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DISCUSSION PAPER

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The COVID-19 Insolvency Gap: First-Round Effects of Policy Responses on SMEs

The COVID-19 Insolvency Gap: First-round Effects of Policy Responses on SMEs

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Abstract COVID-19 placed a special role to fiscal policy in rescuing companies short of liquidity from insolvency. In the first months of the crisis, SMEs as the backbone of Europe's real economy benefited from large and mainly indiscriminate aid measures. Avoiding business failures in a whatever it takes fashion contrasts, however, with the cleansing mechanism of economic crises: a mechanism which forces unviable firms out of the market, thereby reallocating resources efficiently. By focusing on firms' pre-crisis financial standing, we estimate the extent to which the policy response induced an insolvency gap and analyze whether the gap is characterized by firms which had already struggled before the pandemic. With the policy measures being focused on smaller firms, we also examine whether this insolvency gap differs with respect to firm size. Based on credit rating and insolvency data for the near universe of actively rated German firms, our results suggest that the policy response to COVID-19 has triggered a backlog of insolvencies in Germany that is particularly pronounced among financially weak, small firms, having potential long term implications on economic recovery.

Keywords: COVID-19 policy response, Corporate bankruptcy, Cleansing effect, SMEs

JEL: C83, G33, H12, O38

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1. Introduction

COVID-19 and its unprecedented economic impacts have ground economies worldwide to a halt. With the early lockdown measures in place to contain the spread of the virus, many firms faced a situation of reduced business activity and declining sales, which had immediate consequences on their liquidity positions. Both the negative demand shock paired with a negative supply shock in most industries have indeed brought numerous firms under strong pressure in keeping their operations alive. Previous crises have taught that smaller companies are particularly prone to considerable liquidity constraints in deep recessions. For example, literature on the financial crisis of 2007–2009 shows that especially small and entrepreneurial enterprises were exposed to severe liquidity shocks due to the collapse of the interbank market and its negative impact on corporate lending (Iyer et al. 2014; McGuinness and Hogan 2016). While in the Great Recession a large contraction in corporate lending caused a severe liquidity squeeze in the real economy hitting smaller firms disproportionately hard (Buckley 2011), the major impact of the combined negative supply and demand shock in the COVID-19 crisis is also characterized by a deep liquidity shock in the real sector. Drop of trading activities and lack of business revenues made many firms dependent on their cash reserves in order to meet their unchanged fixed cost obligations. As smaller companies are characterized by strong dependence on internally generated funds to capitalize their business and provide the liquidity needed to finance day-to-day operations, both their cash reserves and collateral for external financing are generally limited (Cowling et al. 2011). In times of financial distress as in the current COVID-19 crisis, this makes small ventures particularly vulnerable candidates for financial insolvency. Trapped in a situation of thin financial reserves and lack of collateral for drawing new credit lines, small businesses face therefore a particularly high risk of business failure without the relief through policy intervention.

Conscious of the far-reaching consequences of systematic business failures, governments in almost all countries have initiated a series of emergency measures to strengthen liquidity positions of their national companies (International Monetary Fund 2020), some of which exclusively focusing on the relief of Small and Medium-sized Enterprises (SMEs) (OECD 2020). In the European Union (EU), for instance, member states' liquidity support in form of public loan guarantees and tax deferrals for distressed sectors has increased by an estimated 6 percentage points (pp) of EU GDP compared to pre-crisis levels (Council of the European Union 2020). While fiscal policy measures in most countries have gone beyond deferrals and loan guarantees, including instruments such as wage subsidies or adjustments in bankruptcy regimes, these measures were undoubtedly necessary to keep a struggling economy afloat and avoid large-scale insolvencies. However, since the COVID-19 crisis required a rapid policy response, it is reasonable to assume that few, if any, screening mechanisms could be implemented based on firms' pre-crisis financial position. Thus, evaluating the viability of firms that received early state aid has been very limited. In fact, the fast growing literature on business failures in response to the adverse economic impacts of COVID-19 stresses that the early assistance packages may bare high economic costs if they keep unviable firms alive (Kalemli-Ozcan et al. 2020; Barrero et al. 2020; Cowling et al. 2011; Juergensen et al. 2020; OECD n.d.).

We argue that the early policy measures in most countries were poorly targeted large-scale interventions to prevent bankruptcies in a 'whatever it takes' fashion. Even though we acknowledge that it is difficult for policy-makers to determine whether a firm's finances are strained because of the pandemic or because of other circumstances predating this crisis, undifferentiated relief measures can be costly in many respects. Kalemli-Ozcan et al. (2020) provide an early contribution in assessing the costs associated with poorly targeted policy measures in response to COVID-19. In their analysis, they distinguish between 'survivor', 'viable' and 'ghost' firms with the latter characterized as companies which would have failed even without being exposed to the adverse COVID-19 shock. In their simple cost minimization model, comprising data of 17 European countries, they find that without proper targeting of policy instruments, the costs of intervention are substantially higher compared to a scenario in which measures target 'viable' firms only (Kalemli-Ozcan et al. 2020).[1]

Despite the direct fiscal costs that come along with undifferentiated policy interventions there is another source of economic costs associated with keeping unviable firms alive. In Schumpeterian economics, it may also impede the cleansing effect of creative destruc-

[1]Moreover, their findings suggest that 19% of 'ghost' firms are kept alive in case of undifferentiated intervention (Kalemli-Ozcan et al. 2020).

tion (Guerini et al. 2020). The cleansing effect of creative destruction describes a process in which resources are reallocated from less efficient and less creative firms to more efficient ones enhancing overall economic productivity and innovation (Schumpeter 1942). Typically, this process of efficient resource reallocation is particularly strong in times of economic crisis, allowing viable and innovative firms to gain market share as unprofitable firms exit the market (Caballero and Hammour 1994; Archibugi et al. 2013; Carreira and Teixeira 2016). As such, without the intervention of fiscal policy, business failures of unviable firms are expected to be substantial in economic recessions and, given the strong vulnerability of small firms, the effect is expected to be particularly pronounced among smaller businesses. In the current crisis however, there is growing public concern that this process of creative destruction and 'cleaning up' of unviable firms is seriously hampered by an increasing policy-induced 'zombification' of the economy (see, for example, The Economist (2020a), Financial Times (2020), The Japan Times (2020), The Washington Post (2020)). Even though we do not want to go as far as speaking of a zombification, we still hypothesize that the first-round policy measures with strong focus on SME relief induced a serious *insolvency gap*, defined as backlog of corporate insolvencies which are usually to be expected in a crisis such as this. Looking at corporate insolvency numbers after the outbreak of the crisis for selected countries, it becomes indeed apparent that insolvencies strongly decreased compared to 2019 levels (see Appendix A). The observation that bankruptcy filings are lower in an economic crisis than in non-crisis times appears counter-intuitive at first and underpins that the large-scale governmental support programs have led to substantial distortions.

Making use of unique credit rating and insolvency data, the central purpose of this paper is to analyze whether indeed such an insolvency gap exists and by which companies it is mainly driven. Our hypothesis is that the risk of unviable 'survivors' is particularly severe among mainly small and micro companies as they tend to be particularly prone to liquidity shortages in times of crises and therefore benefit most from state support compared to a situation in which the policy maker does not step in. The strong policy focus on SMEs reinforces this hypothesis (OECD 2020). Finally, the prolonged expansion prior to the COVID-19 pandemic and the low interest rate environment suggest that a significant number of financially weak companies that were already on the brink of bankruptcy before the onset of the crisis have accumulated over time (Barrero et al. 2020). Given this interplay between prolonged expansion and sudden economic decline with strong policy response, it is likely that the insolvency gap is driven by firms with weak financial pre-crisis conditions.

Our contribution to the fast growing literature on the economic effects of the COVID-19 crisis is manifold. First, we examine the heterogeneity with respect to firm size in policy makers' response to the risk of large-scale business failures. By doing so we focus on Germany, a country where SME state support is particularly strong by international comparison (Anderson et al. 2020; OECD 2020). Building on Schumpeter's theory of the cleansing effect in economic crises, undifferentiated first-round policies in the current crisis may have favored unviable firms to stay in the market, hampering the release and efficient reallocation of resources. We transfer this theoretical concept into an empirical assessment by estimating a COVID-19-induced insolvency gap using firm-specific credit rating data combined with information on insolvency filings. Controlling for updates in a firm's credit rating, we estimate insolvency rates after the COVID-19 outbreak in a counterfactual setting of no policy intervention. Comparable firms with closely matching changes in their credit rating in non-crises times are used as control group. Hence, we estimate the insolvency gap induced by COVID-19-related policy measures using a potential outcome setting. As the COVID-19 pandemic hits sectors asymmetrically[2] and policy measures were relatively more generous to micro and SMEs businesses[3], we conduct the insolvency gap estimation at the sector-size-level. Unlike Kalemli-Ozcan et al.'s (2020) work, our contribution builds upon a representative sample with respect to firm size allowing a nuanced differentiation between medium-sized, small and micro-enterprises.

The remainder of the paper proceeds as follows. In Section 2 we discuss the fiscal policy responses to the COVID-19 outbreak in Germany emphasizing their different focus with respect to firm size. Section 3 introduces the data sources and variables used to estimate the insolvency gap. Moreover, the matching framework for the matching of counterfac-

[2]See Section 4.1 for a survey-based examination of the negative economic impacts of the pandemic on German firms controlling, among other factors, on the firms sector affiliation. The results suggest heterogeneous effects across sectors.

[3]See Section 2 for an assessment how state response to the COVID-19 crisis differs with respect to firm size.

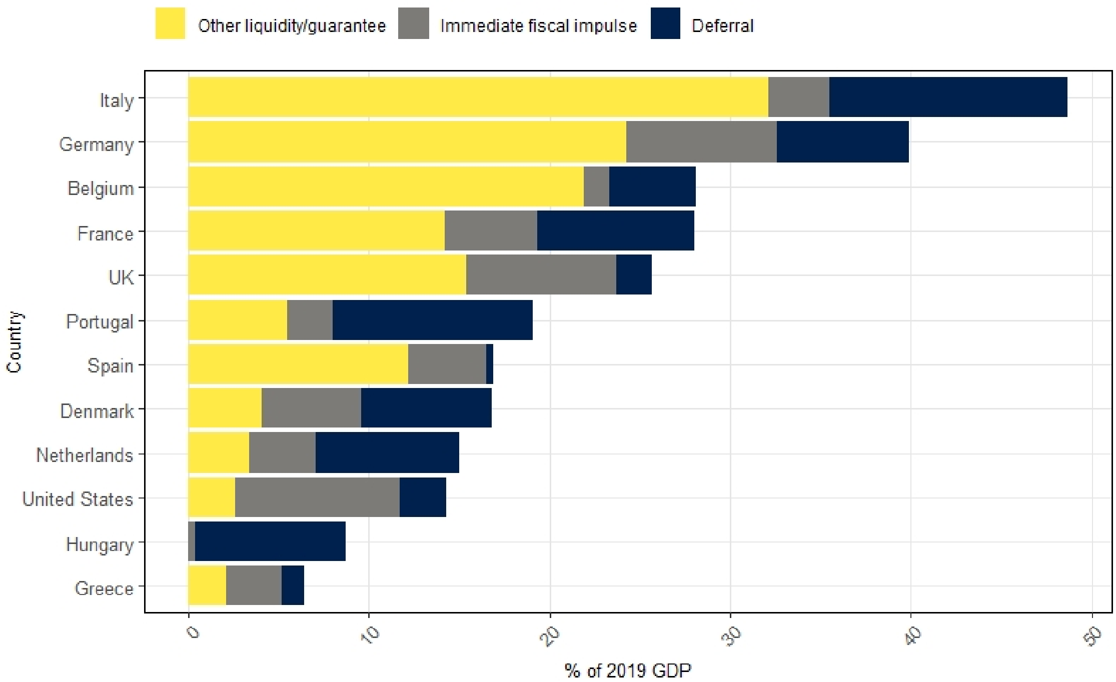
tual survival states is introduced. Section 4 empirically examines the heterogeneity of the economic effects of the COVID-19 pandemic across firms of different size and sector affiliation. Ultimately, it presents the empirical results of the insolvency gap estimation and discusses its implications. Section 5 concludes.

2. Fiscal policy response in Germany

Official figures show that in Germany, the fiscal policy response to prevent corporate insolvencies due to crisis-related liquidity bottlenecks is particularly pronounced by international comparison. According to a comparative study of the economic think tank Bruegel analyzing the fiscal response to the economic fallout from the pandemic, nearly 40% of Germany's 2019 GDP was spent on COVID-19 measures to strengthen companies' liquidity positions (Anderson et al. 2020). Compared with a number of selected Organization of Economic Cooperation and Development (OECD) countries, this is the second strongest response in terms of a country's overall economic performance (see Figure 1). The German Federal Government itself describes the response as the 'largest assistance package in the history of the Federal Republic of Germany' (Federal Ministry of Finance 2020d, p. 3).

From a small business economics view it is interesting to see that many of the intervention measures adopted by the German Federal Government have been specifically designed to target SMEs (OECD 2020). For example, in immediate response to the early lockdown measures, the government granted one-off cash injections for self-employed persons and micro-businesses with up to 10 employees ('Soforthilfen') in form of a stimulus package worth €50 billion (Federal Government of Germany 2020). These immediate subsidies have been accompanied by the provision of loans from Germany's government-owned promotional bank KfW for which the government assumes 100% of the credit risk ('KfW-Schnellkredite'). The volume of the loan program and the related government guarantees are potentially unlimited and they were designed to improve liquidity positions especially of SMEs (Federal Ministry of Finance 2020d). Moreover, as part of a large-scale stimulus package worth €25 billion, SMEs that had to cease or severely restrict their business operations in the wake of the COVID-19 pandemic have become eligible for state-financed liquidity support ('Überbrückungshilfen') covering a substantial part of their fixed oper-

Figure 1 COVID-19 fiscal policy response by international comparison



Note: Calculations are retrieved from Anderson et al. (2020). Numbers reflect the amount (as share of 2019 GDP) of policy measures to address adverse COVID-19 impacts on companies for selected OECD countries. Numbers are as of by 18 November 2020.

ating costs (Federal Ministry of Finance 2020c). In the following, we describe the fiscal policy instruments to counter the economic impacts of the COVID-19 crisis in more detail, focusing on how the instruments differ with respect to firm size.

Liquidity subsidies and government guarantees

The most important instrument is the provision of liquidity, either through direct cash transfers like the aforementioned 'Überbrückungshilfen' or through loans backed by public guarantees. The extent of liquidity support is primarily determined by company size, measured by the number of employees or previous revenues. In case of the one-off grants, for instance, only micro-firms with up to 10 employees were eligible to receive injections between €9,000 and €15,000 for three months to cover their operational costs (Federal Ministry of Finance 2020d). This support was granted in a non-bureaucratic fashion easily accessible to all micro-businesses which assured that they were suffering financial distress as a result of the COVID-19 pandemic (Federal Government of Germany 2020).

For SMEs with more than 10 employees the KfW Instant Loan Program has been launched. The program offers SMEs loans that are fully collateralized by the state. These loans amount up to 25% of a firm's 2019 revenues with a cap of €500k for small companies and €800k for medium-sized companies, respectively. No credit risk assessments are taking place and no collaterals are required. The only eligibility criterion is that the company was profitable in 2019 or at least on average profitable between 2017 and 2019 (Federal Ministry for Economic Affairs and Energy 2020). This fairly broad criterion shows that the process is focused on speed and ease applied 'without red tape' Federal Ministry of Finance (2020b, p. 1) and not on elaborate screening mechanisms that could prevent providing liquidity to unviable firms.

Furthermore, the COVID-19 support package includes additional government guarantees on loans for both small and larger businesses. Similar to the Instant Loan Program, the loans are channeled through commercial banks and the state-owned bank KfW assumes risk coverage of 80% for large enterprises and 90% for SMEs with a highly simplified risk assessment (Federal Ministry of Finance 2020a). In addition, interest rates are lower for SMEs than for large firms (Federal Ministry for Economic Affairs and Energy 2020). This makes lending to SMEs particularly attractive for commercial banks and, given that they only bear 10% of the risk, further reduces the need for a comprehensive risk assessment.

Short-time work (STW) scheme

Another form of liquidity support to companies is the use of short-time compensations ('Kurzarbeitergeld') which are direct subsidies on firms' labor costs. This instrument has been available for quite some time; however, it's eligibility criteria were relaxed in the pandemic. Now companies with only 10% of employees being on STW qualify for a wage subsidy (instead of one third) (OECD n.d.). In addition, the subsidy has been increased compared to pre-crisis levels, ranging now from 60% to 87% of the worker's last net income. From the company's perspective, short-time compensations reduce labor costs, allow the company to retain specific human capital and avoid the costs of new hires and training when the economy recovers again. Drawing on literature from the Great Recession, the usage of STW has a positive impact on firm survival (Cahuc et al. 2018; Kopp and Siegenthaler 2020) but at the same time low productivity firms have been much more likely to take up STW (Giupponi and Landais 2018, 2020). From a welfare perspective, this may have adverse effects as it impedes the reallocation of workers from low- to high-productivity firms. Moreover, SMEs tend to be active in more labor-intense business activities than larger firms (Yang and Chen 2009). Therefore, it is reasonable to assume that SMEs as well as labor-intense sectors benefit disproportionately from short-time compensations. Since the eligibility criteria for STW are unrelated to firms' pre-crisis performance, also unviable companies benefit from the instrument.

Tax deferrals

To further improve the liquidity situation of companies, authorities have granted tax payment deferrals, allowed lower tax prepayments and suspended enforcement measures for tax debts. The tax-related assistance amounts to an estimated €250 billion and the policy measure applies equally to all company size classes (Anderson et al. 2020).

Temporary change in insolvency law

Finally, the Federal Government enacted a temporary amendment to the German insolvency law that is closely related to the possible existence of a policy-induced insolvency gap. On March 27, 2020, it decided to temporarily suspend the insolvency filing obligation in order to avoid a massive increase in insolvencies as a result of COVID-19-induced liquidity shortages. The obligation to file an insolvency has been suspended until September 30th, 2020, with an adjusted extension until the end of 2020. This suspension enables both small and large companies to avert insolvency and possibly survive the crisis by taking advantage of state aid (Federal Ministry of Justice and Consumer Protection 2020). Although the amended law stipulates that only those firms that are insolvent or over-indebted due to the COVID-19 pandemic are temporarily exempt from insolvency proceedings, policy makers face the dilemma that it is barely possible to assess whether insolvent *non-filers* fulfill these eligibility criterion. This is particularly true for smaller firms, whose limited disclosure requirements make such an assessment even harder. While there is no doubt that many viable companies facing illiquidity and over-indebtedness as a result of the economic shock will benefit from the change in the law, it also creates loopholes for smaller, non-viable companies to stay in the market and absorb liquidity subsidies.

This section has highlighted the role of fiscal policy to counter the economic consequences of the pandemic in Germany - a country that has provided substantial assistance to businesses to avoid large-scale bankruptcies. While the suspension of the insolvency filing requirement is the driving force behind our assumption of an existing insolvency gap, direct and indirect liquidity subsidies are likely to work in the same direction. Especially for companies that do not meet the eligibility criteria for the insolvency exemption, the provision of liquidity by the state can nevertheless save ailing companies from failure. It has been shown that many of the policies directly target SMEs or provide indirect channels for small businesses to benefit disproportionately. This comes at the potential risk that unviable firms are kept alive, ultimately leading to a possible backlog in insolvencies which is likely to be particularly pronounced among SMEs. In the next section, we introduce the data and methodology we use to estimate the existence and extent of such an insolvency gap.

3. Data, variables and methodology

3.1. Data and variables

The study makes use of two data sources which both originate from the Mannheim Enterprise Panel (MUP) covering the near universe of economically active firms in Germany (Bersch et al. 2014). The first data source is a survey where the questioned companies have been sampled from the MUP. The survey is used to examine how companies of different size and in different sectors are affected by the adverse impacts of the COVID-19 pandemic and motivates why we estimate the insolvency gap distinguishing between sector affiliation and company size. For the estimation of the insolvency gap we use a second data source: a large sample of firm-specific credit rating information along with information concerning the firms' insolvency status. In the following, we will introduce both data sets and the variables used in this study in more detail.

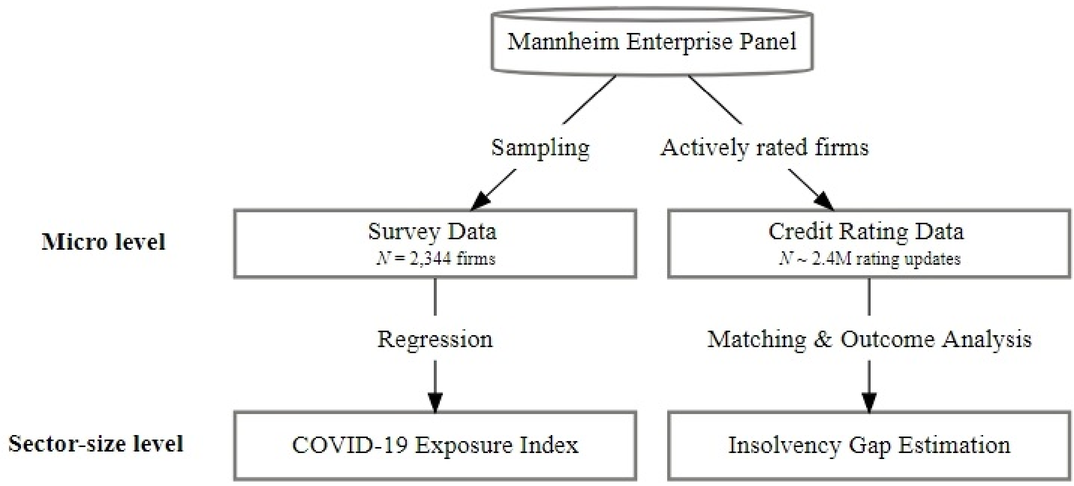
3.1.1. Survey data

We employ the survey to primarily assess which industries and company sizes are affected most by the crisis.[4] Based on a representative random sample of German companies, drawn from the MUP and stratified by firm size and industry affiliation[5], the survey was conducted three times spanning the period in which the German insolvency regime was

[4] The survey has been conducted as part of a joint research project between the German Federal Ministry of Economic Affairs (BMWi), the polling agency Kantar and the Centre for European Economic Research (ZEW).

[5] Table 2 shows the stratification criteria used in the subsequent analysis.

Figure 2 Data sources used in this study



Note: Observations of the survey data (companies) and credit rating data (firm-specific rating revisions) originate from the Mannheim Enterprise Panel (MUP) data base. Survey data allows to estimate exposure to adverse effects of the pandemic on the sector-size level. Credit rating data is used to estimate the existence of an insolvency gap on the sector-size level.

fully suspended.[6] The survey includes questions on COVID-19-related economic effects on various business dimensions. The collected data has then been supplemented with credit rating scores from the MUP, which allows to control for the financial situation of the companies prior to the crisis. As shown in Figure 2, we use the survey data to investigate whether the adverse economic impacts of COVID-19 differ across sectors and firm size classes. These results together with the heterogeneity in public aid programs with respect to firm size as outlined in Section 2 motivates us to conduct our main empirical analysis at the sector-size level.

Table 1 shows summary statistics of the relevant variables used to construct a COVID-19 Exposure Index, CEI, reflecting the extent to which firms experienced negative impacts in relation to the pandemic. Firms were asked on a Lickert scale of 0 to 4 in which of the following areas they experienced negative impacts as a result of the COVID-19 crisis: (1) decrease in demand (2) shutdown of production (3) supply chain interruption (4) staffing shortage (5) logistical difficulties (6) liquidity shortfalls.[7] From these six questions we

[6]The surveys have been conducted in April 2020, in June 2020 and in September 2020 spanning the period of the full suspension of the obligation to file for insolvencies and is therefore particularly suitable for capturing the policy induced effects of the crisis.

[7]0 indicates no negative effects, 4 signals strong negative effects.

construct CEI as simple sum of the response values. The average index is 6.312 out of a maximum possible value of 24. The most common and most severe impact relates to the decline in demand, where respondents reported an average negative impact of 1.851. Shutdown of production facilities and liquidity bottlenecks are also frequently mentioned consequences. Table 1 also displays size and sector dummies which will later be used as stratification criteria in the estimation of the insolvency gap.

Table 1 Descriptive statistics: Survey data

Variables	N	Mean	SD	Min	Max
COVID-19 Exposure Index (CEI)	2,344	6.312	5.397	0	24
Questions used for COVID-19 Exposure Index calculation					
(1) Decrease in demand	2,344	1.851	1.556	0	4
(2) Lockdown of production	2,344	1.048	1.583	0	4
(3) Supply chain interrupted	2,344	0.875	1.236	0	4
(4) Staffing shortage	2,344	0.639	1.044	0	4
(5) Logistical difficulties	2,344	0.813	1.277	0	4
(6) Liquidity shortfalls	2,344	1.084	1.414	0	4
Size of company					
Micro-enterprise	2,344	0.394	0.489	0	1
Small enterprise	2,344	0.300	0.459	0	1
Medium-sized enterprise	2,344	0.204	0.403	0	1
Large enterprise	2,344	0.102	0.302	0	1
Sector affiliation					
Mechanical engineering	2,344	0.081	0.273	0	1
Chemicals & pharmaceuticals	2,344	0.058	0.235	0	1
Data processing equipment	2,344	0.061	0.241	0	1
Food production	2,344	0.071	0.258	0	1
Other manufacturing industries	2,344	0.121	0.326	0	1
Wholesale & retail trade	2,344	0.112	0.316	0	1
Accommodation & catering	2,344	0.060	0.239	0	1
Insurance & banking	2,344	0.063	0.243	0	1
Creative industry & entertainment	2,344	0.061	0.240	0	1
Other business-related services	2,344	0.140	0.347	0	1
Health and social services	2,344	0.095	0.293	0	1

Note: Table shows descriptive statistics of the COVID-19 Exposure Index (CEI). It also displays statistics of the survey questions used to construct the index. Ultimately, the size and sector distribution in the survey data is shown.

3.1.2. Credit rating data

For the purpose of estimating whether the bankruptcy filing behavior has changed significantly as a result of the crisis-related aid measures and possibly created a backlog of insolvencies, we examine credit rating updates of close to all economically active firms listed in the MUP.[8] The Mannheim Enterprise Panel is particularly suited for an analysis of the insolvency-related cleansing effect as it is constructed by processing and structuring data collected by Creditreform, the leading credit agency in Germany. Creditreform regularly measures and updates the creditworthiness of German companies. Overall our sample comprises 2,373,782 credit rating updates of 1,500,764 distinct German businesses whose ratings were updated at least once during the last three years.[9] Table 2 shows that the sample of about 1.5 million companies is very diverse in its industry and size composition. Most important in the context of this study is the coverage of SMEs, which is not only representative for the German economy (Destatis 2020), but also allows for a nuanced differentiation between medium-sized, small and micro-enterprises. Therefore, it suits well to examine the policy-induced heterogeneity of the COVID-19 related effects on business failures with a special focus on possible size differences not only among SMEs and large enterprises but also within the group of SMEs. The latter estimation of the insolvency gap will be conducted on the sector-size level as displayed in Table 2 comprising $S = 52$ distinct sector-size strata.

Assuming that the COVID-19 shock and its economic consequences on liquidity and insolvency distress of German businesses began by the end of March 2020, we split our sample into a 'pre-crisis' period and a 'crisis' period. This cut-off point also captures COVID-19 policy dynamics as the German government imposed the first countrywide lockdown that includes a shutdown of most customer service-related businesses on March 22 and suspended the obligation to file for bankruptcy on March 27 (Federal Ministry of Justice and Consumer Protection 2020). Consequently, the pre-crisis period comprises all credit rating updates which took place between July 2017 and December 2019. The crisis period includes all observations between April 2020 and end of July 2020.[10] In the later estimation of the insolvency gap, rating updates from the pre-crisis period serve as pool of control observations. Closely matching credit rating updates from this pool are

[8] In our analysis a company is defined as economically active if it has received a credit rating update at least once over the last three years spanning the period from July 2017 to July 2020.

[9] We observe one and the same company at most three times in our sample. Thus, credit rating updates normally do not take place more often than once per year but may be conducted in a less regular cycle.

[10] Note that we exclude observations between January 2020 and March 2020 which we see as transitional phase in which assignment to either of the two periods is not straightforward. Also note that July 2020 is the latest month for which we observe credit rating information.

Table 2 Sample decomposition of credit rating data

Sector affiliation	**Size of company**				**Total** (sample)
	Micro	Small	Medium	Large	
Business-related services	89.4%	8.3%	1.9%	0.4%	28.6%
Manufacturing	84.9%	11.8%	2.7%	0.6%	22.5%
Wholesale & retail trade	83.1%	13.4%	2.9%	0.6%	19.9%
Health & social services	84.8%	10.6%	3.5%	1.1%	7.3%
Insurance & banking	93.6%	3.6%	1.8%	1.0%	4.5%
Accommodation & catering	88.5%	9.8%	1.6%	0.1%	4.1%
Logistics & transport	80.5%	15.3%	3.5%	0.7%	4.1%
Others	82.7%	10.2%	4.6%	2.5%	3.9%
Creative industry & entertainment	88.9%	8.8%	2.0%	0.3%	1.6%
Mechanical engineering	54.3%	27.5%	13.0%	5.2%	1.3%
Food production	64.3%	23.0%	10.3%	2.4%	1.0%
Chemicals & pharmaceuticals	49.1%	29.1%	16.5%	5.3%	0.7%
Manufacturing of data processing equipment	58.9%	26.7%	10.9%	3.5%	0.5%
Total (sample)	85.2%	11.1%	2.9%	0.8%	100%
Total (population)[a]	81.8%	15.1%	2.5%	0.6%	100%

Note: Table shows the company size distribution within sectors (rows) as well as the sector distribution (column 'Total (sample)') in our credit rating sample. Size classification is determined by number of employees, annual turnover and annual balance sheet total following the recommendation of the EU Commission (European Commission 2003) as outlined in Appendix B. Sector groups are built to reflect anecdotal heterogeneity in the context of COVID-19. Grouping of sectors is based on EU's NACE Revision 2 classification scheme (European Union 2006). In Appendix C an exact mapping of sector groups and NACE divisions can be found. In all sectors the fraction of SMEs lies far above 90% which makes the data particularly useful to analyze the effects of COVID-19-related policy responses on smaller firms. Also note that the overall size composition of our sample compares well against the official size distribution of the population of German active companies as reported by the Federal Statistical Office (Destatis 2020).
[a] Population size distribution according to official statistics of the Federal Statistical Office (Destatis 2020).

used to estimate counterfactual insolvency rates which will be compared against the actual insolvency rates observed after April 1, 2020.[11]

For the estimation of insolvency rates, we enrich our sample of firm-specific credit rating data with information on the firm's survival status after it has received an update on its rating. Information on firm-specific survival states is obtained by the online register for bankruptcy filings of the German Ministry of Justice. Besides information identifying the companies which have filed for insolvency, the register also contains the filing date, allowing

[11] Figure 3 provides an illustration of how closely matching observations from the pre-crisis period serve as controls for rating changes of firms in the crisis period.

us to match the most recent rating update that predates the filing date for that particular bankrupt firm. Our overall sample comprises 15,634 credit rating updates that were followed by an insolvency and 2,358,148 rating updates which did not result in an insolvency filing. With this data, we are able to estimate two statistics. First, we use this information to estimate bankruptcy rates after the COVID-19 outbreak on the sector-size-level based on firms for which we observe credit rating updates during the pandemic. Second, using comparable firms with closely matching credit rating updates in non-crises times as control group, we are able to estimate counterfactual insolvency rates also on the sector-size-level. Comparing observed insolvency rates with counterfactual insolvency rates within each of the sector-size strata allows us to obtain sector-size-specific estimates of the insolvency gap. In addition to firm size, industry affiliation, and credit rating update, we consider an extensive set of additional firm-specific variables when matching counterfactual survival states of pre-crisis observations with rating updates of firms observed in the COVID-19 period. In the following section, we introduce all of these matching variables and provide some descriptive statistics.

In our data used for the estimation of the insolvency gap firm survival status, f_{t+4}, serves as outcome variable. It is equal to 1 if the company has filed for insolvency no more than four months after its last rating update. If the firm has not gone bankrupt or it has filed insolvency more than four months after its latest rating update, it takes on the value 0. This means that we take four months as maximum time lag between a credit rating update and the date at which the respective firm has filed its bankruptcy to count the rating update as being predictive for the subsequent insolvency filing. We choose this threshold for two reasons. First, we want to ensure that the rating update has a high information content in predicting a potential insolvency filing. If the date of bankruptcy lies more than 4 months after the credit update, it is likely that the update does not reflect the reasons why the company went bankrupt. A more recent update of the firm's rating (if that existed) would be necessary to capture the company's financial deterioration that contributed to the subsequent insolvency. Second, the COVID-19 period for which we have information on credit rating updates spans 4 months from April 2020 to the end of July 2020. Thus, for the latest in-crisis rating updates in July 2020, we can observe the firm's survival status at most 4 months until November 2020 (the time of writing this paper). Therefore, the maximum forecasting horizon for the rating updates observed in the crisis period is limited to 4 months.

The most important variable in finding counterfactual survival states in the matching procedure is Creditreform's credit rating index since it is the basis for the calculation of the credit rating updates. The credit rating is calculated by Creditreform on the basis of a rich information set relevant to assess a company's creditworthiness. The metrics considered in calculating the rating include, among other things, information on the firm's payment discipline, its legal form, credit evaluations of banks, credit line limits and risk indicators based on the firm's financial accounts (if applicable) (Creditreform 2020b). Creditreform attaches different weights to these metrics according to their relevance on determining a firm's risk of credit default and calculates an overall credit rating score which ranges from 100 to 500.[12] The higher the score, the worse the firm's creditworthiness and thus the higher the risk of insolvency. In fact, Creditreform's solvency index has a high forecasting quality to assess a firm's credit default risk (Creditreform 2020b). Assuming that a high credit default risk signals financial distress, which often results in insolvency, we use Creditreform's credit rating as the basis for predicting corporate insolvency risk. The prediction of corporate bankruptcy via a scoring model goes back to the seminal work of Altman (1968) and his development of the Z-score model. Similar to Creditreform's credit rating index, the Z-score model relies on several accounting-based indicators which are weighted and summed to obtain an overall score. This score then forms the basis for classifying companies as insolvent or non-insolvent (Altman 2013). Today, this model approach is still used by many practitioners to predict firm insolvencies (Agarwal and Taffler 2008).

Based on the credit rating index, we construct the following variables. Our main predictor variable is the *update* in the rating index, Δr_t, which is defined as the difference of the new rating assigned by Creditreform an the rating before the update ($\Delta r_t = r_t - r_{t-x}$).[13] Given the logic of the rating index, a positive sign in the rating update reflects a down-

[12] The credit rating index suffers from a discontinuity as in case of a 'insufficient' creditworthiness it takes on a value of 600 (Creditreform 2020a). We truncate credit ratings of 600 to a value 500 - the worst possible rating in our analysis. We do so since our main predictor variable is the *update* in the rating index which can only be reasonably calculated if the index has continuous support.

[13] Reassessments of the rating is conducted in an irregular fashion such that the time between two updates, x, varies. On average, the time between two updates equals 20 months.

grade in financial solvency, a negative sign reflects an improvement in the rating, i.e. an upgrade of the company's financial standing. The amount of the down-/upgrade reflects how severely the company's financial standing has changed.[14]

Apart from the rating update, we also consider the rating before the upgrade, r_{t-x}, as a matching variable when predicting counterfactual insolvency states. This allows us to control for where the company is located in the rating distribution and consequently how high the default risk was before the down-/upgrade. Moreover, we form two additional variables from the firm's credit rating information, both of which control for the medium-term path of the firm's financial standing. First, we count the number of downgrades in the three years preceding the update at hand, d_t. Second, we calculate the average credit rating in the three years prior to the current update under consideration, $\bar{r}_t$.[15] Finally, we consider firm age, a_t, as further matching variable acknowledging that younger firms tend to be more prone to insolvency.

Table 3 shows descriptive statistics of the variables considered in the matching procedure. We see that an update which is followed by a bankruptcy filing relates to a downgrade of close to 70 scoring points on average. This is a substantial deterioration in the rating index compared to an update which is not followed by an insolvency filing. In fact, the difference in means between non-insolvency-related updates and insolvency-related updates, as reported in column 'Δ Mean', amounts to more than 65 index points and is statistically significant. For all other matching variables, we also find statistically meaningful differences suggesting that firms which go bankrupt have a worse credit rating both short-term and mid-term, have experienced more downgrades in the past and are younger on average. The economically and statistically significant differences between non-insolvency-related and insolvency-related credit updates across all variables suggest that they serve well as matching variables in a counterfactual estimation of insolvency

[14] Note that we define a rating update as a reassessment of the company's creditworthiness performed by Creditreform. We have precise information on the date of reassessment, which allows us to accurately assign the update to either the pre-crisis or the crisis period and also to accurately match the updates with insolvency dates. It should also be noted that a reassessment does not necessarily lead to a change in the rating index. If the creditworthiness of the company has not changed since the last rating, the company gets assigned the same index as before, resulting in a value of 0 in Δr_t.

[15] For example, for a credit rating observation in July 2017, we count how often the firm experienced a downgrade over the period June 2014 to June 2017 and also calculate the average rating over that period.

rates.

Table 3 Descriptive statistics: Non-insolvent observations & insolvent observations

Variable	non-insolvent					insolvent					Δ Mean
	N	N firms	Min	Mean	Max	N	N firms	Min	Mean	Max	
Predictor variables											
Credit rating update: Δr_t	2,358,148	1,489,376	-356	4.0099	351	15,634	15,634	-226	69.6892	359	−65.6793***
Credit rating (prior to update): r_{t-x}	2,358,148	1,489,376	100	266.5879	500	15,634	15,634	141	414.6607	500	−148.0728***
Number of downgrades (3-year horizon): d_t	2,358,148	1,489,376	0	0.4797	3	15,634	15,634	0	0.5051	3	−0.0254***
Average credit rating (3-year horizon): $\bar{r}_t$	2,358,148	1,489,376	100	265.8216	500	15,634	15,634	138	367.6691	500	−101.8475***
Company age: a_t	2,346,686	1,479,383	1	22.2604	1,017	15,166	15,166	1	13.3199	400	8.9405***

Note: Non-insolvent observations comprise credit rating updates which have not resulted in an insolvency filing in the first four months after filing. Insolvent observations include observations which have been followed by an insolvency filing in the first four months after filing. N refers to the number of rating updates, $N firm$ to the number of unique firms which experienced at least one rating update. Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

Table 4 Descriptive statistics: Pre-crisis observations & crisis observations

Variable	pre-crisis					crisis					Δ Mean
	N	N firms	Min	Mean	Max	N	N firms	Min	Mean	Max	
Outcome variable											
Survival status: f_{t+4}	2,036,103	1,377,671	0	0.0071	1	337,679	337,679	0	0.0033	1	0.0038***
Predictor variables											
Credit rating update: Δr_t	2,036,103	1,377,671	-356	3.9825	359	337,679	337,679	-293	7.2161	349	−3.2336***
Credit rating (prior to update): r_{t-x}	2,036,103	1,377,671	100	267.5344	500	337,679	337,679	100	267.7361	500	−0.2017**
Number of downgrades (3-year horizon): d_t	2,036,103	1,377,671	0	0.4812	3	337,679	337,679	0	0.4714	3	0.0098***
Average credit rating (3-year horizon): $\bar{r}_t$	2,036,103	1,377,671	100	266.3589	500	337,679	337,679	100	267.2973	500	−0.9384***
Company age: a_t	2,024,173	1,367,244	1	22.0970	1,017	337,679	337,679	1	22.8378	1,016.00	−0.7408***

Note: Pre-crisis period comprises all credit rating observations from July 2017 to December 2019. Crisis period includes all observations starting from April 2020 to July 2020. Although the mean differences in the predictor variables (except credit rating update) are statistically significant, their magnitude seems to be rather negligible, particularly when comparing with the differences between non-insolvent and insolvent observations (Table 3). This suggests that the crisis sample is not biased in the sense that it primarily includes credit updates of firms with poor financial records. Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

We also report univariate descriptive statistics of our credit rating sample differentiating between the pre-crisis and the crisis period in Table 4. We see that in the period before the COVID-19 crisis has hit the German economy, 0.71% of rating updates were followed by a bankruptcy filing. This translates into an insolvency filing rate of 1.05% on the firm level (note that firms can receive more than one credit rating update in that period). In the crisis period, however, despite the worsened economic conditions, it turns out that only 0.33% of rating updates were followed by a bankruptcy filing. This fraction also equals the firm-level insolvency filing rate as in the 4-months crisis period each firm is only observed once. 'Δ Mean' reporting the difference between the variable means of the pre-crisis and the crisis period suggests that the difference of 0.38 pp in the average survival status is statistically significant. The lower average insolvency rate in the crisis period contrasts with the finding that the financial rating of firms observed in the crisis period has deteriorated on average. In fact, firms experience, on average, a significantly higher downgrade of more than three index points during the crisis period.[16] This is a first indication that there may indeed be an insolvency gap in the German economy. Despite the deterioration in financial solvency, there are fewer bankruptcy filings compared to pre-crisis times. The strong political reaction to strengthen firms' liquidity and to prevent German companies from going bankrupt is likely to be a driving force behind the low insolvency rate.

It remains to be analyzed if there are specific sector-size combinations for which the number of insolvencies is significantly below the counterfactual number that one would expect given the observed rating updates and information from pre-crisis insolvency paths. Also we aim to tackle the question whether the gap is mainly driven by firms which already before the crisis were characterized by a weak financial standing. In the next section, we introduce a matching approach that allows us to predict counterfactual insolvency filings if there was no policy intervention for the firms for which we observe rating updates during the crisis. With this approach, we are able to derive counterfactual insolvency rates at the sector-size level and provide an estimate regarding the existence of an insolvency gap by comparing them with the actual filings observed during the crisis period.

[16] See also Appendix D for a comparison of the distribution of the credit rating updates in the pre-crisis and the crisis period.

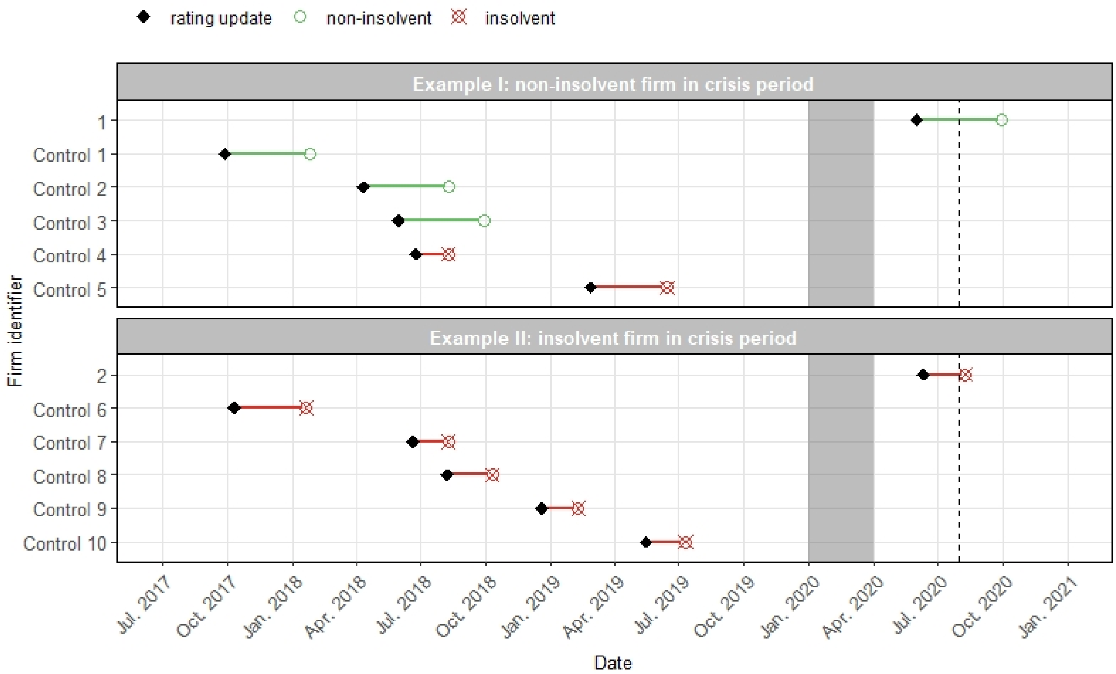
3.2. Methodology

3.2.1. Nearest neighbor matching

This paper focuses on the extent to which state aid measures that address the economic impact of the COVID-19 crisis may have induced ailing firms to stay in the market. To answer this question, we compare the survival status of closely matching firms observed before the COVID-19 outbreak with the survival status of firms observed during the pandemic. Besides general company characteristics such as company size, industry affiliation and company age, our matching approach takes particular account of firm-specific solvency information as presented in the previous section. The core idea of the matching procedure is to find comparable firms which have experienced very similar rating updates and have followed an almost identical path in their financial solvency but in times prior to COVID-19 and the related policy interventions that keep struggling firms afloat.

In order to find for each of the in-crisis observations a number of matches from the pre-crisis period, we conduct a nearest neighbor matching approach. Nearest neighbor matching in observational studies goes back to the work of Donald Rubin (Rubin 1973) and aims at reducing bias in the estimation of the sector-size-specific insolvency gap. A simple comparison of the mean values of the survival status of observations before the crisis and during the crisis (as in Table 4) is likely to give a highly biased picture of the insolvency gap. First, policy measures to rescue firms from failing have been highly heterogeneous with respect to firm size as highlighted in Section 2. Therefore, comparing the survival status of firms of different size bears high risk of firm size acting as confounding variable in the estimation of a policy-induced backlog of insolvencies. For this reason, we only search for matches within the same company size group. Next, the evaluation of our survey suggests that there is great heterogeneity in the COVID-19 exposure across sectors (see Section 4.1). For this reason, we only match firms that are in the same sector class. Ultimately, the previous section has shown that in the crisis period the distribution of rating updates has systematically shifted to the right implying that the in-crisis observations have, on average, experienced larger downgrades in their ratings. For an unbiased estimation of the insolvency gap, this shift needs to be controlled for. Our nearest neighbor matching aligns the in-crisis distribution of updates with the distribution of matched observations as we put a strict caliper on the credit rating variable when searching for matching observations. In fact, comparing the distribution of the predictor variables between pre-crisis and crisis period before and after matching indicates that control observations and crisis observations are much more balanced after matching (see Appendix E for an assessment of covariate balance).

Figure 3 Matching: Illustration



Note: Figure illustrates the nearest neighbor matching for two micro-enterprises in the accommodation and catering sector. In the top panel, we see that firm 1 experienced a rating update in the crisis period which did not result in an insolvency filing. Furthermore, we see, however, that two out of the $k = 5$ nearest neighbors from the pre-crisis control period filed for insolvency after they received a very similar rating update. This signals that firm 1, given its financial information, faces a relatively high insolvency risk as almost half of its nearest neighbors indeed went bankrupt in times without policy intervention.
The bottom panel shows the same approach but for firm 2 which filed for insolvency shortly after its rating update during the crisis period. We see that all of the nearest neighbors also filed for insolvency and thus closely reflect the actual survival status of firm 2.
If we do not observe an insolvency filing four months after the rating update, we treat the update as non-insolvent. Therefore, the time between rating update and the non-insolvent labelling in the visualization always spans 4 months. The area shaded in gray highlights a transitional phase which we intentionally exclude from our analysis since assignment of observations falling in that phase to either the pre-crisis or the crisis period is not straightforward. The dashed vertical line at the end of July 2020 signals that we only have credit rating updates available up to this point. Note, however, that we observe insolvency filings beyond this point in time.

The details of our matching algorithm look as follows. Acknowledging the heterogeneity with respect to firm size and sector affiliation, we estimate the insolvency gap within each of the 52 sector-size combinations. Therefore, we only consider pre-crisis observations that share the same sector-size stratum as the crisis observation of interest. In that sense we perform exact matching on both sector affiliation and company size group. Next, within each sector-size stratum the algorithm selects for each in-crisis observation i the k nearest neighbors from the pre-crisis period which have the smallest distance from i. The maximum number of nearest neighbors, k, reflects the ratio of pre-crisis and crisis observations within each sector-size stratum. Distance is measured by the Mahalanobis distance metric (Rubin 1980), MD, which is computed on all predictor variables $\mathbf{X} = (\Delta r_t \; r_{t-x} \; d_t \; \bar{r}_t \; a_t)'$. For the key predictor variable, Δr_t, we additionally impose a caliper, c, of 0.25 standard deviations. Thus, a pre-crisis observation, j, only falls under the k nearest neighbors if it does not exceed the caliper on Δr_t.

$$MD_{ij} = \begin{cases} (\mathbf{X}_i - \mathbf{X}_j)'\mathbf{\Sigma}^{-1}(\mathbf{X}_i - \mathbf{X}_j) & \text{if} \quad |\Delta r_{t,i} - \Delta r_{t,j}| \leq c \\ \infty & \text{if} \quad |\Delta r_{t,i} - \Delta r_{t,j}| > c \end{cases}$$

with $\mathbf{\Sigma}$ as the variance covariance matrix of $\mathbf{X}$ in the pooled sample of in-crisis and all pre-crisis observations. The strict caliper implies that the number of matches on each crisis observation can be smaller than k or, in case that there is no control observation fulfilling the caliper condition, there may even be no match. If this the case, the crisis observation for which no match could be found is disregarded from further analysis. Moreover, we conduct matching with replacement allowing pre-crisis units to match to more than one crisis observation. This requires us to consider weights which reflect whether a pre-crisis unit falls in the matched sample more than once. In the outcome analysis in Section 4.2 where we estimate the insolvency gap on the sector-size level, we need to consider these weights for inference (Stuart 2010). In this way, we can not only predict the crisis observations' probability to file for bankruptcy if there was no policy intervention but can also make a statement whether the differences between the observed insolvency rates and the predicted counterfactual insolvency rates on the sector-size-level are statistically significant.

Before presenting the results of the counterfactual insolvency rate prediction and insolvency gap estimation, we use our survey results in the next section to show how the pandemic affected sectors to varying degrees. The observed heterogeneity in sector exposure motivates our further empirical analysis.

4. Empirical results

4.1. COVID-19 exposure and firm characteristics

Anecdotal evidence suggests that industries are asymmetrically affected by the COVID-19 recession because lockdown measures as well as supply and demand effects differed between sectors. To verify this observation, we empirically investigate to what extent the economic effects of the COVID-19 crisis has asymmetrically hit sectors by making use our survey data. In addition, we analyze whether firm size and the pre-crisis credit rating is correlated with the perceived shock by the COVID-19 recession at the firm level.

The regression results of the analyses are shown in Table 5. Model (1) reveals that the COVID-19 Exposure Index indeed significantly differs between sectors. We choose chemicals and pharmaceuticals as reference category since this sector is least negatively affected. The sectors accommodation and catering as well as creative industry and entertainment experience very strong and significant negative shocks in comparison to the baseline sector. This is in line with the strong restrictions experienced in these sectors. Since the business activities in these sectors often require direct human interactions, corresponding companies have been severely affected by lockdown measures. The sectors mechanical engineering, food production, wholesale and retail as well as logistics and transport also experience stronger negative effects compared to the baseline sector but at a lower magnitude. Interestingly, firm size categories show no statistically significant heterogeneity in their correlation with the COVID-19 Exposure Index as Model (2) shows. The effects with respect to sectors and firm size also hold when both measures are incorporated simultaneously as in Model (3). Controlling further on the firms' pre-crisis credit rating and thus on the financial situation prior to the outbreak shows that the rating is significantly correlated with the perceived COVID-19 impact. Although the effect is low in magnitude, the marginal effect suggests that a higher (worse) credit rating is associated with a stronger exposure to the negative impact of the crisis. A standard deviation increase of the credit rating (56.8) is associated with a 0.558 higher value of CEI. Ultimately, the strong heterogeneity in the negative exposure to the economic consequences of the pandemic with respect to sector affiliation hold when controlling for the firms' pre-crisis credit rating in Model (4).

Table 5 Regression: COVID-19 Exposure Index on firm characteristics

	(1) *CEI*	(2) *CEI*	(3) *CEI*	(4) *CEI*
Business-related services	0.637		0.646	0.473
	(0.611)		(0.609)	(0.615)
Manufacturing	-0.004		-0.023	-0.073
	(0.605)		(0.603)	(0.604)
Wholesale & retail	1.479**		1.476**	1.427**
	(0.647)		(0.644)	(0.646)
Health & social services	1.087*		1.085*	0.855
	(0.660)		(0.657)	(0.661)
Insurance & banking	0.643		0.618	0.653
	(0.689)		(0.686)	(0.682)
Accommodation & catering	6.024***		6.046***	5.835***
	(0.711)		(0.710)	(0.712)
Logistics & transport	1.454**		1.464**	1.396**
	(0.650)		(0.647)	(0.646)
Creative industry & entertainment	5.444***		5.445***	5.224***
	(0.832)		(0.831)	(0.831)
Mechanical engineering	2.464***		2.477***	2.433***
	(0.665)		(0.659)	(0.658)
Food production	2.564***		2.559***	2.394***
	(0.701)		(0.699)	(0.696)
Manufacturing of data processing equipment	0.147		0.156	0.208
	(0.653)		(0.652)	(0.650)
Micro-enterprise		0.311	-0.048	-0.509
		(0.423)	(0.418)	(0.455)
Small enterprise		0.269	-0.248	-0.538
		(0.447)	(0.433)	(0.448)
Medium-sized enterprise		-0.0216	-0.128	-0.209
		(0.457)	(0.440)	(0.444)
Credit rating (pre-crisis)				0.008***
				(0.003)
N	2,344	2,344	2,344	2,344

Note: Chemicals and pharmaceuticals serve as baseline sector among the sector dummies, large enterprises serve as baseline size group. Dummy coefficient estimates need to be read relative to the baseline group(s). Standard errors are reported in parentheses. Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$

The heterogeneous COVID-19 exposure at the sector level shows that differences in insolvency dynamics with respect to industry affiliation may play an important role. Taking further into consideration that many of the policy measures in Germany have been specifically tailored to SMEs, the subsequent estimation of the insolvency gap is conducted at the sector-size level.

4.2. The COVID-19 insolvency gap

4.2.1. Results on the sector-size level

Estimating the insolvency gap requires us to derive two statistics. First, we calculate actual insolvency rates, IR_s^{actual}, observed after the COVID-19 outbreak for each sector-size stratum s.[17] The calculation is based on firms for which we observe credit rating updates after April 1, 2020.

$$IR_s^{actual} = \frac{N_s^{insolvent}}{N_s}$$

Second, taking the matched sample of observations from the pre-crisis period which includes for each firm observed in the crisis period at most k nearest neighbors, we are able to estimate counterfactual insolvency rates, $IR_s^{counterfactual}$, as follows

$$IR_s^{counterfactual} = \frac{\sum_{j=1}^{\tilde{N}_s} w_{j,s}\, \mathbb{1}(f_{j,t+4} = 1)}{\sum_{j=1}^{\tilde{N}_s} w_{j,s}}$$

with $\tilde{N}_s = \sum_{j=1}^{\tilde{N}_s} w_{j,s}$ as the number of matched observations from the pre-crisis period for stratum s. $w_{j,s}$ is the weight assigned to pre-crisis observation j reflecting how often j is selected as control observation in the matching process and $\mathbb{1}(f_{j,t+4} = 1)$ equals 1 if control observation j filed for insolvency at most four months after its last rating update and 0 otherwise.

Comparing actual insolvency rates with counterfactual insolvency rates for each of the sector-size strata allows us to obtain sector-size-specific estimates of the insolvency gap,

[17] $s \in [1, 52]$.

IG_s, defined as

$$IG_s = IR_s^{counterfactual} - IR_s^{actual}.$$

In other words, the insolvency gap measures the extent to which observed insolvencies during the pandemic deviate from the counterfactual insolvencies that would be expected in a pre-crisis setting without policy intervention. Figure 4 contrasts actual insolvency rates against counterfactual insolvency rates and Table 6 displays the sector-size specific insolvency gap estimates along with their statistical significance. Several insights can be gained from there.

First of all, it becomes obvious that actual insolvency rates, displayed in blue, are in almost all sectors highest among micro-enterprises (except for some outliers in the large enterprise size class). In the group of micro-enterprises, we see that actual insolvency rates are highest in the sectors which according to our survey results are also severely affected by the negative impacts of the crisis. In the accommodation and catering sector, for example, the actual insolvency rate amounts to 1.11%, in the logistics and transport sector which includes the strongly affected aviation industry we observe an insolvency rate of 0.94% and in the creative industry and entertainment sector the rate is 0.76%. These results appear intuitive and are in line with the survey results. At the same time, we find that in all sectors within the group of micro-enterprises the expected insolvency rates exceed the actual rates and in most sectors this gap is statistically significant. The average insolvency gap across all sectors in the group of micro-enterprises amounts to 0.80 pp which is substantial when being compared to the overall pre-crisis insolvency rate of 1.05%.

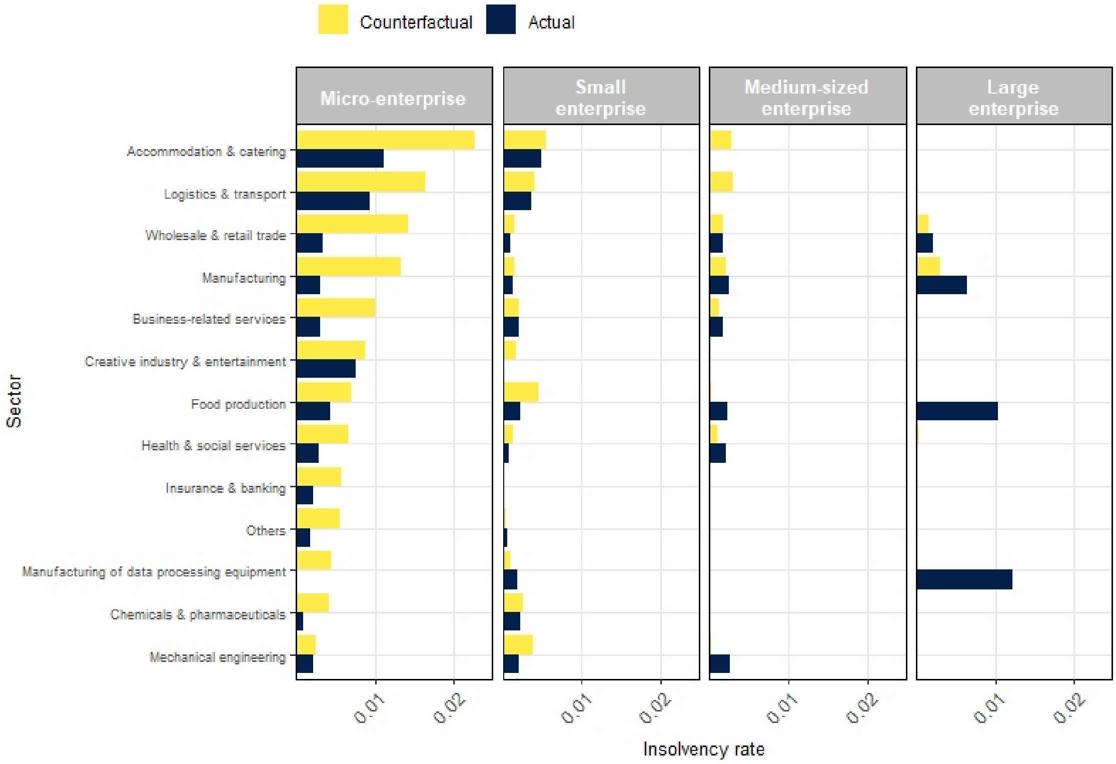
In the group of small enterprises, we see similar patterns although at a lower magnitude both in terms of actual insolvency rates and counterfactual rates. In fact, Table 6 suggests that the rates expected in most sectors exceed actual rates for small enterprises; however, this gap is in no sector statistically significant. On average, the insolvency gap in the group of small businesses amounts to 0.03 pp.

Moving on to the group of medium-sized enterprises, the patterns observed in the smaller size classes start to vanish. While in two of the most severely hit sectors accommodation and catering as well as logistics and transport expected insolvency rates are higher than the ones observed, the difference (i.e. the insolvency gap) is not statistically significant. For the other sectors, the picture is even more mixed. In two sectors (food production and mechanical engineering), some insolvencies took place yet almost none were predicted in the counterfactual scenario. For all other sectors, actual and counterfactual rates are very similar. Table 6 shows that none of the differences (except for the sector mechanical engineering) are statistically significant.

Ultimately, the patterns break down completely for the group of large enterprises. Barely any insolvency filing can be observed in either the crisis period or the counterfactual setting. In general, insolvencies among large corporations are rather rare events which is reflected by our results. Two sectors stand out with high actual insolvency rates: food production and manufacturing of data processing equipment. Both cases are somewhat special as they are each driven by only one insolvency for which no insolvent pre-crisis control observation with comparable financial characteristics exists. Thus, one needs to be cautious when interpreting the results of the large size class.

The finding that counterfactual insolvency rates persistently, and in most sectors also significantly, exceed actual rates among micro-enterprises strongly suggests that there is a substantial backlog of insolvencies in this size class. As company size increases, the backlog of insolvencies gradually vanishes which is in line with our hypothesis that Germany's fiscal policy response in the COVID-19 crisis disproportionately favored the survival of smaller companies. Both the temporary change in Germany's insolvency regime and the high provision of liquidity subsidies allowed especially micro-enterprises to stay in the market. We argue that the temporary suspension of the obligation to file for insolvencies has made it particularly easy for smaller firms to use the amendment as a loophole to avert insolvency proceedings. Since disclosure requirements are more limited the smaller a company is, it becomes particularly difficult for policy makers to enforce insolvency filings among non-filing small firms. This becomes particularly problematic if the non-filing firm does not fulfill the criteria to be eligible for the suspension. Similarly, the early on provision of direct and indirect liquidity without red tape has targeted smaller firms in

Figure 4 Actual and counterfactual insolvency rates



Note: Figure displays actual insolvency rates (blue) with estimated counterfactual insolvency rates (yellow) for each of the $S = 52$ sector-size strata.

particular and thus enabled them to bridge plummeting revenues in a situation in which they usually would have been forced out of the market due to illiquidity. Building on this observation, we want to extend our empirical analysis in a final step to examine to which extent the insolvency gap among smaller firms is driven by firm viability.

4.2.2. The insolvency gap and firm viability

In order to examine whether the insolvency gap is driven by companies that had shown an already poor financial standing before the crisis and had faced a particularly high risk of market exit when the pandemic hit, we split the sector-size strata further according to the observations' pre-crisis financial standing. More precisely, we split each sector-size strata into two further sub-strata. The first sub-strata contains all observations whose three year average credit rating prior to the crisis is better than the overall median rating index. We refer to these as observations with 'strong financial standing', viable to survive the crisis based on their pre-crisis conditions. The other sub-strata comprises all observations worse than the the overall pre-crisis median rating. Firms falling in such a sub-strata are referred

Table 6 Outcome Analysis: Insolvency gap estimation results

Sector affiliation	**Size of company**			
	Micro	Small	Medium	Large
Accommodation & catering	+0.0115***	+0.0005	+0.0028	0.0000
Logistics & transport	+0.0070***	+0.0002	+0.0030	0.0000
Wholesale & retail trade	+0.0107***	+0.0004	+0.0001	−0.0006
Manufacturing	+0.0103***	+0.0002	−0.0004	−0.0035
Business-related services	+0.0070***	−0.0001	−0.0005	0.0000
Creative industry & entertainment	+0.0012	+0.0017	0.0000	0.0000
Food production	+0.0027	+0.0024	−0.0019	−0.0105**
Health & social services	+0.0037***	+0.0005	−0.0011	+0.0004
Insurance & banking	+0.0037***	0.0000	0.0000	0.0000
Others	+0.0037***	−0.0002	0.0000	0.0000
Manufacturing of data processing equipment	+0.0044*	−0.0009	0.0000	−0.0122*
Chemicals & pharmaceuticals	+0.0033*	+0.0003	0.0000	0.0000
Mechanical engineering	+0.0003	+0.0018	−0.0025***	0.0000

Note: Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Statistical significance is based on the χ^2-Test for equality in the insolvency proportions in the actual and counterfactual samples using Rao-Scott corrections to the χ^2 statistic (Rao and Scott 1981) to account for the matching weights.

to as having a 'weak financial standing'. Given their pre-crisis financial circumstances, we expect them to be more vulnerable to default in the current crisis or even if the pandemic had not hit the economy.

Table 7 shows the insolvency gap estimates analogous to Table 6 with the additional distinction between strata comprising financially strong companies and financially weak ones. Several aspects become apparent from these results. First, we observe that among micro-enterprises with above median credit rating (top panel) there is in almost no sector a significant deviation between actual and counterfactual insolvency rate. There are, however, two exceptions. Both in the accommodation and catering sector and the creative and entertainment sector observed insolvencies significantly exceed expected insolvencies. We know from our survey that these two sectors are by far the most affected industries. Given the severe impairments in these industries, it seems plausible that companies which had been rated relatively well before the pandemic nevertheless file for insolvency more

Table 7 Outcome Analysis: Insolvency gap estimation results incorporating firms' pre-crisis financial condition

Viability	**Sector affiliation**	**Size of company**			
		Micro	Small	Medium	Large
Strong financial standing	Accommodation & catering	−0.0029***	−0.0013	0.0000	0.0000
	Logistics & transport	−0.0008	−0.0001	+0.0003	0.0000
	Wholesale & retail trade	+0.0003	−0.0001	+0.0005	−0.0007
	Manufacturing	−0.0001	−0.0001	−0.0008	−0.0038
	Business-related services	−0.0002	−0.0006	−0.0010	0.0000
	Creative industry & entertainment	−0.0025**	0.0000	0.0000	0.0000
	Food production	−0.0007	+0.0020	−0.0027*	−0.0112*
	Health & social services	−0.0001	−0.0004	−0.0003	0.0000
	Insurance & banking	+0.0007	0.0000	0.0000	0.0000
	Others	−0.0002	+0.0002	0.0000	0.0000
	Manufacturing of data processing equipment	+0.0007	−0.0015	0.0000	−0.0127*
	Chemicals & pharmaceuticals	+0.0017	+0.0020	0.0000	0.0000
	Mechanical engineering	−0.0003	−0.0017	−0.0015*	0.0000
Weak financial standing	Accommodation & catering	+0.0171***	+0.0018	+0.0030	0.0000
	Logistics & transport	+0.0128***	+0.0004	+0.0049	0.0000
	Wholesale & retail trade	+0.0196***	+0.0020	−0.0035	0.0000
	Manufacturing	+0.0184***	+0.0015	+0.0060	−0.0060
	Business-related services	+0.0122***	+0.0013	+0.0033	0.0000
	Creative industry & entertainment	+0.0029	+0.0032	0.0000	-
	Food production	+0.0051	+0.0030	+0.0025	0.0000
	Health & social services	+0.0059***	+0.0022	+0.0010	+0.0060
	Insurance & banking	+0.0055***	0.0000	0.0000	0.0000
	Others	+0.0073***	−0.0012	0.0000	0.0000
	Manufacturing of data processing equipment	+0.0065	0.0000	0.0000	0.0000
	Chemicals & pharmaceuticals	+0.0050	−0.0050	0.0000	0.0000
	Mechanical engineering	+0.0014	+0.0126*	−0.0056	0.0000

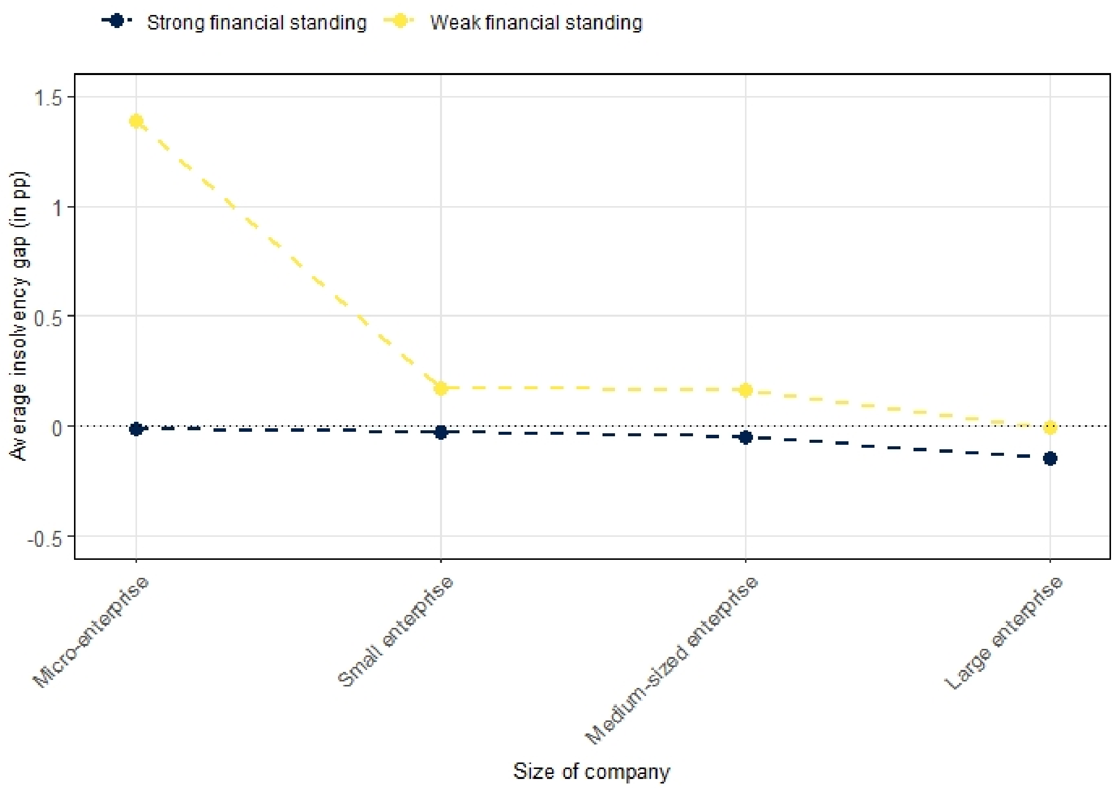
Note: Upper panel displays insolvency gap estimates for firms with 'strong financial standing' comprising all firms whose three year average credit index prior to the crisis is better than the median rating index. The lower panel shows results for companies with a 'weak financial standing' including those with a rating worse than the median rating. For large firms in creative and entertainment sector with weak financial standing insolvency gap could not have been calculated as no firm in this strata has been observed during the crisis period. Significance levels: *: $p < 0.10$, **: $p < 0.05$, ***: $p < 0.01$. Statistical significance is based on the χ^2-Test for equality in the insolvency proportions in the actual and counterfactual samples using Rao-Scott corrections to the χ^2 statistic (Rao and Scott 1981) to account for the matching weights.

frequently than the counterfactual estimation would suggest. This means that, despite the cushioning effect provided by fiscal policy, micro firms with a strong pre-crisis rating filed for bankruptcy more frequently than would have been possible to learn from the financial paths of similarly strong firms in pre-crisis times. Most important, however, is the finding that among micro-enterprises the insolvency gap as backlog of expected insolvencies is *not* driven by firms with a strong financial standing prior to the crisis. In contrast, it is driven by less viable companies with a rating worse than the median rating. This results from the insolvency gap estimates among micro-enterprises with weak financial standing (bottom panel). It becomes apparent that throughout all sectors the counterfactual insolvency rates exceed the actual rates indicating a backlog of insolvencies which in the majority of sectors is not only statistically significant but in some also substantial in magnitude. In fact, the gap amounts to more than 1.70 pp in accommodation and catering, wholesale and retail as well as manufacturing which is a substantial backlog when taking into consideration that the overall pre-crisis insolvency rate lies at 1.05%.

In the small business group, we see that in the strata with strong financial performance, the size and sign of the insolvency gap estimates are comparable to the results in the micro firm group (except for accommodation/catering and creative/entertainment sector). These results indicate that there is no significant gap in insolvency filings among small businesses with above median credit rating. In the strata of small and financially weak businesses, in turn, we observe for most sectors a positive sign in the insolvency gap estimation albeit only statistically significant in the mechanical engineering sector. Again, this suggests that that also in the group of small firms the backlog of insolvencies is driven by companies with weak pre-crisis conditions even if magnitude and significance is less pronounced in comparison to the micro size group.

Similar to the results in Table 6 and in line with our hypothesis that the fiscal policy response in Germany disproportionately favored survival of smaller companies, the observed patterns for small and especially micro-sized firms gradually vanish with increasing firm size as shown in Figure 5. Consequently, the insolvency gap estimates for medium-sized and large enterprises do not reveal clear patterns in the sign of the estimates nor significant deviations between observed and predicted rates (apart for some aforementioned exceptions).

Figure 5 Average insolvency rates by size class and pre-crisis viability



Note: Figure displays average insolvency gaps (weighted by the number of observations falling into the matched strata) distinguishing by company size and pre-crisis financial conditions. It becomes apparent that the backlog of insolvencies is strongly driven by micro-enterprises with weak credit rating prior to the crisis and also that with increasing firm size the gap becomes less pronounced among financially weak companies.

Our results suggests that the COVID-19 induced policy responses have created a non-negligible insolvency gap which is strongly driven by micro firms with comparatively poor credit ratings prior of the pandemic. In times of liquidity crises such as in this pandemic, financially distressed firms are usually forced to exit the market. In order to avoid large-scale bankruptcies, policy makers have made extensive use of instruments to prevent business failures. Arguably, this has been a necessary reaction to save firms short of liquidity but viable in their business models. The problem, however, arises when unviable firms on the brink of business failure already before the crisis take advantage of loopholes concerning the instruments or simply benefit from direct and indirect liquidity subsidies which have been granted in a whatever it takes manner in the early phase of the crisis. We find evidence that this has been the case for smaller financially weak German businesses where fiscal policy helped to avert many insolvencies that would have happened based on our counterfactual analysis. Therefore, it is indeed likely that the early policy answer to dampen the economic impacts of the COVID-19 crisis has hampered the natural cleansing effect typically observed in economic crises.

5. Conclusion

The ongoing COVID-19 crisis has placed a special role on fiscal policy in order to soften the adverse economic impacts faced by many firms. There is little doubt that, in the short term, liquidity subsidies and loan guarantees have been necessary to save companies under severe liquidity pressure from insolvency. In Germany, a country in which fiscal policy played a crucial role in mitigating the crisis' impact, liquidity subsidies were accompanied by a temporary suspension of the insolvency regime. While both measures are different in design, they target at the same objective: preventing an unprecedented wave of corporate insolvencies. Studying Germany's policy response, it becomes also apparent that a number of aid schemes were either explicitly designed to save smaller companies or at least implicitly favored the survival particularly of small firms. This policy environment is the basis for our hypothesis that a substantial backlog of insolvencies has accumulated particularly among SMEs as a result of the COVID-19 policy response. If, however, support schemes postpone or even prevent the exit of financially weak SMEs, there is the danger of negative long-term effects on the entire economy. In fact, in the ongoing crisis it is likely that early liquidity issues increasingly translate into an erosion of firms' equity. Suspending bankruptcy proceedings of such overindebted firms is not only 'to deny reality' (The Economist 2020a, p. 3) but also hampers the efficient reallocation of resources possibly delaying the process of economic recovery. In this vein, economic crises also serve as cleansing mechanism to release resources from inefficient and non-innovative firms leveraging overall productivity. The first-round policy response of the German government has not only been targeted disproportionately at smaller firms but also did so with little screening mechanisms in place rescuing companies from insolvency in a fairly indiscriminate manner (Federal Ministry of Finance 2020b).

Making use of both survey data and a unique and large dataset of firm-specific credit rating data along with information of firm insolvency filings, we investigate whether the German policy response has indeed caused distortions in the natural cleansing mechanism typically encountered in liquidity crises. While the policy response to the economic impact of COVID-19 in Germany suggests notable differences in firm size, our survey results reveal strong heterogeneity across economic sectors in their exposure to the adverse effects in the current crisis. With these findings, we estimate the extent of an insolvency gap, defined as the deviation of observed insolvency rates during the COVID-19 pandemic and expected insolvency rates based on a counterfactual pre-crisis setting with no policy intervention, for 52 distinct sector-size strata. In line with our hypothesis, our results show that the insolvency gap is particularly significant in the group of micro-enterprises (less than 10 employees) and that the gap gradually vanishes with increasing firm size. Furthermore, we distinguish between viable and unviable firms in our analysis with the latter being defined as companies with below median credit rating prior to the crisis. This means that we refer to unviable firms as companies being relatively more vulnerable to default in the current crisis based on their pre-crisis financial standing. Our findings suggest that the backlog of insolvencies is mainly driven by firms with a relatively poor credit rating prior to the crisis. These results indicate that especially small unviable firms may take advantage of the less stringent screening processes associated with many of the COVID-19-related policy instruments or absorb the liquidity injections as windfall gains, especially during the first months of the crisis when eligibility criteria were low. It is likely that once the policy instruments will cease, i.e. liquidity support will terminate and the German insolvency regime returns back to the filing obligation, a large wave of small business insolvencies will follow.

From a welfare perspective this comes at the burden of high fiscal costs associated to financial aid granted to unviable firms. But it also imposes indirect costs in the longer term as such firms tie up resources whose efficient redistribution would allow the economy to speed up its recovery. Binding human capital in struggling firms as it happens through the short-time work scheme employed in Germany, for instance, creates more inert labor markets. This is likely to make it harder for innovative companies to find qualified and experienced human capital. Cooper et al. (2017), for instance, find that although STW saved employment in Germany during the Great Recession, the instrument made it more difficult for productive firms to hire employees because the instrument restricted the release of workers into the pool of unemployed. Their results show that preventing labor from flowing toward the most productive firms is decreasing overall productivity and output. Policy makers will have to think carefully how to extend company assistance in the still ongoing crisis. There are alternative policy approaches. Instead of supporting jobs through short-time schemes, policy makers should focus on supporting workers through improved short-term unemployment benefits allowing workers to migrate to more innovative firms effectively. Finally, policymakers would be well advised to ensure that ailing companies can fail quickly so that they can either be restructured or have their assets and employees redeployed. Bankruptcy courts should be able to restructure businesses with realistic prospects or liquidate resources that find more productive use elsewhere (The Economist 2020a). Understanding the effects of the interplay between liquidity support on the one hand and temporary adjustments to insolvency regimes on the other hand, will be an important lesson from the COVID-19 crisis. Does the interplay of these two instruments impair economic recovery or does it, if well dosed, even serve as a useful fiscal policy mix in liquidity crises? At this point, it is left to future research to investigate the long-term effects on productivity, innovation, and entrepreneurship induced by the early policy responses to COVID-19.

References

Agarwal, V., & Taffler, R. (2008). Comparing the performance of market-based and accounting-based bankruptcy prediction models. *Journal of Banking and Finance*, *32*(8), 1541–1551.

Altman, E. I. (1968). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *The Journal of Finance*, *23*(4), 589–609.

Altman, E. I. (2013). Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA® Models Background. *Handbook of Research Methods and Applications in Empirical Finance*, *1*, 428–456.

Anderson, J., Bergamini, E., Brekelmans, S., Aliénor, C., Darvas, Z., Domínguez Jíménez, M., Lenaerts, K., & Midões, C. (2020). The fiscal response to the economic fallout from the coronavirus. Retrieved 28 December 2020, from https://www.bruegel.org/publications/datasets/covid-national-dataset/

Archibugi, D., Filippetti, A., & Frenz, M. (2013). The impact of the economic crisis on innovation: Evidence from Europe. *Technological Forecasting and Social Change*, *80*(7), 1247–1260.

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). COVID-19 is also a Reallocation Shock. *NBER Working Paper*, *27137*.

Bersch, J., Gottschalk, S., Mueller, B., & Niefert, M. (2014). The Mannheim Enterprise Panel (MUP) and Firm Statistics for Germany. *ZEW Discussion Paper*, *14-104*.

Buckley, A. (2011). *Financial Crisis: Causes, Context and Consequences.* Harlow: Financial Times Prentice Hall.

Caballero, R. J., & Hammour, M. L. (1994). The Cleansing Effect of Recessions. *American Economic Review*, *84*(5), 1350–1368.

Cahuc, P., Kramarz, F., & Nevoux, S. (2018). When Short-Time Work Works. *CEP Discussion Papers*, *13041*.

Carreira, C., & Teixeira, P. (2016). Entry and exit in severe recessions: lessons from the 2008–2013 Portuguese economic crisis. *Small Business Economics*, *46*(4), 591–617.

Cooper, R., Meyer, M., & Schott, I. (2017). The Employment and Output Effects of Short-Time Work in Germany. *NBER Working Paper*, *23688*.

Council of the European Union. (2020). Report on the comprehensive economic policy response to the COVID-19 pandemic. Retrieved 12 December 2020, from https://www.consilium.europa.eu/en/press/press-releases/2020/04/09/report-on-the-comprehensive-economic-policy-response-to-the-covid-19-pandemic/

Cowling, M., Brown, R., & Rocha, A. (2011). Did you save some cash for a rainy COVID-19 day? The crisis and SMEs. *International Small Business Journal: Researching Entrepreneurship*, *38*(7), 593–604.

Creditreform. (2020a). Creditreform Commercial Report International. Retrieved 1 December 2020, from https://www.creditreform.com/fileadmin/user_upload/CR-International/Bilder/PB_International-Commercial-Report_web.pdf

Creditreform. (2020b). Creditreform Solvency Index. Retrieved 1 December 2020, from https://en.creditreform.de/fileadmin/user_upload/crefo/download_eng/commercial_information/Flyer_Solvency_Index.pdf

Destatis. (2020). Shares of small and medium-sized enterprises in selected variables, 2018. Retrieved 17 December 2020, from https://www.destatis.de/EN/Themes/Economic-Sectors-Enterprises/Enterprises/Small-Sized-Enterprises-Medium-Sized-Enterprises/Tables/total-cik.html

European Commission. (2003). Commission recommendation concerning the definition of micro, small and medium-sized enterprises. *Official Journal of the European Union*, *L124*, 36–41.

European Union. (2006). Regulation (EC) No 1893/2006 of the European Parliament and of the Council of 20 December 2006 establishing the statistical classification of economic activities NACE Revision 2 and amending Council Regulation (EEC) No 3037/90 as well as certain EC Regulations on specific statistical domains. *Official Journal of the European Union*, *L393*, 1–39.

Federal Government of Germany. (2020). Soforthilfen für Selbstständige und kleine Unternehmen. Retrieved 29 November 2020, from https://www.bundesregierung.de/breg-de/aktuelles/corona-soforthilfen-1737444

Federal Ministry for Economic Affairs and Energy. (2020). KfW Instant Loan for small and medium- sized enterprises to be launched tomorrow. Retrieved 29 December 2020, from https://www.bmwi.de/Redaktion/EN/Pressemitteilungen/2020/20200414-

kfw-instant-loan-for-small-and-medium-sized-enterprises-to-be-launched-tomorrow.html

Federal Ministry of Finance. (2020a). Additional KfW Special Programme 2020 for the economy to be launched today. Press Release. Retrieved 21 December 2020, from https://www.bundesfinanzministerium.de/Content/EN/Pressemitteilungen/2020/2020-03-23-KfW-special-programme.html

Federal Ministry of Finance. (2020b). Corona virus: immediate federal economic assistance now available. Retrieved 21 December 2020, from https://www.bundesfinanzministerium.de/Content/EN/Pressemitteilungen/2020/2020-04-01-corona-federal-economic-assistance.html

Federal Ministry of Finance. (2020c). German government launches temporary aid scheme as part of coronavirus stimulus. Retrieved 28 July 2020, from https://www.bundesfinanzministerium.de/Content/EN/Standardartikel/Topics/Priority-Issues/Articles/2020-07-08-temporary-aid-scheme-launched.html

Federal Ministry of Finance. (2020d). German Stability Programme 2020. Publication. Retrieved 28 December 2020, from https://www.bundesfinanzministerium.de/Content/EN/Standardartikel/Press_Room/Publications/Brochures/2020-04-17-german-stability-programme-2020.pdf?__blob=publicationFile&v=9

Federal Ministry of Justice and Consumer Protection. (2020). Act to Mitigate the Consequences of the COVID-19 Pandemic under Civil , Insolvency and Criminal Procedure Law. Retrieved 28 July 2020, from https://www.bmjv.de/SharedDocs/Gesetzgebungsverfahren/Dokumente/Bgbl_Corona-Pandemie_EN.pdf?__blob=publicationFile&v=2

Financial Times. (2020). Germany haunted by spectre of zombie companies. Retrieved 11 December 2020, from https://www.ft.com/content/5d5d1bc1-61a3-46a9-915c-1a1e6f2e5fd2

Giupponi, G., & Landais, C. (2018). Subsidizing Labor Hoarding in Recessions : the Employment & Welfare Effects of Short Time Work. *CEP Discussion Papers*, *1585*.

Giupponi, G., & Landais, C. (2020). Subsidizing Labor Hoarding in Recessions : the Employment & Welfare Effects of Short Time Work. *CEP Discussion Papers*, *13310*.

Guerini, M., Nesta, L., Ragot, X., & Schiavo, S. (2020). Firm liquidity and solvency under the Covid-19 lockdown in France. *OFCE Policy Brief*, *76*.

International Monetary Fund. (2020). Policy Responses To COVID-19. Retrieved 9 December 2020, from https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19

Iyer, R., Peydró, J. L., Da-Rocha-Lopes, S., & Schoar, A. (2014). Interbank liquidity crunch and the firm credit crunch: Evidence from the 2007-2009 crisis. *Review of Financial Studies*, *27*(1), 347–372.

Juergensen, J., Guimón, J., & Narula, R. (2020). European SMEs amidst the COVID-19 crisis: assessing impact and policy responses. *Journal of Industrial and Business Economics*, *47*(3), 499–510.

Kalemli-Ozcan, S., Gourinchas, O. P., Penciakova, V., & Sander, N. (2020). COVID-19 and SME Failures. *IMF Working Paper*, *20/207*.

Kopp, D., & Siegenthaler, M. (2020). Short-time work in and after the Great Recession. *Journal of the European Economic Association*, *upcoming*.

McGuinness, G., & Hogan, T. (2016). Bank credit and trade credit: Evidence from SMEs over the financial crisis. *International Small Business Journal*, *34*(4), 412–445.

OECD. (2020). Coronavirus (COVID-19): SME Policy Responses. OECD Library. Retrieved 17 December 2020, from https://read.oecd-ilibrary.org/view/?ref=119_119680-di6h3qgi4x&title=Covid-19_SME_Policy_Responses

OECD. (n.d.). Corporate sector vulnerabilities during the Covid-19 outbreak: Assessment and policy responses. OECD Library. Retrieved 17 December 2020, from https://read.oecd-ilibrary.org/view/?ref=132_132712-uivd1yagnx&title=Corporate-sector-vulnerabilities-during-the-Covid-19-outbreak-assessment-and-policy-responses

Rao, J. N., & Scott, A. J. (1981). The analysis of categorical data from complex sample surveys: Chi-squared tests for goodness of fit and independence in two-way tables. *Journal of the American Statistical Association*, *76*(374), 221–230.

Rubin, D. B. (1980). Bias Reduction Using Mahalanobis-Metric Matching. *Biometrics*, *36*(2), 293–298.

Rubin, D. B. (1973). Matching to Remove Bias in Observational Studies. *Biometrics*, *29*(1), 159–183.

Schumpeter, J. A. (1942). *Capitalsim, Socialism and Democracy.* New York: Harper.

Stuart, E. A. (2010). Matching methods for causal inference: A review and a look forward. *Statistical Science*, *25*(1), 1–21.

The Economist. (2020a). The corporate undead: What to do about zombie firms. Retrieved 30 December 2020, from https://www.economist.com/leaders/2020/09/24/what-to-do-about-zombie-firms

The Economist. (2020b). The corporate undead: Why covid-19 will make killing zombie firms of harder. Retrieved 30 December 2020, from https://www.economist.com/finance-and-economics/2020/09/26/why-covid-19-will-make-killing-zombie-firms-off-harder

The Japan Times. (2020). Bank of Japan coronavirus loans may ensure 'zombie' firms limp on. Retrieved 11 November 2020, from https://www.japantimes.co.jp/news/2020/09/10/business/economy-business/bank-japans-coronavirus-crisis-loans-risk-revival-zombie-firm-fears/

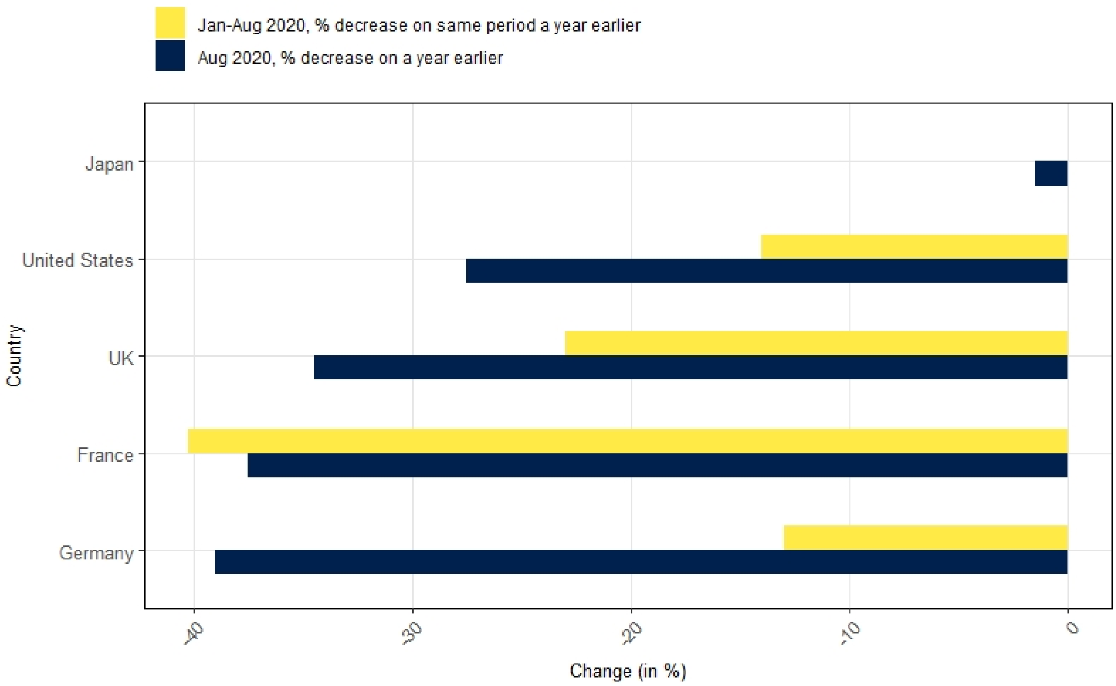
The Washington Post. (2020). Here's one more economic problem the government's response to the virus has unleashed: Zombie firms. Retrieved 11 November 2020, from https://www.washingtonpost.com/business/2020/06/23/economy-debt-coronavirus-zombie-firms/

Yang, C. H., & Chen, K. H. (2009). Are small firms less efficient? *Small Business Economics*, *32*(4), 375–395.

Appendices

A. Corporate Insolvencies 2019 versus 2020

Figure 6 Decline in corporate insolvencies during the COVID-19 crisis



Note: Figure shows the percentage change of insolvencies in the crisis year 2020 compared to 2019 for a number of selected countries. Bar chart is adapted from The Economist (2020b).

B. Size definition

Table 8 Mapping firm characteristics to size group

	Size of company			
	Micro	Small	Medium	Large
Number of employees	≤ 10	$11 - 49$	$50 - 249$	≥ 250
Annual tunover in M €	≤ 2	$2 - 10$	$10 - 50$	> 50
Annual balance sheet total in M €	≤ 2	$2 - 10$	$10 - 43$	> 43

Note: Table shows translation of firm characteristics into company size classes used in this study as defined by European Commission (2003).

C. Sector definition

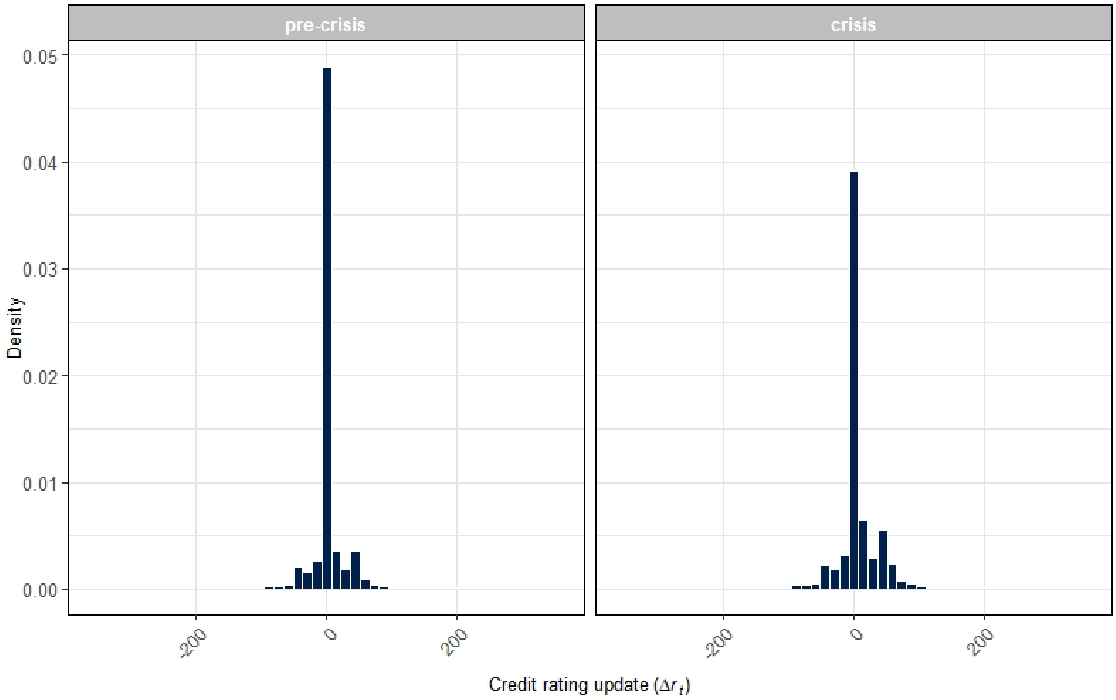
Table 9 Mapping sector definition to EU NACE Revision 2 divisions

Sectors	Divisions
Business-related services	58-63, 68, 69-82
Manufacturing	5-9, 12-19, 23-25, 27, 31-33, 35-39, 41-43
Wholesale & retail trade	45-47
Health & social services	86-88, 94-96
Insurance & banking	64-66
Accommodation & catering	55, 56
Logistics & transport	49-53
Creative industry & entertainment	90-93
Mechanical engineering	28-30
Food production	10, 11
Chemicals & pharmaceuticals	20-22
Manufacturing of data processing equipment	26
Others	any division not listed above

Note: Table shows translation of EU's NACE Revision 2 divisions (European Union 2006) into sector groupings used in this study.

D. Distribution of credit rating update

Figure 7 Distribution of credit rating update in pre-crisis and crisis period



Note: There is a rightward shift in the distribution of rating updates during the crisis period, indicating that there were more credit rating downgrades as compared to the pre-pandemic period. This reflects that the financial situation deteriorated for a larger share of companies in the crisis period than in the three years preceding the crisis.

E. Balance Assessment

Table 10 Improvement in balance through matching

Sector	**Size**	% Improvement in eCDF mean					Variance ratio				
		Δr_t	r_{t-x}	$\bar{r}_t$	d_t	a_t	Δr_t	r_{t-x}	$\bar{r}_t$	d_t	a_t
Accommodation & catering	Micro	97	89	90	96	71	1.00	1.01	1.01	1.01	1.38
	Small	96	47	45	67	-15	1.00	1.10	1.11	1.04	1.66
	Medium	96	6	6	-16	-119	1.00	1.25	1.26	1.10	2.26
	Large	91	22	3	47	-71	1.13	0.71	0.67	1.31	6.59
Business-related services	Micro	95	91	92	99	89	1.01	1.01	1.01	1.00	1.02
	Small	88	57	72	95	81	1.02	1.05	1.06	1.01	1.09
	Medium	83	78	84	88	65	1.02	1.06	1.09	1.01	1.14
	Large	74	22	-2	47	25	1.04	1.09	1.12	1.05	1.21
Chemicals & pharmaceuticals	Micro	81	40	41	19	40	1.01	1.09	1.12	1.04	1.09
	Small	74	47	64	83	47	1.02	1.07	1.10	1.06	1.16
	Medium	81	14	63	66	-13	1.03	1.14	1.13	1.09	1.22
	Large	74	-30	1	3	11	1.01	1.23	1.23	1.18	1.22
Creative industry & entertainment	Micro	95	71	76	59	36	1.01	1.03	1.03	1.02	1.09
	Small	95	53	26	65	23	1.01	0.99	0.97	1.08	1.26
	Medium	94	-71	-64	-3	-79	1.03	1.29	1.33	1.11	2.15
	Large	87	1	19	87	-19	1.07	0.81	0.72	1.05	0.60
Food production	Micro	85	77	79	67	32	1.01	1.04	1.03	1.04	1.16
	Small	83	36	42	89	-28	1.00	1.03	1.03	1.02	1.18
	Medium	71	-50	-19	12	-58	1.03	1.28	1.29	1.07	1.14
	Large	62	55	47	33	34	1.00	1.48	1.48	1.22	1.02
Health & social services	Micro	95	89	91	92	80	1.01	1.01	1.01	1.01	1.18
	Small	89	47	50	25	35	1.02	1.05	1.05	1.03	1.17
	Medium	84	42	24	78	30	1.01	1.12	1.12	1.08	1.11
	Large	71	54	39	79	-39	1.03	1.24	1.27	1.10	1.44
Insurance & banking	Micro	90	86	88	89	80	1.01	1.02	1.02	1.00	1.05
	Small	73	49	67	82	73	1.03	1.04	1.04	1.07	1.07
	Medium	52	61	50	92	63	1.04	1.05	1.07	1.00	1.06
	Large	79	59	59	96	71	1.08	1.17	1.16	1.02	0.98
Logistics & transport	Micro	93	87	87	93	62	1.01	1.02	1.02	1.01	1.05
	Small	89	-27	49	0	53	1.02	1.12	1.13	1.04	1.09
	Medium	84	-9	35	52	11	1.02	1.14	1.16	1.07	1.19
	Large	85	-78	-107	77	-9	1.05	1.30	1.26	1.09	1.26
Manufacturing	Micro	93	92	93	97	82	1.01	1.01	1.01	1.00	1.03
	Small	87	72	80	99	68	1.02	1.04	1.05	1.00	1.04
	Medium	84	-2	54	67	37	1.02	1.09	1.11	1.03	1.07
	Large	85	-27	19	73	-23	1.03	1.23	1.20	1.12	1.25
Data equipment	Micro	74	-20	0	89	44	1.01	1.06	1.05	1.05	1.19
	Small	71	19	43	81	32	1.01	1.20	1.16	1.07	1.28
	Medium	73	-31	23	-35	45	1.05	1.55	1.58	1.11	1.27
	Large	79	32	56	65	3	1.04	1.11	1.04	1.17	1.60
Mechanical engineering	Micro	83	27	31	92	45	1.01	1.07	1.06	1.01	1.11
	Small	77	-9	37	89	25	1.02	1.10	1.13	1.02	1.12
	Medium	85	-22	37	78	-7	1.01	1.22	1.18	1.05	1.19
	Large	87	3	18	54	28	1.02	1.30	1.39	1.08	1.16
Others	Micro	93	88	90	91	64	1.01	1.01	1.02	1.01	1.12
	Small	86	32	52	93	35	1.02	1.02	1.04	1.01	1.26
	Medium	84	45	63	72	42	1.03	1.08	1.08	1.02	1.05
	Large	74	25	48	80	-47	1.01	1.08	1.06	1.12	1.11
Wholesale & retail trade	Micro	96	91	92	98	82	1.01	1.01	1.01	1.00	1.03
	Small	92	11	49	93	67	1.01	1.04	1.04	1.01	1.04
	Medium	87	33	66	82	42	1.02	1.11	1.11	1.02	1.10
	Large	83	30	45	75	20	1.03	1.18	1.17	1.08	1.15

Note: Table shows balance assessment statistics for all matching variables. % improvement in empirical cumulative density function (eCDF) mean shows by how much percent the deviation in the eCDF mean between pre-crisis and crisis observations has improved through nearest neighbor matching. It becomes apparent that for most covariates in all sector-size strata a substantial improvement in balance has been achieved through the matching process. Variance ratio statistics refer to the ratio of the variance among the matched control observations and the variance among the crisis observations for the respective variable. Values closer to zero indicate better balance in variance.

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