

Estimation results by size groups are displayed in Table 7. The results show that the medium-sized firms appear to experience the largest impact on their employment practices relative to their pairs. On average, the CGF-supported medium-sized firms recorded almost 20 percent more employment than their pairs. In contrast, the program's impact on employment appears to be the smallest among the large firms. The CGF program's impact on sales is the largest among the CGF-supported micro firms, while the magnitude of the impact on the CGF receiving small and medium-sized firms is similar. This is to say that the CGF-supported micro-firms recorded about 81 percent higher sales than their pairs in 2018. This number is 70 percent for small firms and 71 percent for medium-sized firms. However, the CGF-supported large firms experienced the least increase in sales, 35 percent, relative to their pairs. The CGF program's impact on credit default varies across size groups. On average, the CGF-supported micro and large firms experienced a moderate increase in credit default probability in 2018 relative to their

[20]The size groups are determined based on the official definition for 2018 which is reported in Appendix B.

non-CGF pairs. On the contrary, the CGF-supported SMEs recorded a reduction in their credit default probability relative to their pairs. In particular, the credit default probability for the CGF supported small and medium-sized firms is estimated to be 1.4 and 1.3 percentage points less than their pairs. These results are consistent across the three specifications.

Table 7: Short-Run Impact of the CGF Program by Size Groups, Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Micro									
POSTxCGF	0.17907***	0.15763***	0.15164***	0.81220***	0.71631***	0.66273***	0.00620**	0.00573**	0.00862***
	(0.00651)	(0.00645)	(0.00648)	(0.03359)	(0.03210)	(0.03409)	(0.00247)	(0.00248)	(0.00246)
CGF	-0.13637***	-0.17704***		0.01215**	-0.16975***		-0.00010	-0.00102**	
	(0.00629)	(0.00664)		(0.00495)	(0.00985)		(0.00024)	(0.00048)	
Non-CGF credit		0.01795***	0.02273***		0.08032***	0.12317***		0.00040**	-0.00221***
		(0.00084)	(0.00096)		(0.00348)	(0.00541)		(0.00019)	(0.00031)
Observations	60,776	60,776	60,776	60,776	60,776	60,776	59,912	59,912	59,912
R-squared	0.55667	0.56318	0.84175	0.57095	0.57883	0.71484	0.27820	0.27827	0.51944
Panel B: Small									
POSTxCGF	0.17244***	0.15224***	0.14844***	0.69175***	0.62805***	0.59181***	-0.01362***	-0.01277***	-0.01003***
	(0.00517)	(0.00511)	(0.00506)	(0.02025)	(0.01947)	(0.02024)	(0.00184)	(0.00184)	(0.00182)
CGF	0.02011***	-0.02098***		0.02448***	-0.10503***		-0.00031**	0.00158***	
	(0.00547)	(0.00564)		(0.00271)	(0.00560)		(0.00013)	(0.00030)	
Non-CGF credit		0.02895***	0.03389***		0.09124***	0.13950***		-0.00133***	-0.00546***
		(0.00099)	(0.00106)		(0.00322)	(0.00521)		(0.00019)	(0.00032)
Observations	126,772	126,772	126,772	126,772	126,772	126,772	123,728	123,728	123,728
R-squared	0.62505	0.63071	0.88275	0.50279	0.51219	0.67364	0.27880	0.27918	0.52096
Panel C: Medium									
POSTxCGF	0.19728***	0.16962***	0.16765***	0.70995***	0.65235***	0.62174***	-0.01251***	-0.01155***	-0.00925***
	(0.01137)	(0.01116)	(0.01099)	(0.03633)	(0.03476)	(0.03516)	(0.00348)	(0.00346)	(0.00345)
CGF	0.13941***	0.08611***		0.02629***	-0.08472***		-0.00004	0.00230***	
	(0.01253)	(0.01282)		(0.00566)	(0.00990)		(0.00037)	(0.00056)	
Non-CGF credit		0.05495***	0.05537***		0.11444***	0.17611***		-0.00239***	-0.00704***
		(0.00311)	(0.00318)		(0.00817)	(0.01277)		(0.00045)	(0.00070)
Observations	37,128	37,128	37,128	37,128	37,128	37,128	35,956	35,956	35,956
R-squared	0.64629	0.65498	0.90290	0.52288	0.53398	0.69388	0.29418	0.29499	0.53236
Panel D: Large									
POSTxCGF	0.10396***	0.09153***	0.09812***	0.36259***	0.34827***	0.34433***	0.02449***	0.02453***	0.02353***
	(0.02187)	(0.02128)	(0.02099)	(0.05431)	(0.05244)	(0.05476)	(0.00642)	(0.00641)	(0.00642)
CGF	0.11551***	0.03677		0.00349	-0.08719***		0.00145	0.00307**	
	(0.02757)	(0.02814)		(0.01075)	(0.01663)		(0.00095)	(0.00126)	
Non-CGF credit		0.09604***	0.08012***		0.11060***	0.17483***		-0.00198*	-0.00609***
		(0.00865)	(0.00911)		(0.01555)	(0.02596)		(0.00103)	(0.00152)
Observations	11,124	11,124	11,124	11,124	11,124	11,124	10,676	10,676	10,676
R-squared	0.72049	0.73236	0.93892	0.62747	0.63609	0.75873	0.30946	0.30985	0.54550

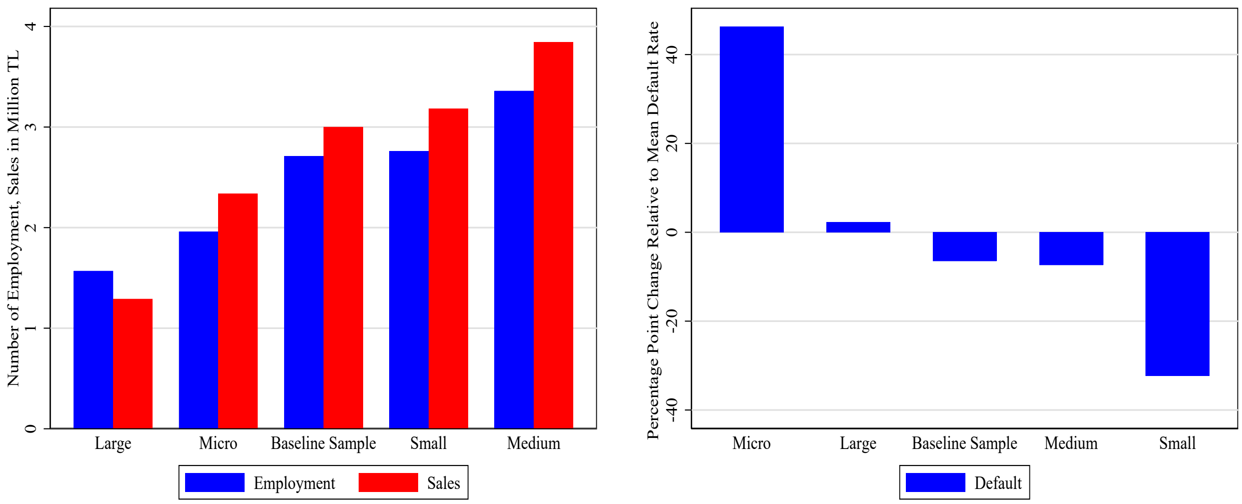
*Notes: The table presents the regression results for the CGF program's effect on firm performance in a binary setting across size groups. Columns 3-6-9 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors are in parentheses. All dependent variables except Default are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Short-Run" covers the impact of the program in 2018.*

Figure 11 shows the implied impact of an extra 1 million TL CGF on employment and sales in Panel (a) and on firms' credit default probability in Panel (b). According to the figure, 1 million TL loans generated via the CGF program preserved the most employment (3.5 employment) and sales (3.8 million sales) among the medium firms, and it is the least among the large firms. An extra 1 million TL loan generated via the CGF program reduced the credit default probability for small firms by up to 30 percent (of the mean credit default probability in 2018 for small firms), while it increased the default probability for micro firms by up to 45 percent.

Figure 11: Average Monetary Impact of CGF-Supported Loans by Size Groups (per 1 million TL of CGF loan)

(a) Employment and Sales

(b) Credit Default



Source: Authors' calculation from the CGF, FTR and CR databases.
Notes: In panel (a), the first bar shows the number of preserved employment while the second bar represents the amount of sales generated for receiving 1 million TL of CGF loan for each size group. In panel (b), each bar shows the percentage point change in default rate relative to the mean default rate by receiving 1 million TL of CGF loan. We follow the KOSGEB's definition for firm size.

In general, large firms are relatively less credit constrained than micro and SMEs, which may explain at least some of the heterogeneity in program impact across size groups. Therefore, extending new credit lines to large firms may not directly improve their credit access, but rather substitute their non-CGF credits (Banerjee and Duflo, 2014). Some of the limiting attributes of the CGF program toward large firms, such as balance limits and favoring TL lending instead of FX, might have also contributed to this result. Considering their large scale, supporting large firms' credit access may be beyond the scope of CGF.

6.2 Estimations by Firm Sector Groups

The estimation results by sector groups are presented in Table 8.[21] The table displays only the short run impact results with the binary treatment specification. As usual, we present all the three specifications for each dependent variable separately in the table. The estimation results indicate significant differences across sectors. The CGF-supported firms in the construction sector preserved 27 percent more employment than their pairs, while this effect for the remaining sectors is between 14 - 18 percent. In terms of sales, the CGF-supported firms in the construction also recorded the highest increase relative to their pairs. Similar to employment, the CGF-supported firms in the remaining sectors experienced an increase of a similar magnitude in their sales. Moreover, the CGF-supported firms in the manufacturing and construction sectors

[21] As our sample coverage of energy and agriculture & mining sector firms is limited, we report the results for these sectors in Appendix B.

recorded a significant reduction (around 1.25 percentage point) in credit default probability. The CGF-supported firms in the wholesale & trade sector recorded a moderate reduction in credit default probability (0.5 percentage point) relative to their pairs. However, the impact is statistically insignificant in the remaining two service sectors, tourism and services.

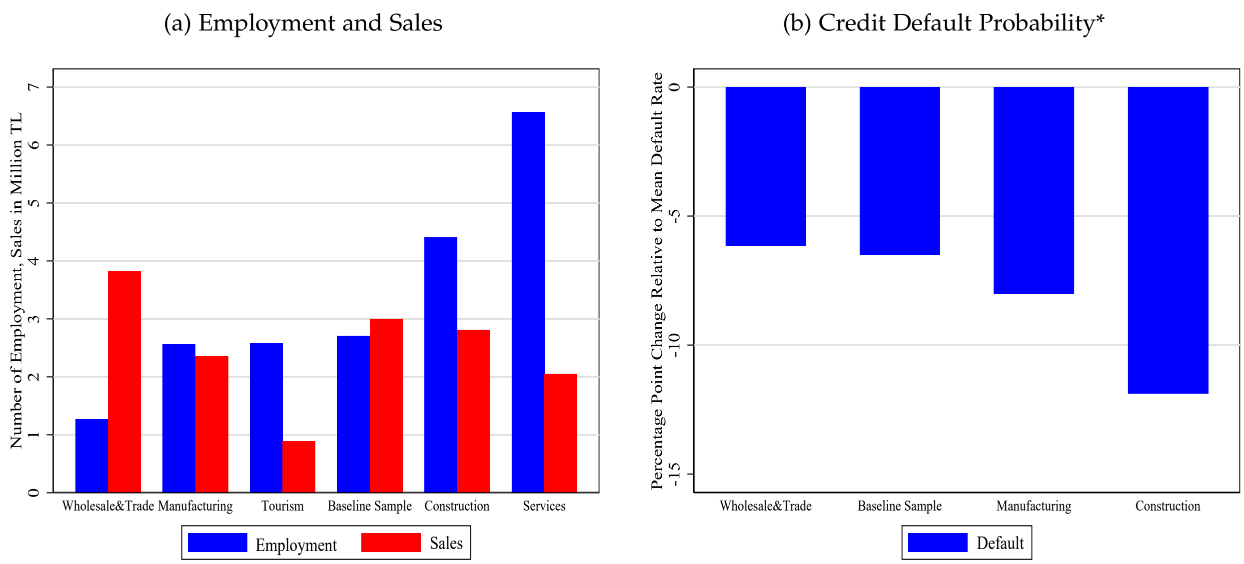
Table 8: Short-Run Impact of the CGF Program by Sector Groups, Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Wholesale & Trade									
POSTxCGF	0.13849***	0.12265***	0.11730***	0.66271***	0.60353***	0.56077***	-0.00478**	-0.00412**	-0.00157
	(0.00496)	(0.00490)	(0.00485)	(0.02318)	(0.02220)	(0.02235)	(0.00206)	(0.00206)	(0.00204)
CGF	-0.02371***	-0.06051***		0.02149***	-0.11606***		-0.00013	0.00154***	
	(0.00603)	(0.00636)		(0.00300)	(0.00649)		(0.00014)	(0.00034)	
Non-CGF credit		0.02320***	0.03095***		0.08670***	0.14732***		-0.00105***	-0.00514***
		(0.00098)	(0.00098)		(0.00350)	(0.00569)		(0.00020)	(0.00033)
Observations	94,500	94,500	94,500	94,500	94,500	94,500	92,528	92,528	92,528
R-squared	0.75462	0.75766	0.93696	0.60984	0.61737	0.74945	0.27470	0.27498	0.51788
Panel B: Manufacturing									
POSTxCGF	0.17639***	0.16086***	0.15107***	0.57448***	0.52362***	0.49379***	-0.01252***	-0.01221***	-0.01002***
	(0.00767)	(0.00751)	(0.00737)	(0.02800)	(0.02685)	(0.02696)	(0.00281)	(0.00280)	(0.00275)
CGF	-0.00835	-0.04062***		0.02005***	-0.08560***		0.00002	0.00077*	
	(0.00845)	(0.00870)		(0.00427)	(0.00793)		(0.00023)	(0.00046)	
Non-CGF credit		0.02487***	0.03902***		0.08143***	0.12763***		-0.00058*	-0.00461***
		(0.00165)	(0.00171)		(0.00474)	(0.00747)		(0.00030)	(0.00050)
Observations	49,480	49,480	49,480	49,480	49,480	49,480	48,068	48,068	48,068
R-squared	0.82794	0.82982	0.95288	0.66515	0.67178	0.78570	0.27907	0.27914	0.52313
Panel C: Services									
POSTxCGF	0.16135***	0.13991***	0.13772***	0.53378***	0.48284***	0.46144***	-0.00407	-0.00383	-0.00188
	(0.01008)	(0.01002)	(0.00985)	(0.03580)	(0.03445)	(0.03485)	(0.00308)	(0.00308)	(0.00307)
CGF	0.03488***	-0.00719		0.02457***	-0.07539***		-0.00049	-0.00001	
	(0.01159)	(0.01205)		(0.00558)	(0.00997)		(0.00030)	(0.00056)	
Non-CGF credit		0.02632***	0.02872***		0.06255***	0.08839***		-0.00030	-0.00273***
		(0.00185)	(0.00180)		(0.00473)	(0.00724)		(0.00029)	(0.00048)
Observations	36,200	36,200	36,200	36,200	36,200	36,200	35,396	35,396	35,396
R-squared	0.79025	0.79282	0.94385	0.62290	0.62770	0.75654	0.28364	0.28367	0.52243
Panel D: Construction									
POSTxCGF	0.26918***	0.22940***	0.22311***	1.13599***	1.01325***	0.96240***	-0.01231***	-0.01219***	-0.00887**
	(0.01301)	(0.01298)	(0.01309)	(0.04741)	(0.04542)	(0.05151)	(0.00383)	(0.00385)	(0.00380)
CGF	0.09640***	0.03503***		0.01971***	-0.16967***		0.00005	0.00026	
	(0.01186)	(0.01225)		(0.00624)	(0.01282)		(0.00034)	(0.00062)	
Non-CGF credit		0.03725***	0.04268***		0.11493***	0.15790***		-0.00013	-0.00380***
		(0.00171)	(0.00205)		(0.00608)	(0.00956)		(0.00032)	(0.00052)
Observations	39,032	39,032	39,032	39,032	39,032	39,032	38,032	38,032	38,032
R-squared	0.65569	0.66308	0.86466	0.60049	0.60931	0.72304	0.28869	0.28870	0.52818
Panel E: Tourism									
POSTxCGF	0.15748***	0.14132***	0.13560***	0.58695***	0.52596***	0.50803***	0.00751	0.00890	0.01047*
	(0.01753)	(0.01749)	(0.01759)	(0.06771)	(0.06572)	(0.06716)	(0.00602)	(0.00606)	(0.00608)
CGF	-0.01352	-0.04739***		0.02493**	-0.10291***		-0.00014	0.00292**	
	(0.01567)	(0.01617)		(0.01022)	(0.01934)		(0.00064)	(0.00115)	
Non-CGF credit		0.02140***	0.02874***		0.08079***	0.10024***		-0.00193***	-0.00502***
		(0.00287)	(0.00318)		(0.00957)	(0.01483)		(0.00060)	(0.00096)
Observations	12,248	12,248	12,248	12,248	12,248	12,248	12,020	12,020	12,020
R-squared	0.81768	0.81947	0.93338	0.58520	0.59207	0.73092	0.29100	0.29192	0.52726

*Notes: The table presents the regression results for the CGF program's effect on firm performance in a binary setting across sectors. Columns 3-6-9 include firm fixed effect instead of pair fixed effect. Robust standard errors are in parentheses. All dependent variables except Default are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Short-Run" covers the impact of the program in 2018.*

Evaluating the estimation results at variable averages, as discussed in the previous section, we present the impact of an extra 1 million TL loan generated via the CGF program by sector groups in Figure 12. The figure shows that an extra 1 million TL loan generated via the CGF program preserved the most employment in the service sector and the least employment in the wholesale & trade sector. A negative correlation between the cost of preserving employment and labor intensity is strongly evident from our results. In contrast, generating one extra TL in sales via the CGF program is the cheapest in the wholesale & trade sector and the most costly in the tourism sector. An extra 1 million TL loan via the CGF program leads to a higher reduction in credit default in the construction and manufacturing sectors, 12 percent reduction in the former, and 7.5 percent reduction in the latter, Figure 12b.[22]

Figure 12: Average Monetary Impact of CGF-Supported Loans by Sector Groups (per 1 million TL of CGF loan)



Source: Authors' calculation from the CGF, FTR and CR databases.
Notes: In panel (a), the first bar shows the number of preserved employment while the second bar represents the amount of sales generated for receiving 1 million TL of CGF loan for each sector. In panel (b), each bar shows the percentage point change in default rate relative to the mean default rate by receiving 1 million TL of CGF loan.
** We do not find statistically significant estimates for services and tourism sectors; hence, we intentionally do not present monetary impact calculations for these sectors.*

According to these results, the CGF program was more effective in preserving employment in labor-intensive sectors, particularly the services sector, and generated more sales for sectors serving more to domestic markets, especially the wholesale & trade sectors. By the same token, the lower impact of the CGF support for the sales of firms in the tourism sector may be because most of their sales come from foreign tourists in the form of service exports. Given the significant slowdown in the construction sector in 2016, the CGF program appears to have a significant positive impact on the performance of the CGF-supported construction firms, including a large decline in the credit default probability.

6.3 Counter-Factual Policy Discussion

As discussed above, the CGF program impact varies significantly across size and sector groups. Utilizing this heterogeneity, we provide a counter-factual analysis to show that substantial effi-

[22] As the program impact on credit default probability for the firms in services and tourism sectors is statistically insignificant, we excluded these sectors from the Figure.

ciency gains can be achieved by reallocating the resources across size and sector groups based on different policy priorities (e.g., preserving more employment and generating more sales).

The counter-factual policy exercise for the size and sector groups is presented in Table 9 and Table 10. The tables provide three main sub-headings: the original CGF program allocation, the scenario allocation, and finally, the percentage change in the dependent variable with the new scenario relative to the original. The original program allocation shows the share and volume distribution of the total CGF-backed loan amount in 2017 and 2018 across size and sector groups, as well as the implied employment and sale impact of the program based on the estimates presented above. Under the scenario allocation, we take one percent of the total loans generated via the CGF program from the least cost-effective group and redistribute the funds to the most cost-effective group. Finally, we present the change in the implied employment and sale effects under the allocation scenarios relative to the actual allocation. To provide an overall impact of the CGF program, we use the official total CGF-backed loan volume for 2017 and 2018, 293 billion TL loans. The loan distribution across the size and sector groups comes from the sample utilized in our analysis.

Moreover, we present the counter-factual analysis results regarding the size groups in Table 9, where we take 1 percent of the total CGF loans from large firms (i.e., the least cost-effective group) and redistribute it to medium-sized firms (i.e., the most cost-effective group). With the redistribution of only one percent of the total CGF loans (2.93 billion TL loan) from large firms to medium-sized firms, without changing the total size of the CGF program, we can generate roughly a 0.74 percent increase in employment and a 1 percent increase in sales relative to the original program design.

Table 9: Counter-Factual Policy Analysis across Size Groups

	Original CGF Program				Scenario				Change in	
	Credit Allocation		Estimated Impact		Credit Allocation		Estimated Impact		Estimated Impact	
	Shares	Loans (Bn TL)	Employment (number)	Sales (Bn TL)	Shares	Loans (Bn TL)	Employment (number)	Sales (Bn TL)	Employment	Sales
Micro	0.019	5.67	11117.34	13.28	0.019	5.67	11117.34	13.28	0.000%	0.000%
Small	0.175	51.35	141841.14	163.52	0.175	51.35	141841.14	163.52	0.000%	0.000%
Medium	0.354	103.63	348929.46	398.58	0.364[a]	106.56	358794.78	409.85	2.827%	2.827%
Large	0.452	132.35	208427.74	171.01	0.442[b]	129.42	203813.57	167.21	-2.214%	-2.214%
Total	1.00	293	710315.68	746.38	1.00	293	715566.82	753.87	0.739%	1.003%

Notes: The impact analysis is based on "Short-Run Effect" estimations, which covers the impact of the program in 2018. Bn is billions. The official figure for the total volume of loans generated via the CGF program in 2017 and 2018, 293 Bn TL, is used in the analysis. The original program allocation across the size groups is computed based on the data utilized in the analysis. "a" implies a 1% increase in the CGF program share and "b" implies a 1% reduction in the CGF program share under the designed scenario. Firm size is based on official KOSGEB definition, as described in Table B1.

Considering sectoral heterogeneity in the cost of preserving extra employment and generating an extra sale, we provide two scenarios in Table 10. More specifically, Scenario A focuses on generating more employment, and Scenario B considers generating more sales relative to the original program design. Under Scenario A, we take 1 percent of the total CGF loans from the wholesale & trade sector (i.e., the least cost-effective group in generating employment) and redistribute it to the most cost-effective sector, service sector firms. Our redistribution of only one percent of the total funds to the service sector firms generates roughly 2 percent more employment; however, the program's total sale impact decreases by 0.6 percent relative to the original distribution. Now, we repeat the policy exercise to improve the implied impact of the program on sales under Scenario B, whereby we take 1 percent of the CGF loans from the tourism sector (i.e., the least cost-effective group in generating sales) and redistribute it to the most cost-effective wholesale & trade sector firms in generating sales. Under Scenario B, we can generate 1 percent more sales; however, the program's total employment impact decreases by 0.5 percent relative to the original allocation. By the same token, one can focus on intermediary cases where improving the program's employment and sales impact is feasible, which appears to be feasible by reallocating some of the resources to the manufacturing sector.

Table 10: Counter-Factual Policy Analysis across Sectors

	Original CGF Program				Scenario				Change in	
	Credit Allocation		Estimated Impact		Credit Allocation		Estimated Impact		Estimated Impact	
	Shares	Loans (Bn TL)	Employment (number)	Sales (Bn TL)	Shares	Loans (Bn TL)	Employment (number)	Sales (Bn TL)	Employment	Sales
Scenario A: Preserving More Employment										
Manufacturing	0.356	104.21	267202.48	245.78	0.356	104.209	267202.48	245.78	0.000%	0.000%
Wholesale & Trade	0.363	106.25	135181.10	407.10	0.353[b]	103.322	131453.37	395.87	-2.758%	-2.758%
Construction	0.137	40.04	177163.88	112.79	0.137	40.039	177163.88	112.79	0.000%	0.000%
Services	0.075	21.87	143861.07	44.90	0.085[a]	24.797	163137.39	50.92	13.399%	13.399%
Tourism	0.044	13.04	33682.89	11.56	0.044	13.035	33682.89	11.56	0.000%	0.000%
Agriculture & Mining	0.017	5.02	8255.08	15.68	0.017	5.019	8255.08	15.68	0.000%	0.000%
Energy	0.009	2.58	6894.12	16.12	0.009	2.578	6894.12	16.12	0.000%	0.000%
Total	1.00	293	772240.62	853.92	1.00	293	787789.20	848.71	2.013%	-0.610%
Scenario B: Preserving More Sales										
Manufacturing	0.356	104.21	267202.48	245.78	0.356	104.209	267202.48	245.78	0.000%	0.000%
Wholesale & Trade	0.363	106.25	135181.10	407.10	0.373[a]	109.182	138908.84	418.32	2.758%	2.758%
Construction	0.137	40.04	177163.88	112.79	0.137	40.039	177163.88	112.79	0.000%	0.000%
Services	0.075	21.87	143861.07	44.90	0.075	21.867	143861.07	44.90	0.000%	0.000%
Tourism	0.044	13.04	33682.89	11.56	0.034[b]	10.105	26111.83	8.96	-22.477%	-22.477%
Agriculture & Mining	0.017	5.02	8255.08	15.68	0.017	5.019	8255.08	15.68	0.000%	0.000%
Energy	0.009	2.58	6894.12	16.12	0.009	2.578	6894.12	16.12	0.000%	0.000%
Total	1.00	293	772240.62	853.92	1.00	293	768397.29	862.54	-0.498%	1.010%

Notes: The impact analysis is based on "Short-Run Effect" estimations and covers the impact of the program in 2018. Bn is billions. The official figure for the total volume of loans generated via the CGF program in 2017 and 2018, 293 Bn TL, is used in the analysis. The original program allocation across the sector groups is computed based on the data utilized in the analysis. "a" implies a 1% increase in the CGF program share and "b" implies a 1% reduction in the CGF program share under the designed scenario.

Overall, our simple policy exercise indicates that using the heterogeneity in the program impact across the firm size and sector groups, one can re-design the CGF program with different policy priorities (e.g., more employment or sales). This may bring about significant efficiency gains.

7 Further Extensions

In this section, we shift our focus toward different firm assets types, liabilities and exit. We then aggregate our data to province and NACE Rev-2 Classification levels to provide further estimation results on macro implications of the program via re-distributional effects.

7.1 Impact on Other Firm Outcomes

The program's impact on various asset types can potentially differ based on firms' short- and long-run perspectives in managing risks and exploiting growth opportunities while using the funds. For instance, firms may prefer to respond to uncertainty (the geopolitical shocks in the second half of 2016 in Türkiye) by increasing their precautionary funds in liquid form, suggesting a positive relationship between the CGF support and liquid assets. On the contrary, one of the expected outcomes of the CGF program was an increase in inventories. This argument was while many non-CGF firms were negatively affected by the distortions on domestic supply networks and the demand as a result of the increased uncertainty, the CGF-supported firms presumably experienced relatively less financial stress, and hence, were able to continue with production even though they may not find appropriate demand for their products. In turn, they would be expected to experience a temporary increase in their inventories.

Similarly, firms may postpone their investments in response to increased uncertainty. However, given that many capital assets are also perceived as collateral and also provide a cushion to macro shocks, such as currency fluctuation[23] (especially during times of high uncertainty), some of the CGF-supported firms might have still considered investing in these assets. Our results on tangible assets, containing land and buildings, machinery and equipment, and vehicles, shed light on these diverging incentives. Finally, the CGF program's impact on firms' intangible capital (i.e., patents, R&D activities) and indebtedness (e.g., the differential between asset and liability growth) is particularly crucial to provide a perspective on the long-term implications of the CGF program. The former tells us about future firm productivity and growth potential, while the latter is informative about firms' future financial sustainability.

As a compliment to our earlier estimates on credit default probability, the program presumably has also reduced firm exits by reducing the financial stress on CGF-supported firms. To test this argument, we assign one to exiting firms (i.e., not reporting balance sheet) and zero for others in our base sample, we estimate the program impact on firm exit.[24]

Thereby, we estimate our main model for different asset types, liabilities, and firm exit and present the results with the baseline specifications only for brevity in Table 11.

[23]Most of the machinery and equipment type capital, and vehicles are imported from abroad in Türkiye, and thus, their prices are pegged to foreign currency prices.

[24]Various definitions of firms exit, e.g., filing bankruptcy, balance sheet reporting status, the decline in employment or sales to zero, etc., are used in the literature given that identifying year-on-year firm exit is a difficult one. We define year-on-year exit based on firms' financial statement reporting status for tax purposes, as the Turkish Tax Code requires legal firms to report balance sheets as long as they legally remain in operation, and thus, it is legitimate to interpret not reporting balance sheet as firm exit.

Table 11: The CGF Program's Effect on Firm Performance: Binary Treatment for Other Firm Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dependent Variables:	Total Assets	Liquid Assets	Inventory	Tangible Assets	Land & Buildings	Machinery & Equipment	Vehicles	Intangible Assets (R&D)	Total Liabilities	Exit
Panel A: Very Short-Run										
POSTxCGF	0.23990***	0.34052***	0.43803***	0.28893***	0.33821***	0.21926***	0.40993***	0.22936***	0.36616***	-0.02559***
	(0.00718)	(0.01032)	(0.01701)	(0.00931)	(0.01589)	(0.01140)	(0.01588)	(0.01324)	(0.00859)	(0.00063)
CGF	-0.02157***	-0.08360***	0.33647***	-0.03425***	-0.02747	-0.15491***	0.37274***	-0.16384***	-0.02730***	0.00001
	(0.00225)	(0.00870)	(0.01779)	(0.00282)	(0.02554)	(0.02477)	(0.01850)	(0.02522)	(0.00488)	(0.00004)
Observations	372,330	372,330	372,330	372,330	372,330	372,330	372,330	372,330	372,330	382,500
R-squared	0.80023	0.55867	0.62514	0.83013	0.69822	0.70557	0.65924	0.60964	0.71756	0.19040
Panel B: Short-Run										
POSTxCGF	0.23234***	0.18695***	0.35870***	0.29037***	0.35804***	0.25597***	0.30802***	0.27233***	0.36789***	-0.04252***
	(0.00870)	(0.01273)	(0.02102)	(0.01158)	(0.01976)	(0.01409)	(0.02002)	(0.01647)	(0.01048)	(0.00101)
CGF	0.00068	-0.08056***	0.43778***	-0.01769***	-0.01065	-0.14193***	0.40844***	-0.13453***	0.01134**	0.00011
	(0.00259)	(0.01011)	(0.02010)	(0.00321)	(0.02772)	(0.02619)	(0.02032)	(0.02665)	(0.00535)	(0.00007)
Observations	235,800	235,800	235,800	235,800	235,800	235,800	235,800	235,800	235,800	255,000
R-squared	0.72822	0.55865	0.61585	0.77589	0.69044	0.69873	0.63218	0.60617	0.67125	0.29780

*Notes: The table presents the regression results for the short run effect of the CGF program on other firm outcomes in a binary setting. Each column includes a pair fixed effect. Robust standard errors are in parentheses. All dependent variables except exit are in logarithmic form. For estimating column 10, we assign one to exiting firms (i.e., not reporting balance sheet) and zero for others in our base sample in 2017 and 2018. "Very Short-Run" covers the impact of the program only in 2017, while "Short-Run" covers the impact of the program in 2018. *** p<0.01, ** p<0.05, * p<0.1.*

According to the results, the CGF-supported firms increased their total assets by 24 percent in the very short run that magnitude is similar in the short run. Liquid assets are also affected positively by the program, as CGF-supported firms increased their liquid assets by 34 percent more than their pairs in the very short run, while the effect drops to half in the short run. The CGF-supported firms on average experienced a 44 percent increase in their inventories relative to their pairs in the very short run. However, the increase in inventories was temporary, as the estimated coefficient falls in the short run specification. The increase in both liquid assets and inventories appears to be temporary, given some of the effects diminish in the short run.

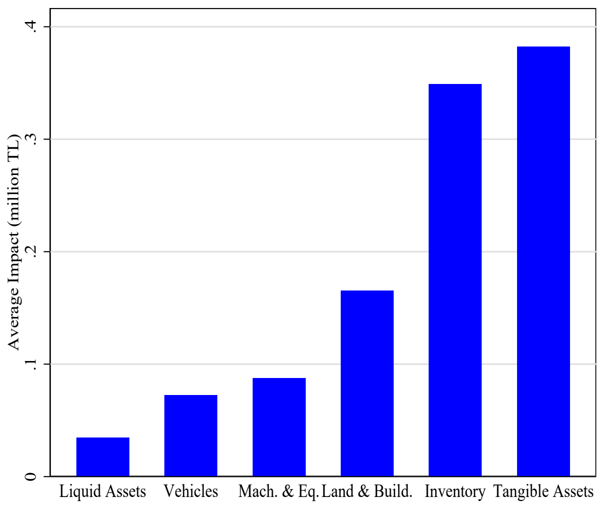
The program's impact is estimated to be positive for the tangible assets, whereby the CGF-supported firms, on average, increased their tangible assets about 29 percent more than their pairs in the very short run. The effect remains to be the same in the short run. Among the constituting asset types of tangible assets, the CGF program generally has a positive impact on all three classes. However, the size of the impact across asset types, as well as the very short run and the short run attributions differ significantly. More specifically, the CGF-supported firms on average invested 34 percent more in land and buildings, 22 percent more in machinery and equipment, and 41 percent more in vehicles than their pairs in the very short run.

In the short run, the impact on land and buildings remains mostly similar to that of the impact in the very short run; the program effect on machinery and equipment increases moderately; and finally, the impact on vehicles drops to 31 percent. Vehicle purchases are higher in the very short run among other asset types that significantly decrease in the short run. The impact on intangible assets and total liabilities are 23 percent and 36 percent in the very short run those estimates remain in similar magnitude in the short run. The CGF program appears to have reduced firm exit probability in the short run, as the CGF-supported supported firms, on average, experienced a 4.3 percentage point less exit in the short run relative to the control group.

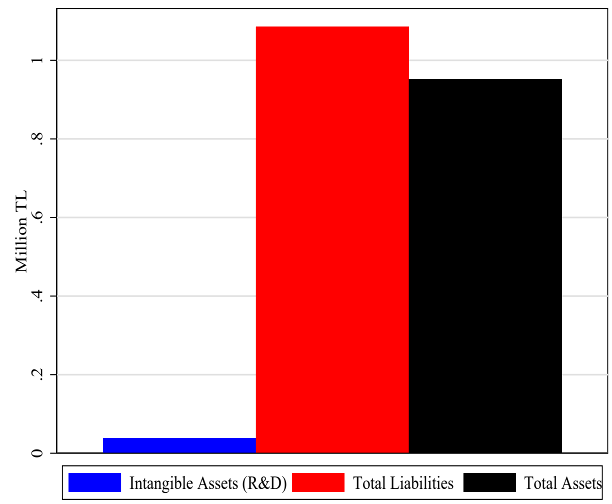
We summarize the economic significance of the estimates for an extra 1 million TL CGF-backed loan in Figure 13. According to the figure, the program's impact on tangible assets and inventories are sizable, while a minimal impact is observed in intangible assets. On the contrary, the program impact on total liabilities is much larger than the total assets among the CGF-supported firms, which in turn implies an overall increase in firm indebtedness.[25]

Figure 13: Average Monetary Impact of CGF-Supported Loans (per 1 million TL of CGF loan), Other Firm Outcomes

(a) Various Asset Classes



(b) Intangible Assets, Total Liabilities and Assets



Source: Authors' calculations.
Notes: The figures present the average monetary impacts of receiving 1 million TL of CGF loan. Mach. & Eq. represents machinery and equipment while Land & Build. represents the land and buildings.

The program's impact on fixed capital (e.g., tangible assets) seems to be sizable, yet only a small proportion of this investment went into productive capital, such as machinery and equipment. Additionally, its impact on long-term capital, such as intangible assets, appears to be weak, which is perhaps not too surprising given that the CGF program was initially designed to improve firm resilience to the temporary negative shocks in the domestic economy. However, our results also indicate an increase in firm indebtedness, where liabilities grew faster than assets with the CGF program. This high indebtedness can threaten firms' financial health in the long run, especially given the weak impact of the program on long-term firm perspectives. Such risks may be particularly acute for certain types of firms. Given our results in Section 6.1, for instance, especially the CGF-supported micro-firms appear to experience a significant increase in credit default probability in 2018.

[25] As an alternative indebtedness measure, we also re-estimated our model with leverage being the dependent variable. The results are qualitatively similar, where the CGF-supported firms on average experienced a larger increase in total leverage relative to their matched pairs.

7.2 Macro Implications

We have talked little about the re-distributional effects of the CGF program until now. This is to say that a new hire of a firm (the CGF-supported firm) may be an employee or layoff of another firm (control group). In other words, we may observe, for instance, an increase in employment, motivated by the CGF program at the firm-level; however, because of the possibility that the new hire may not come from the unemployment pool, but rather from other firms, total employment may not increase in the country. To capture this, we estimated our main model at sector-province level to check if the positive and statistically significant impact of the CGF program prevails after accounting for general equilibrium effects (GE). In identifying the GE effects, we assume that employees may frequently switch between firms, while this switch is less frequent across the broadly defined NACE Rev-2 classification level sectors in the same province or across provinces for a given sector.[26]

The estimation results for employment and sales are presented in Table 12. The results show that a one percent increase in the CGF program at the sector–province-level increases employment by 0.2 percent and sales by 3 percent. This is in line with our earlier expectations, where the impact is much lower at the macro level due to the program's re-distributional impact. Nevertheless, the coefficient estimates remain statistically significant and economically consistent across different specifications, and hence, further reinforce the positive impact of the CGF program at the macro level.

Table 12: Province–Sector Level Aggregate Regressions

	(1)	(2)	(3)	(4)
Dependent Variables:	Employment	Employment	Sales	Sales
log CGF credit	0.00217*	0.00346***	0.03018***	0.03447***
	(0.00130)	(0.00127)	(0.00518)	(0.00512)
log non CGF credit		0.05390***		0.17931***
		(0.00606)		(0.02176)
Observations	10,303	10,303	10,303	10,303
R-squared	0.98472	0.98571	0.93990	0.94345

*Notes: The table presents the results of the province-sector level aggregate regressions on the impact of the CGF program. *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses. "Short-Run" impact model is presented at province – sector (NACE Rev-2 Classification) level. All the models contain, provinceXsector fixed effects.*

8 Robustness Checks

We have presented various results besides our baseline specification throughout the discussion above, which already reinforces the robustness of our results to several checks, including controlling for several fixed effects, firm fixed effects, NACE Rev. 2 Classification level sector–time and province–time fixed effects, additional controls (non-CGF loans) and estimations with different

[26]Further aggregations of the sample, to only sector or province level, significantly reduce the number of observations and, thus, the estimates' reliability.

sub-samples. Therefore, we focus on other potential concerns in this section.

Our main sample, used in the baseline analysis, requires firm survival both in the matching/control and treatment years. In other words, firms that did not report balance sheets are "treated" as exiters in our base sample (*Sample* 1). In the discussion above, we have already stated that the share of exiting firms is small. However, to remove this restriction from our estimates, we impute zeros to the employment and sales of exiting firms in 2017 and in 2018 that form our new sample, *Sample 1 with filling*. This is a well-applied method in the empirical literature (e.g., Brown and Earle, 2017). However, we do not apply the same idea to credit default, where assuming credit default for an exiting firm (i.e., assigning one for the credit default of exiting firms) may actually not always be the case in reality, as firms may not have outstanding credit or had already liquidated the outstanding credit balance through the bankruptcy process. By the same token, we construct another sample (*Sample 2*), where we add firms that were around only in 2016 (not in 2015) to our matching methodology. As done for *Sample 1*, we present our main results for *Sample 2* with a requirement on survival in 2017 and in 2018 (i.e., *Sample 2 without filling*) and also, without a requirement on survival (i.e., *Sample 2 with filling*).

Firms in the energy sector usually tend to be large and use FX-denominated credits to finance large-scale investment projects, given the very nature of the sector that highly relies on imported capital goods.[27] As a result, energy sector firms' coverage of the CGF program is relatively small. On the contrary, firms in the agriculture & mining sector, especially agriculture, generally tend to be micro-family firms, whose coverage is limited in our sample given the exclusion of unincorporated businesses from the analysis. Overall, the CGF program's coverage of these sectors is only 3 percent, and thus, excluding these sectors from the analysis should not affect our results. While sector-specific characteristics are mostly captured by the sector-specific fixed effects in our baseline specification, we still find it useful to note that our main results are robust to the exclusion of firms in these sectors from the analysis.

For brevity, we discuss only the robustness of our estimates from the binary treatment specification in this section. However, we should note that the continuous treatment results are very similar as reported in Appendix B.[28]

Robustness Test 1: Sample 1 with Filling

Table B3 presents the results from the binary treatment with *Sample 1 with filling*. According to the results, the main dependent variables' estimated effects are slightly higher than those without the imputation; however, the significance levels and signs do not change in all specifications. Given our credit default results, the CGF program has a positive impact on firm survival. Thereby, the exiting firms tend to be the control firms in the matched pairs, as the CGF-supported firms tend to default less and survive more. In turn, putting the exiting firms back to the estimation with zero imputations for their employment and sales seems to slightly increase the CGF program's impact

[27] See Footnote 9.
[28] Continous treatment results are available upon request.

on employment and sales. The statistical significance and the sign of the estimates, however, are preserved across all the specifications.

Robustness Test 2: Sample 2 without Filling

Table B4 shows the results for the binary treatment specification with *Sample 2 without filling*. The number of the matched CGF firms with controls increases to 67,446 in this sample, as we no longer require firms to exist in both years, 2016 and 2015, to be included in the matching. The estimated treatment effects for all variables do not change across all specifications, suggesting that our baseline results are robust to different sample selections.

Robustness Test 3: Sample 2 with Filling

Table B5 displays the results for the binary treatment specification with *Sample 2 with filling*. The results for the estimated treatment effects for all variables do not change across all specifications, suggesting that our baseline results are robust to imputing zeros for the exiting firms in *Sample 2*.

Robustness Test 4: Excluding Firms in Energy, Agriculture & Mining Sectors

Table B6 displays the results for the binary treatment specification with the *original sample* after excluding the firms in the energy, agriculture & mining sectors. The results imply that excluding firms in the energy and agriculture & mining sectors does not affect our main findings for the binary treatment specification with the *original sample*.

9 Conclusions

Using novel administrative databases, this paper evaluates one of the world's largest CGF programs recently implemented in Türkiye. We first matched our sample of the CGF-supported firms with their close pairs via coarsened and exact matching method and then implemented a difference-in-difference estimation to evaluate the program's impact on the performance of treated firms relative to their matched pairs. Our results show that the CGF-supported firms, on average, preserved 17 percent more employment, generated 70 percent more sales, and experienced 0.6 percentage point less credit default than their matched pairs in 2018. Evaluating these estimates at their sample averages implies that an extra 1 million TL loan generated via the CGF program preserved roughly 2.7 more employment, generated about 3 million more sales, and reduced the average credit default probability by nearly 6.5 percent in 2018. Considering the official figure, a total of 293 billion TL loan volume generated via the CGF program in 2017 and 2018, and assuming linear applicability of our estimates to this figure, the implied overall program impact of the program on the Turkish economy in 2018 was roughly 794 thousands more employment and 879 billion TL more in sales.

Our results identify that the program impact is the highest among SMEs, where the cost of preserving one more unit of employment, sales, and reducing credit defaults on average is the cheapest. On the contrary, the results for cross-sector groups show that the cost of preserving one more employment is cheaper in more labor-intensive sectors (e.g., services), and the cost of generating one extra TL sales is cheaper in sectors that serve more to the domestic economy (e.g., wholesale & trade). Exploiting the program impact heterogeneity across size and sector groups, we provide counter-factual policy analysis. The results from the counter-factual analysis indicate that moving only one percent of the TL loans generated via the CGF program from the least cost-effective size group (i.e., large size) to the most cost-effective size group (i.e., medium size) increases total employment and sales impact of the program roughly one percent. Cross-sectoral redesign of the program is less straightforward. Moving one percent of the total CGF loans from the least cost-effective (and the least labor-intensive) sector (i.e., wholesale & trade) to the most cost-effective (and the most labor-intensive) sector (i.e., the service sector) increases the employment impact of the program for about 2 percent, although this decreases the sales impact of the program. Similarly, redistributing one percent of the total CGF loans from the tourism sector (serving the least to the domestic sector) to the wholesale & trade sector increases the program's sales impact by about 1 percent, although this decreases the employment impact of the program. The manufacturing sector appears to provide an intermediate case, where both employment and sales impact of the program can be improved by redesigning the program.

The program's impact on assets that can stimulate long-run firm growth via productivity enhancements seems relatively weak. This is perhaps not surprising given the aim of the CGF program in 2017 was to minimize the negative impact of the geopolitical developments on domestic real sector firms. Thereby, the CGF program seems to achieve its initial aim by restoring firm strength in the short run via preserving employment and sales, although it contributes less to firms' long-term growth prospects. In this regard, the CGF-type short-term-focused programs should not be considered as an alternative to the programs aiming to simulate productive capital investment. Our results also highlight an increase in firm indebtedness as a result of the CGF program. We observe a more acute increase in firm liabilities than assets. This finding coupled with the results that the CGF program's mitigating impact on credit default probability fades over time, implying credit risks may increase in the long run. One way to tackle this issue is to closely monitor firm indebtedness and ensure the necessary debt management practices are being implemented. In this regard, the micro firms should be closely monitored and mentored to sustain their financial resilience in the long run.

Our findings provide important insights from a rare public credit guarantee implementation experience that has two distinct characteristics from other country experiences: the program size was considerably large and it was utilized as a fiscal-response measure to a negative aggregate shock. These distinct characteristics make the Turkish experience particularly relevant to think about the potential short-run impact of the large public credit guarantee programs implemented in many countries during the recent pandemic crises. In particular, our results imply that public credit guarantees seem to be effective fiscal-response measures in the short run; however, they can be more effective if designed to be more selective with certain policy objectives (e.g., preserving more employment). Secondly, their long-run consequences on firm performance - e.g., productivity and financial stability - need to be closely monitored.

Due to data restrictions, we had to exclude unincorporated businesses from the analysis. Although their size is relatively small both in the CGF program and in the Turkish economy, they may be especially important for our risk analysis and firm credit default results. Mainly because micro firms are usually more vulnerable to shocks and, thus, riskier. However, we cannot provide a direct analysis of this concern, which remains a caveat for our results. Secondly, our analysis covers one full year (2018) in the post-CGF program and the year 2017, which contains both the program implementation and impact. Therefore, the observed positive impacts along with the negative ones may amplify over time. Lastly, our results do not account for firm-to-firm spillovers. However, we know that fiscal policy multiplies through the interactions of agents in an economy. That suggests some of our results may amplify once the firm-to-firm interactions are considered.

While the current study evaluates the first-order firm-level impact of the Turkish CGF program in the short run, further research on the micro, macro, and distributional implications of the program is deemed necessary to identify the overall program impact. Presumably, an extensive program of this size can have implications for the banking sector and the financial network, while at the macro level, the potential impact on inflation, economic growth, financial stability, and productivity are also worth noting. These considerations will be further explored in our future research agenda.

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Appendix A: Risk Assessment and Further Credit Distributions

A Risk Assessment

This section describes the details of our risk-scoring methodology. We use information from the credit registry (CR) and comprehensive financial tax records (FTR) for the period 2006-2017 in the analysis. All firm-bank relationships below 1000 TL were excluded to clean insignificantly small or zero firm-bank relations. Firms with no bank relations are excluded from the estimated model, as we cannot assign financial history to these firms. We also exclude self-employed individual firms and legal firms with incomplete or incoherent data, such as observations with negative fixed assets, negative current assets, and negative net sales, to mitigate potential FTR reporting errors. Using the described data, we develop a method to select explanatory variables and then estimate a logit model to produce a financial score for each firm.

Logit analysis is a conditional probability technique that allows studying the relationship between a series of characteristics of an individual and the probability that is individual belongs to one of two groups defined as a prior. The Logit model used in our methodology represents the probability of default, a number between 0 and 1. A binary variable $default_{t+1}$ showing the status of the firm at time $t+1$ is explained by a set of factors x_t. The probability of default is given by Equation (1):

$$Pr\{default_{t+1} = 1|x_t\} = \frac{1}{1 + e^{-\beta x_t}} \tag{1}$$

where x_t is a vector of regressors in year t, including a constant and variables characterizing the firm and economy, β is a vector of coefficients. The main property of these β-coefficients is that the in-sample average of the predicted default rates, estimated by the equation, is equal to the observed average default rate. The z-score of each firm can be defined as the latent variable's estimated value, that is, $z_{t+1} = \beta x_t$. Hence, the z-score, z_{t+1}, is the probability of default during the period $t+1$, conditional on the variables that characterize firms in the previous periods, summarized by x_t. The lower the z-score, the lower the estimated probability of default of the firm.

The default event is defined as a past-due payment of more than 90 days on any credit obligation in a given year, which coincides with the Basel II default definition. Therefore, a firm is considered to be *in default* in the banking system if it fails to repay its debt in three consecutive months. As firms have multiple bank relations in the monthly Credit Registry, they may have multiple defaults in a given month, and can technically be in and out of default status in a year. Since our primary firm's financial information comes from tax records, which are in annual frequency, we need to annually adjust our monthly credit default event. Therefore, we define firm default in a given year if the firm shows at least one default event in any of its bank relations in one year term. Moreover, it is possible that some defaulted firms may stay in that status for more than a year term.[29] One way to control for the dynamic bias in the sample toward firms with repeated defaults is to exclude all observations belonging to the same firm after the first default event, â la Antunes et al. (2016). In this way, we impose a non-default status condition on firms in time t and estimate their default status in time $t+1$.

The selection of the independent variables (x_t) is crucial for the model's performance, since they must be significant and relevant to differentiate between *good* and *bad* firms. We start with a sample of 52 financial variables, which are commonly used by the related literature. According to the literature, this set of variables includes several financial ratios of the firm, which have a strong discriminating power for credit risk. Some macroeconomic variables, including real effective exchange rate, inflation rate, and real GDP growth rate, are also considered. Additionally, we include three categorical variables such as the sector of firms based on NACE Rev. 2 Classification, legal status of each firm, and firm type (micro, small, medium, or large) for controlling fixed-effects related to the activity sector, legal status, and firm size, which might persist after controlling for the individual characteristics of the firms. We also control for the number of default event $(CR_{default})$ for each firm during the period of analysis to improve the model's prediction power. Moreover, we anecdotally know that if a firm gets credit once, this firm is more likely to get new credit in the next periods, indicating the intensity of appearance in the credit registry system $(CR_{intense})$ might affect the probability of default. We expect the number of default events and intensity of appearance in the credit registry system to be positively and negatively associated with the probability of default. Table A1 describes the all variables used in the logit regressions.

All independent variables are divided into eight groups according to the aspect of the firm they measure. In the variable selection process, we aim to include at least one variable from each group of variables, namely at least one measure for each of the followings: liquidity position, financial position, turnover, profitability, BACH ratios, WGA ratios, size, and macroeconomic environment, taking the issue of collinearity into account. The variable selection process ends when none of the remaining variables in the set of potential variables can improve the AUROC criterion[30] given that they are statistically significant at the 1 percent level in the new regression and all the previously included variables remain statistically significant. The next step in the setup of a firm rating system is to estimate the best model so that observed default rates of firms are consistent with the default rates used to define them. After several accuracy and robustness checks, our model predicts the probability of default based on 14 financial ratios, size (number of employees), the incidence in the CR system for each firm, total number of default events prior to time t, real effective exchange rate, GDP growth rate, and inflation rate. The sectoral, legal status and firm-type dummies are also found to be statistically significant determinants of the probability of default. All signs are as expected. Table A2 summarizes the signs of the estimated

[29] For instance, a firm that is identified to be in default as of November of 2016 for the first time may continue to be in that status in 2017.

[30] AUROC stands for "area under the Receiver Operator Characteristic" and measures the ability of a variable (or a model) to correctly classify the dependent variable for a particular sample. See Lingo and Winkler (2008) and Wu (2008) for the definition of this synthetic measure.

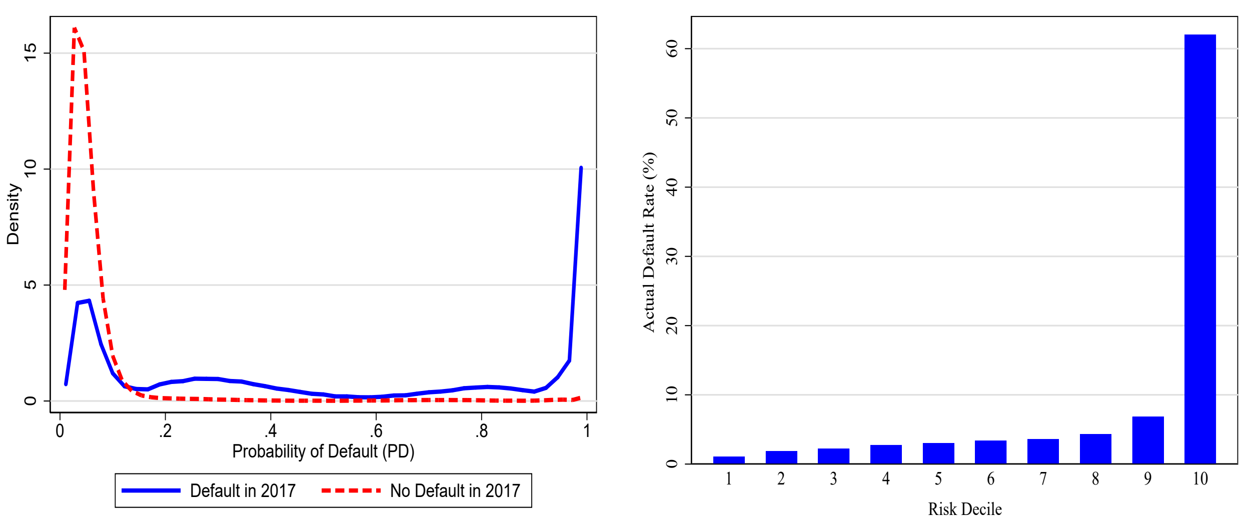
coefficients of our general model.[31]

It is important for a model to discriminate between bad and good (defaulting and non-defaulting) firms. In that respect, Panel (a) of Figure A1 presents the histograms of estimated probabilities for defaulting and non-defaulting firms and realized default rates for firms in each risk group for the year 2017. There is a clear distinction between defaulting and non-defaulting firms regarding their estimated default probabilities, where estimated probabilities are concentrated around 1 for defaulting firms and around 0 for non-defaulting firms. Moreover, Panel (b) of Figure A1 also presents another test for the estimated logit model's performance. When we divide the estimated default probabilities into deciles, we see a positive and monotonic relationship between the estimated probability and the actual default rate. It is clear that the default rate is the highest for the firms in the 10^{th} decile, namely that more than 62 percent of the firms that are classified as highly risky firms according to previous years' balance sheets went bankrupt in 2017. In Figure A2, we also present the ROC curves, which are derived from the estimated default model. According to the results, our selected model reaches ROC areas around 0.84 for 2015 and around 0.87 for 2016, which seem to have high predictive power according to the previous literature.[32]

Figure A1: Performance Tests for Logit Model

(a) PDs for Default vs. No-default Firms

(b) Default Rates for Risk Deciles



Source: Authors' calculation.
Notes: Default in 2017 is an indication of a realized default event in 2017 while No Default in 2017 represents the firms without a realized default event in 2017. Risk deciles are based on the estimated PDs for 2017, namely by using the data from 2016.

[31] Due to confidentiality reasons, we only report the sign and significance level of the coefficients.

[32] The predictive power of a discrete-choice model such as the logit is measured through its sensibility and its specificity. The sensibility is the probability of correctly classifying an individual whose observed situation is the *default*, while the specificity is the probability of correctly classifying an individual whose observed situation is the *non-default* (ECCBSO, 2007).

Table A1: Definition of Variables Used in the Regressions

Group	Variables	Definitions
Liquidity position	Current Ratio	Current assets/Short term liabilities
	Quick(Acid-Test)Ratio	(Current assets-Inventories-prepayments and accrued income for the next months-other current assets)/Short term liabilities
	Cash Ratio	Liquid assets+marketable securities/Short-term liabilities
	Inventories to Current Assets	Inventories/Current Assets
	Inventories to Total Assets	Inventories/Total Assets
	Inventory Dependency Ratio	(Short term liabilities-Liquid assets-Marketable Securities) / Inventories
	Short-term receivables to Current Assets	(Short term trade receivables+Other short term receivables)/Current Assets
	Short-term receivables to Total Assets	(Short term trade receivables+Other short term receivables)/Total Assets
Financial position	Total liabilities to Total Assets	(Short term liabilities+Long term liabilities)/Total Assets
	Own funds to Total Assets	Own funds/Total Assets
	Own funds to Total Liabilities	Own funds/(Short term liabilities+Long term liabilities)
	Short-term liabilities to Total Liabilities	Short term liabilities/Total liabilities
	Long-term liabilities to Total Liabilities	Long term liabilities/Total liabilities
	Long-term liabilities to Long-term liabilities and Own funds	Long term liabilities/(Long term liabilities+Own funds)
	Tangible Fixed Assets to Long-term liabilities	Tangible fixed assets (net)/Long term liabilities
	Fixed Assets to Long-term Liabilities and Own funds	Fixed Assets/(Long term liabilities+Own funds)
	Bank loans to Total Assets	(Short term bank loans+Principal Installments and interest payments of long term bank loans+Long-term bank loans)/Total assets
	Short-term bank loans to Short-term Liabilities	(Short term bank loans+Principal Installments and interest payments of long term bank loans)/Short term Liabilities
	Current Assets/Total Assets	Current Assets/Total Assets
	Tangible Fixed Assets/Total Assets	Tangible Fixed Assets (Net)/Total Assets
	Exports/Net Sales	Exports/Net Sales
Turnover ratios	Inventory Turnover	Cost of goods sold/(Previous Year's Inventory+Current Year's Inventory)/2
	Receivables Turnover	Net Sales/(Short term trade receivables+Long term trade receivables)
	Working Capital Turnover	Net Sales/Current Assets
	Net Working Capital Turnover	Net Sales/(Current Assets-Short term liabilities)
	Tangible Fixed Assets Turnover	Net Sales/Tangible Fixed Assets
	Fixed Assets Turnover	Net Sales/Fixed Assets
	Total Assets Turnover	Net Sales/Total Assets
Profitability ratios	Profit before interest and tax to Total Liabilities	(Profit Before Tax+Financing Expenses)/Total Liabilities
	Net Profit to Total Assets	Net Profit/Total Assets
	Operating Profit to Assets used in carrying out the operations	Operating Profit/(Total Assets-Financial Fixed Assets)
	Cumulative Profitability Ratio	Reserves from Retained Earnings/Total Assets
	Operating profit to Net sales	Operating profit/Net Sales
	Gross Profit to Net Sales	Gross profit/Net Sales
	Net Profit to Net Sales	Net Profit/Net Sales
	Cost of Goods Sold to Net Sales	Cost of Goods Sold/Net Sales
	Operating Expenses to Net Sales	Operating Expenses/Net Sales
	Interest Expenses to Net Sales	Financing Expenses/Net Sales
	Profit before Interest and Tax to Interest Expenses	(Profit Before Tax+Financing Expenses)/Financing Expenses
	Net profit and Interest Expenses to Interest Expenses	(Net Profit+Financing Expenses)/Financing Expenses
BACH ratios	Other financial assets and cash and bank/Total Assets	(Cash+Bank+Marketable Securities)/Total Assets
	Days Sales Outstanding	360*(Trade receivables-customer prepayments)/Net Sales
	Days Payables Outstanding	360*(Trade payables-advances to suppliers)/Cost of goods sold
WGA ratios	Net worth/Total Assets	(Equity-Intangible Assets)/Total Assets
	Self financing ability	Retained earnings/Total Assets
	Net indebtedness ratio	(Interest bearing borrowings-cash and cash equivalents)/Total Assets
	Growth-Change in revenue	(Revenue$_t$-Revenue$_{t-1}$)/Revenue$_{t-1}$
	Growth-Change in revenue and financial income	Revenue and Financial Income$_t$-Revenue and Financial Income$_{t-1}$/Revenue and Financial Income$_{t-1}$
	Growth-Change in equity	(Equity$_t$-Equity$_{t-1}$)/Equity$_{t-1}$
Size	Sales	Log of Net Sales
	Assets	Log of Total Assets
	Number of employees	Log of Total Number of Employees
Other variables	$CR_{intense}$	The total number of years that a firm appears in the credit registry
	$CR_{default}$	The total number of default events prior to time t
	Real GDP growth	Real GDP growth rate
	Inflation	Inflation rate
	Real effective exchange rate	Real effective exchange rate
	SME dummy	Dummy takes values of 1, 2, 3, 4 for large, small, micro and medium firms, respectively.
	Legal status dummy	Dummies for showing the legal status of each firm.
	Nace2 dummy	NACE Rev. 2 Classification sectoral codes

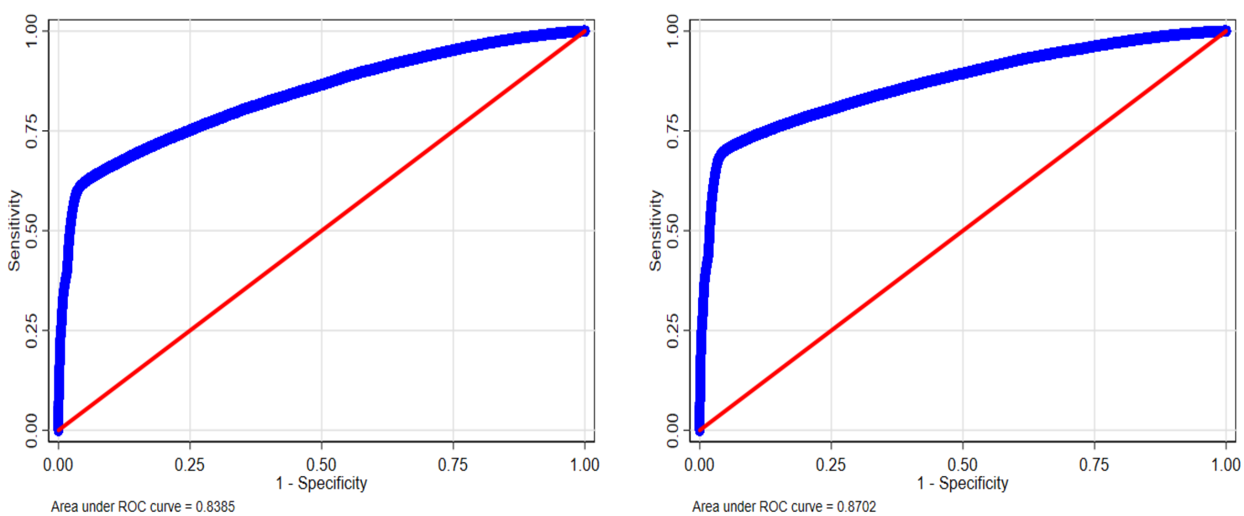
Table A2: Estimating Probability of Default (Dependent variable: $Default_{t+1}$).

Variables	Sign of Coefficient	Significance Level
Current Assets to Short Term Liabilities	+	*
Short-term Receivables to Total Assets	+	*
Total Liabilities to Total Assets	+	*
Short-term Liabilities to Total Liabilities	+	*
Tangible Fixed Assets to Long Term Liabilities	-	*
Bank Loans to Total Assets	+	*
Current Assets to Total Assets	+	*
Exports to Net Sales	-	*
Fixed Assets Turnover	+	*
Net Profit to Total Assets	-	*
Operating Profit to Net Sales	+	*
Days Sales Outstanding	+	*
Retained Earnings to Total Assets	-	*
Net Indebtedness Ratio	+	*
CR_intense	-	*
CR_default	+	*
Log(Number of Employees)	-	*
Real Effective Exchange Rate	+	*
Real GDP Growth Rate	-	*
Inflation Rate	+	*
Pseudo R Square	0.1477	
Area under ROC Curve (year 2016)	0.8702	
Sector Fixed Effects	YES	
Legal Status Fixed Effects	YES	
Firm Type Fixed Effects	YES	

*Notes: * denotes the 1% significance level. To estimate the general model of estimating the probability of default, we construct a panel data set for the period 2006-2015. We then estimate the coefficients using the best-fit model. We finally apply the estimated coefficients to the 2016 data and estimate the probability of default for 2017. Firm-type fixed effect is the SME dummy, which distinguishes between micro, small, medium, and large firms, and follows the KOSGEB definition.*

Figure A2: ROC Curves for the Estimated Logit Model

(a) ROC Curve for 2015 (b) ROC Curve for 2016

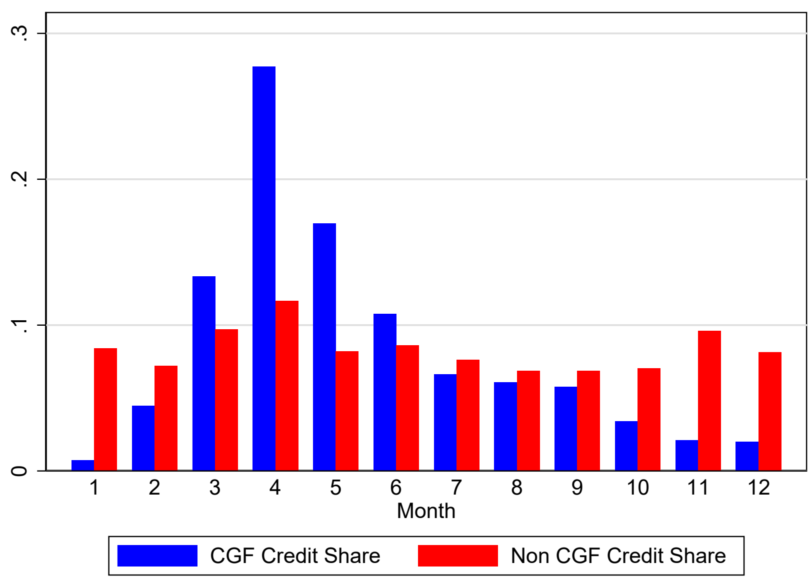


Source: Authors' calculation.

B Monthly Credit Distributions

In Figures A3 and A4, we present the distributions of monthly loan issuance by credit type (e.g., CGF vs non-CGF loans), firm size, and sector in 2017.[33] In particular, Figure A3 shows the monthly shares of loans issued under the CGF program and outside the program (non-CGF loans) in 2017. The figure implies that the general monthly credit issued under the CGF program follows a similar trend to the non-CGF loan issuance, except in the last quarter, as the CGF program reaches its capacity limits. Moreover, the figure also shows a significant jump in the credit issuance under the CGF program following the policy change in mid-March, where most of the CGF loans were issued in April and May of 2017. However, it is not clear whether this is due to the increase in program size or the eligibility criteria' relaxation. According to Figure A4b, the share of large firms increased significantly following the March revision, while the share of micro and SMEs significantly decreased. In fact, large firms continued to account for roughly 50 percent of the CGF-issued loans after the March revision that used to be less than 30 percent before the revision. On the other hand, following the revision in March, the manufacturing sector started to receive a larger share of monthly CGF flows, while the portion of the loans going to the wholesale & trade sector started to shrink (Figure A4a).

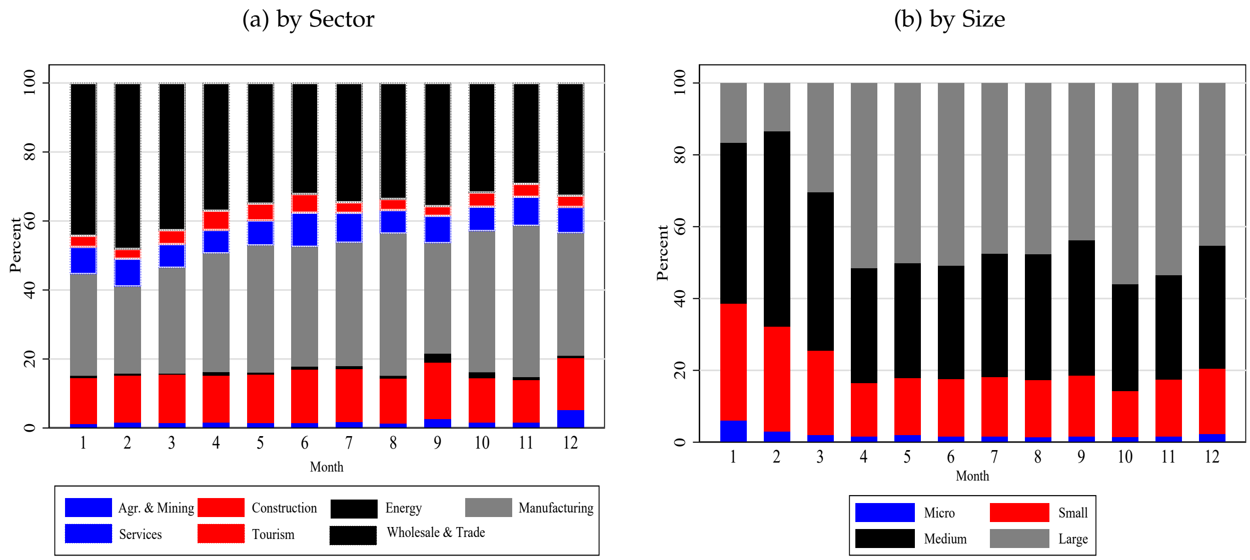
Figure A3: Monthly Credit Issuance by Credit Type in 2017



Source: Authors' calculation from the CGF, FTR, and CR databases.
Notes: The figure presents the distribution of monthly loan issuance by credit type.

[33]Firm size is based on the official KOSGEB definition.

Figure A4: Monthly CGF Credit Distribution by Sector and Size



Source: Authors' calculation from the CGF, FTR and CR databases.
Mean PD is calculated as the weighted average of each firm's PD by the monthly CGF credit amount given to each firm. Agr. & Mining represents the agriculture & mining sector.

Appendix B: Further Summary Statistics and Estimation Results

Table B1: SME Classification

Criteria	Micro-Sized Enterprise	Small-Sized Enterprise	Medium-Sized Enterprise
Number of Employees	< 10	< 50	< 250
Annual Net Sales Income	< 3 Million TL	< 25 Million TL	< 125 Million TL
Annual Financial Balance Sheet	< 3 Million TL	< 25 Million TL	< 125 Million TL

Source: KOSGEB.

Table B2: Summary Statistics for Evaluating the Monetary Impact of CGF Program

Groups	Employment	Net Sales (TL)	CGF Loan (TL)	Log (CGF Loan)	Default*	CGF Loan (TL)*
Panel A: Samples						
Main Sample (Sample 1 Without Filling)	29.7277	8,041,853	1,900,368	13.1318	0.0525	1,873,520
Sample 1 With Filling	29.4420	8,007,751	1,891,305	13.1380	0.0509	1,865,491
Sample 2 Without Filling	28.6315	7,730,147	1,844,216	13.1078	0.0522	1,817,498
Sample 2 With Filling	28.2833	7,685,197	1,831,971	13.1116	0.0505	1,805,972
Panel B: Sectors						
Agriculture & Mining	24.7922	6,205,479	1,984,643	13.4576	0.0481	1,979,288
Construction	24.0845	3,637,492	1,469,536	13.0735	0.0720	1,438,021
Energy	76.6158	15,811,098	4,632,290	14.0382	0.0353	4,739,057
Manufacturing	47.9288	13,535,572	3,302,894	13.4522	0.0481	3,245,630
Services	48.6620	4,589,208	1,194,232	12.8139	0.0429	1,186,240
Tourism	36.4432	3,354,719	2,221,998	12.9377	0.0539	2,194,594
Wholesale & Trade	14.2148	8,921,696	1,547,608	13.1154	0.0507	1,534,136
Panel C: Size						
Micro	3.1399	826,801	287,316	12.1057	0.0466	287,408
Small	12.4523	3,582,127	778,171	13.0117	0.0543	776,573
Medium	51.8505	16,469,682	3,041,200	14.3397	0.0558	3,030,481
Large	298.0270	70,156,368	19,694,438	16.0750	0.0547	19,590,850

Notes: Each column presents the mean values of the related variable for CGF-supported firms in each group for the year 2016 and Short-Run equation. "Short-Run" equation covers the impact of the program in 2018.
** We exclude the firms with at least one default event prior to receiving CGF loan in 2017; hence, we have a smaller sample for the regressions with default outcomes, although the total number of such firms is not much. Moreover, in order to make ex-post estimations in terms of firm default, we present the mean default rate for CGF and non-CGF firms in 2018 different from the other variables.*

Table B3: Robustness Test 1 (Sample 1 with Filling): The CGF Program's Effect on Firm Performance, Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales
Panel A: Very Short-Run						
POSTxCGF	0.21349***	0.18550***	0.17815***	0.86701***	0.75683***	0.70596***
	(0.00324)	(0.00306)	(0.00310)	(0.01401)	(0.01261)	(0.01336)
CGF	-0.00656*	-0.05032***		0.00496***	-0.16731***	
	(0.00380)	(0.00389)		(0.00180)	(0.00362)	
Non CGF credit		0.03226***	0.04021***		0.12698***	0.18496***
		(0.00054)	(0.00053)		(0.00199)	(0.00270)
Observations	382,500	382,500	382,500	382,500	382,500	382,500
R-squared	0.78782	0.79377	0.93157	0.65324	0.67313	0.72732
Panel B: Short-Run						
POSTxCGF	0.25488***	0.20304***	0.18897***	1.30779***	1.06315***	0.94342***
	(0.00441)	(0.00424)	(0.00418)	(0.02065)	(0.01877)	(0.01933)
CGF	0.02082***	-0.04934***		0.02234***	-0.30877***	
	(0.00405)	(0.00424)		(0.00220)	(0.00621)	
Non CGF credit		0.04516***	0.05682***		0.21313***	0.31082***
		(0.00074)	(0.00087)		(0.00321)	(0.00459)
Observations	255,000	255,000	255,000	255,000	255,000	255,000
R-squared	0.75148	0.76046	0.91535	0.53372	0.56371	0.71636

*Notes: Columns 3 and 6 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors are in parentheses. All dependent variables are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Very Short-Run" covers the impact of the program only in 2017, while "Short-Run" covers the impact of the program in 2018.*

Table B4: Robustness Test 2 (Sample 2 without Filling): The CGF Program's Effect on Firm Performance, Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Very Short-Run									
POSTxCGF	0.16280***	0.14604***	0.14013***	0.52275***	0.46912***	0.43531***	-0.02925***	-0.02881***	-0.02848***
	(0.00290)	(0.00286)	(0.00295)	(0.01095)	(0.01060)	(0.01199)	(0.00085)	(0.00085)	(0.00085)
CGF	-0.01195***	-0.04508***		0.00686***	-0.09917***		-0.00005	0.00092***	
	(0.00374)	(0.00382)		(0.00174)	(0.00281)		(0.00004)	(0.00008)	
Non CGF credit		0.02434***	0.03068***		0.07790***	0.12018***		-0.00071***	-0.00183***
		(0.00047)	(0.00042)		(0.00146)	(0.00201)		(0.00005)	(0.00008)
Observations	386,606	386,606	386,606	386,606	386,606	386,606	375,652	375,652	375,652
R-squared	0.80023	0.80363	0.93854	0.71675	0.72451	0.76369	0.19271	0.19330	0.35823
Panel B: Short-Run									
POSTxCGF	0.18134***	0.15376***	0.14372***	0.74945***	0.65293***	0.59747***	-0.00502***	-0.00452***	-0.00200
	(0.00381)	(0.00376)	(0.00380)	(0.01524)	(0.01452)	(0.01584)	(0.00129)	(0.00129)	(0.00128)
CGF	0.01063***	-0.03804***		0.02212***	-0.14820***		-0.00015	0.00080***	
	(0.00401)	(0.00418)		(0.00203)	(0.00441)		(0.00009)	(0.00020)	
Non CGF credit		0.03155***	0.04299***		0.11042***	0.17352***		-0.00061***	-0.00368***
		(0.00065)	(0.00073)		(0.00232)	(0.00358)		(0.00012)	(0.00019)
Observations	248,824	248,824	248,824	248,824	248,824	248,824	243,260	243,260	243,260
R-squared	0.78007	0.78448	0.93077	0.63278	0.64328	0.75487	0.27688	0.27698	0.51839

*Notes: Columns 3-6-9 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors are in parentheses. All dependent variables except Exit are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Very Short-Run" covers the impact of the program only in 2017, while "Short-Run" covers the impact of the program in 2018.*

Table B5: Robustness Test 3 (Sample 2 with Filling): The CGF Program's Effect on Firm Performance, Binary Treatment

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales
Panel A: Very Short-Run						
POSTxCGF	0.21795***	0.18615***	0.17670***	0.90370***	0.77653***	0.71384***
	(0.00322)	(0.00304)	(0.00307)	(0.01397)	(0.01256)	(0.01350)
CGF	-0.00551	-0.05044***		0.00578***	-0.17393***	
	(0.00373)	(0.00381)		(0.00179)	(0.00358)	
Non CGF credit		0.03302***	0.04146***		0.13206***	0.19186***
		(0.00051)	(0.00051)		(0.00192)	(0.00261)
Observations	397,284	397,284	397,284	397,284	397,284	397,284
R-squared	0.78656	0.79298	0.93030	0.65811	0.67859	0.73401
Panel B: Short-Run						
POSTxCGF	0.26367***	0.20345***	0.18602***	1.35473***	1.07339***	0.94660***
	(0.00435)	(0.00418)	(0.00417)	(0.02048)	(0.01862)	(0.01966)
CGF	0.02140***	-0.05256***		0.02301***	-0.32254***	
	(0.00393)	(0.00411)		(0.00221)	(0.00611)	
Non CGF credit		0.04770***	0.06102***		0.22287***	0.31853***
		(0.00069)	(0.00080)		(0.00304)	(0.00423)
Observations	269,784	269,784	269,784	269,784	269,784	269,784
R-squared	0.74756	0.75830	0.91155	0.53937	0.57176	0.71695

*Notes: Columns 3 and 6 include firm fixed effect instead of pair fixed effect. The sector-time and province-time fixed effects are included in all specifications to control for overtime industry and province-specific shifts. Robust standard errors are in parentheses. All dependent variables are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Short-Run" covers the impact of the program in 2018.*

Table B6: Sectoral Impact of CGF Program in the Short-Run: Binary Treatment for Main Variables–Other Sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent Variables:	Employment	Employment	Employment	Sales	Sales	Sales	Default	Default	Default
Panel A: Energy									
POSTxCGF	0.16133**	0.10364	0.12007	1.76736***	1.14783***	0.91167*	0.01253	0.01080	0.01498
	(0.08169)	(0.08439)	(0.08459)	(0.43486)	(0.37792)	(0.52390)	(0.02567)	(0.02657)	(0.02706)
CGF	0.12844	0.08595		-0.31220**	-0.76853***		-0.00014	-0.00144	
	(0.10817)	(0.10674)		(0.15715)	(0.18109)		(0.00343)	(0.00387)	
Non CGF credit		0.03114***	0.03721***		0.33439***	0.47134***		0.00093	-0.00114
		(0.01024)	(0.00769)		(0.06002)	(0.07665)		(0.00166)	(0.00214)
Observations	760	760	760	760	760	760	736	736	736
R-squared	0.89747	0.89989	0.96429	0.84335	0.86453	0.90309	0.37539	0.37572	0.58059
Panel B: Agriculture & Mining									
POSTxCGF	0.13157***	0.11347***	0.11069***	0.99692***	0.93321***	0.85695***	0.01552	0.01591	0.01586
	(0.03005)	(0.02997)	(0.02960)	(0.15094)	(0.14775)	(0.14737)	(0.01058)	(0.01065)	(0.01072)
CGF	-0.04630	-0.09092***		0.01511	-0.14197***		-0.00275*	-0.00177	
	(0.03122)	(0.03267)		(0.02864)	(0.04522)		(0.00166)	(0.00236)	
Non CGF credit		0.02410***	0.02681***		0.08485***	0.13147***		-0.00053	-0.00170
		(0.00533)	(0.00516)		(0.01914)	(0.03045)		(0.00101)	(0.00173)
Observations	3,580	3,580	3,580	3,580	3,580	3,580	3,492	3,492	3,492
R-squared	0.83432	0.83685	0.94957	0.70338	0.70812	0.81087	0.31628	0.31637	0.54139

*Notes: Columns 3-6-9 include firm fixed effect instead of pair fixed effect. Robust standard errors are in parentheses. All dependent variables except Exit are in logarithmic form. *** p<0.01, ** p<0.05, * p<0.1. "Short-Run" covers the impact of the program in 2018.*