Pandemic Effects: Is the German Innovation System Suffering from Long-COVID?

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Abstract

The COVID-19 pandemic has adversely impacted firms in all economies worldwide. We investigate the impact of the pandemic on firms' innovation activities. Employing data from a representative sample of German firms, we find that negatively affected firms substantially reduced R&D and other innovation expenditures not only in the first year of the pandemic (2020), but also in the two subsequent years. Firms with high pre-pandemic digital capabilities show a significantly lower negative response. Firms profiting from the pandemic situation also cut their innovation activities substantially in favor of increasing short-run production.

Keywords: COVID-19 pandemic, innovation activities, Difference-in-Differences, Mannheim Innovation Panel

JEL Classification: H12, L29, L0

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1 Introduction

The COVID-19 pandemic was an exogenous shock that hit societies and economies around the world in early 2020. Most countries imposed immediate measures and restrictions to cope with the pandemic and prevent healthcare systems from breaking down. Face-to-face meetings and communication as well as national and international travel were highly restricted with adverse impacts on supply chains, working from home became compulsory, and selling goods and services was limited or even prevented by lockdowns (Brodeur et al. 2021). As a result, the pandemic and its counter measures had severe negative impacts on economies worldwide. Many firms experienced a sharp decline in revenues (Bloom et al. 2021a; Paunov and Planes-Satorra 2021) and a deep recession occured, with GDP falling by 3.6% worldwide in 2020.[1] In order to combat the crisis and continue business, firms had to adjust their strategies and procedures, including the reallocation of resources and the reorganization of internal processes, including innovation which constitues an important strategic choice variable under these circumstances (Aghion et al. 2012; Bloom 2007). At the same time, some firms experienced positive economic consequences from the COVID-19 pandemic, e.g., higher sales of products needed for responding to the crisis, such as vaccines or other health protection devices.

Most empirical evidence from previous crises shows that innovation activity is procyclical, i.e., firms respond to lower demand and worsened market prospects, higher liquidity constraints and increased uncertainty during recessions by reducing innovation activities (Aghion et al. 2012; Archibugi et al. 2013; Hud and Hussinger 2015; Hud and Rammer 2015; Laperche et al. 2011; Paunov and Planes-Satorra 2021). However, the COVID-19 pandemic constitutes a unique situation and is therefore not directly comparable to previous economic crises. First, the pandemic caused substantial disruptions of internal processes due to temporary lockdowns and mandatory home working. However, R&D activity is often tied to specific technical facilities such as laboratories. Lack of or limited access to R&D laboratories and as a result to tools such as equipment and research materials impact internal RD activities. Second, labor shortages occured due to illness and quarantine rules (Paunov and Planes-Satorra, 2021), which also affected R&D personnel and the execution of innovation activities. Third, travel restrictions made it difficult to carry out collaborative activities with external cooperation partners, particularly also in the course of innovation projects. Fourth, disrupted supply chains may not only have affected firm's production but also material needed for innovation activities. Finally, COVID-19 led to a disproportionate increase in financial restrictions as well as in uncertainty (Bloom et al. 2021a). In particular, firms had to deal with high uncertainty about the length of the crisis and future changes in the course of the crisis (e.g. new and more severe lockdowns). The absence of prior experience with such a crisis made it difficult for firms to decide how to best adjust to this unique situation. On the other hand, COVID-19 restrictions forced many firms to develop new products, processes and change their business model. In addition to new health related products and devices, this relates especially to new digital

[1] In Germany, the country of observation in our study, GDP growth declined by even 4.6% in 2020

online offerings and delivery services. As a consequence, impacts from the pandemic are likely to differ from those seen in previous economic crises.

This paper studies the resilience of innovation activities during the COVID-19 pandemic. It focuses on the impact of the COVID-19 pandemic on innovation activities of German firms, looking both at immediate responses (in 2020) and consequences on medium-term prospects of innovation activities in the years 2021 and 2022. Furthermore, we study whether firms' innovation activities have been more resilient during the crisis if they had already been more digitized before the pandemic. This analysis extends primary evidence of the immediate impact of COVID-19 on firms' innovation behavior (see Brodeur et al. (2021) and Allen (2022) for summaries). Our analysis uses information from two waves of the Mannheim Innovation Panel (MIP), which is the German contribution to the European Commission's Community Innovation Survey (CIS). We employ a difference-in-differences design to evaluate the immediate innovation response of affected firms in 2020 as well as their expected innovation expenditures in the following years. In addition, we balance treatment and control groups by weighting observations using an entropy balancing procedure to minimize a potential bias in the analysis caused by selection into treatment.

We find that firms negatively affected by the COVID-19 pandemic show an immediate and strong negative response in R&D activities in 2020 compared to less affected firms. They decreased their total R&D expenditure growth in 2020 by 12.9% more than the control group. Innovation expenditure growth (which includes additional expenditures in innovation that are not only R&D related.) is lowered by about 17.6%, compared to a 29% decrease in investment growth in physical capital. In addition, our results show Long-COVID effects for the German innovation system. The immediate decline is followed by long-lasting adverse effects on innovation activities in the following years. Firms negatively affected by the COVID-19 planned to further reduce their innovation expenditure by 2.3% in 2021. Even in 2022, the same firms still plan to continue reducing their innovation expenditures compared to 2021 by 0.9%. As a result, firms negatively hit by COVID-19 did not recover in terms of innovation spending by 2022. Instead, a significant decline in innovation spending can be observed between the pre-crisis year 2019 and the post-crisis year 2022. Finally, our results show that innovation activities of more digitalized firms have been more resilient in the crisis. Highly digitalized firms that are negatively affected by the pandemic do not reduce their innovation activities as strongly as not highly digitalized firms. Thus, firms' existing digital capabilities were highly beneficial also for innovation activities in the COVID-19 pandemic. This result extends prior studies showing that firms with higher digital capabilities performed better during the COVID-19 pandemic (Pierri and Timmer 2020). We further find that firms that have been positively affected by the COVID-19 pandemic also reduced their R&D- and innovation activities by almost 20% and 26%, respectively, in favor of extending short-term revenues and production capabilities. This result follows Aghion and Saint-Paul (1998)'s argument that firms increase production and reduce innovation activities when demand for their products rises.

Our findings show that COVID-19 negatively influenced innovation behavior as an immediate response in 2020, which is in line with empirical evidence on innovation behavior during crises and recessions (Aghion et al. 2012). However, we also find that this negative effect is still present in the following two years. Especially because innovation is a main driver of firm performance, it is likely that a continuing decrease in innovation activities of already negatively affected firms will further harm their competitiveness. This highlights the importance of policies aiding firms that were strongly negatively affected by the COVID-19 pandemic.

2 COVID-19 and Firm Innovation

2.1 COVID-19 Pandemic and the Economy

The COVID-19 pandemic directly affected firms worldwide through four main channels (Brodeur et al. 2021; Carlsson-Szlezak et al. 2020a,b). First, lockdowns reduced consumption greatly, leading to demand shocks in most consumer goods sectors which gradually diffused to most other sectors (Coibion et al. 2020; Eichenbaum et al. 2021). As a result, firm revenues decreased substantially. Bloom et al. (2021b) found, for example, that revenues of US firms have decreased substantially in the first quarter of 2020 by 29%.

Second, restrictions to international communication disrupted global supply chain and created shortages of raw materials and intermediate products (Bonadio et al. 2021; Bartik et al. 2020). This either directly reduced production output through limited availability of crucial production inputs or substantially increased production costs through increased input prices or search costs for alternative inputs that might be less productive (Baldwin and Freeman 2020). Wohlrabe (2021) reports for 2020 that 45% of German manufacturing firms have faced supply issues of intermediates. Lafrogne-Joussier et al. (2022) show that the first lockdown in China caused a 5% reduction of domestic sales of French firms relying on Chinese imports.

Third, the worsened financial situation of firms and households put stress on financial markets. Both firms and households relied heavily on financial intermediaries to cover their revenue drop. Firms were in need of financial resources to withstand a period of low to no revenues and higher costs or to finance important business strategy changes (De Vito and Gómez 2020). Households needed financial resources to cover income decreases through job losses. This increased credit demand met stressed financial markets (Li et al. 2020; Zhang et al. 2020). However, negative impacts through liquidity constraints were partially dampened by intensive policy interventions as Elenev et al. (2022) and Dörr et al. (2022) describe.

Fourth, firms had to change organizational routines to cope with the pandemic.[2] Be-

[2]Brodeur et al. (2021); Carlsson-Szlezak et al. (2020a,b) focus only on the first three channels but neglect the effect of the frictions and costs of reorganizing production processes to comply with social distancing measures and searching for alternative sales channels etc. However, Kraus et al. (2020) and Balla-Elliott et al. (2020) show that these measures constituted major costs and obstacles for firms at the beginning of the pandemic.

cause of health risks associated with face-to-face interactions and the implementation of social distancing measures, firms needed to reorganize relations with both customers and suppliers (Criscuolo 2021; Kraus et al. 2020). To guarantee the safety of their employees, firms needed to implement measures that allowed them to operate while complying with social distancing measures. Such steps included acquiring protective equipment or implementing remote work capabilities (Kraus et al. 2020). Because of the high demand for such solutions, supply issues, and tense financial markets, these types of reorganization became costly for already struggling firms.

But not all firms were negatively affected by the pandemic. Some industries faced a strong demand increase for their products and services, including medical equipment, health services, IT services, food delivery services or cleaning services. There were also indirect positive demand effects for industries such as financial consultants in order to help businesses in applying to government support schemes related to the pandemic.

In addition to this direct economic impact, the pandemic situation resulted in a huge increase in economic uncertainty. Both the further development of the pandemic in terms of lockdowns and other restrictions to social interaction, as well as the length of the pandemic were unknown Bloom et al. (2021b,a). As a consequence, any planning process in firms was heavily complicated, with adverse effects on investment decisions.

2.2 The Impact of the Pandemic on Innovation

The literature on the impact of economic crisis on innovation found both positive and negative effects. Positive crisis impacts on innovation tend to occur as a result of lower opportunity costs of innovation expenditure compared to capital investment Aghion and Saint-Paul (1998). Since expanding capacity in a situation of decreasing demand is less profitable than investing into the development of new products or more efficient processes, firms will shift available human and financial resources towards innovation. Negative crisis impacts are often related to liquidity constraints which result from a decrease in cash-flow and profits, restricting the financial means of firms to invest into innovation (Himmelberg and Petersen 1994; Aghion et al. 2012; Ouyang 2011; Paunov and Planes-Satorra 2021). In addition, low demand during crisis urges firm to postpone the market introduction of innovations until demand will increase again, which will allow innovators to charging higher prices for new products (see Shleifer (1986); Barlevy (2007); Fabrizio and Tsolmon (2014); Paunov and Planes-Satorra (2021)). Finally, high uncertainty may motivate firms to delay innovation activities until more information on the development of markets is available (Bloom 2007, 2009, 2014).

The relevance of these findings for the specific situation of the COVID-19 crisis is limited, however, owing to the peculiarities of the pandemic as described above. On the one hand, counter-cyclical (i.e. positive) innovation impacts by shifting resources from production and delivery to innovation are less likely for the COVID-19 situation since firms had to use scarce resources to adapt various business activities at the same time and on short notice, leaving little capacity for starting new innovation projects. On the other hand, however, the need to adjust internal processes and external relations. Both could lead to additional innovation activity in the short run by introducing new product and services offerings, adapting delivery modes, and implementing new procedures for maintaining business operations and interaction with customers and suppliers (Paunov and Planes-Satorra 2021). At the same time, some of these changes such as the shift to working from home may have adversely impact the firms' innovative capabilities. A lack of face-to-face contacts, for example, may reduce researchers' creativity and productivity, and complicate collaborative R&D activities (Xiao et al. 2021; DeFilippis et al. 2020).

Another factor in favor of a negative impact on innovation is related to the exceptionally high uncertainty associated with the COVID-19 crisis, at least in the first year of the pandemic. Differently to prior economic crisis, firms had no experience about how long the exceptional circumstances will last, which government measures will be imposed that may further restrict business operations, and how goods, financial and labor markets will respond to the situation. This clearly constituted a different setting for decisions on future business activities, including innovation, compared to prior crisis, which is likely to result in more conservative and restrained planning on investment with a medium-term horizon, which is characteristic to R&D and innovation.

COVID-19 and Digitalization

A specific feature of the COVID-19 pandemic, compared to other economic crisis, is the role of digitalization. The government measures to combat COVID-19 included travel restrictions, restricted access to the workplace and mandatory rules for working from home. These social distancing measures required firms to rely more on digital technologies for both in-house operations and external relations. Most prominently, firms implemented working-from-home solutions to allow employees to continue to work in a safe environment (Brynjolfsson et al. 2020; Criscuolo 2021). Many firms also had to employ digital technologies for sourcing and marketing, e.g. by advancing digital sales channels and digital connections to suppliers and other business partners (see Diekhof et al. (2021)). An OECD (2021) report also already showed a substantial increase in the usage of digital platforms during the first half of 2020.

Advanced pre-COVID digital capabilities are likely to mitigate the negative impact of COVID-19 to some extent. It is likely that firms with high digital capabilities at the beginning of the pandemic were better prepared to adjust to the new situation and show a higher resilience to likely negative impacts, including a better ability to continue innovation activities. Bai et al. (2021) show that firms with high pre-pandemic share of employees working from home performed better during the pandemic in terms of higher revenues and stock returns. Firms that had already built digital capabilities such as work-from-home solutions, social network usage, or the digital integration of suppliers and customers before the pandemic were able to benefit from their existing competencies, while others had to make costly investments using their scarce monetary resources. These investments became especially expensive during the pandemic because of the increased demand for ICT and disrupted global supply chains.

Hypotheses

Based on the discussion above, we derive three hypotheses that guide our empirical analysis:

H1: Firms experiencing high negative economic impacts from the COVID-19 pandemic will experience stronger immediate (i.e. in the first pandemic year 2020) negative consequences on their innovation activities.

H2: Firms experiencing high negative economic impacts from the COVID-19 pandemic will also show stronger medium-term (i.e. in the years 2021 and 2022) negative consequences on their innovation activities, resulting from the high uncertainty associated with the pandemic situation in 2020.

H3: Firms with high digital capabilities at the beginning of the COVID-19 pandemic are more resilient to adverse impacts compared to firms with low digital capabilities.

3 Data

3.1 Mannheim Innovation Panel

We use data from the Mannheim Innovation Panel (MIP), which collects data on innovation inputs and outputs of firms as well as general firm characteristics that may affect innovation behaviour. The MIP is the German contribution to the harmonized Community Innovation Survey (CIS) coordinated by the European Commission. Like the CIS, the MIP follows the Oslo Manual which provides definitions and methodologies on how to collect innovation indicators and thus provides internationally comparable data (OECD and Eurostat 2019). First conducted in 1993, the MIP is a representative stratified random sample of firms in Germany with more than five employees, using industry, size and region as stratification criteria. It covers manufacturing, mining, energy and water supply, wholesale, transportation, information and communication technology, as well as financial- and additional business-related services. Different from most other national CIS, the MIP is designed as an annual panel survey. Each year, the same stratified random sample of firms is surveyed. Every second year, the panel sample is refreshed to compensate for panel mortality. The MIP is a voluntary survey with an annual response rate of about 25-35%, implying an unbalanced nature of the panel. An additional non-response analysis controls for possible non-response bias (see Peters and Rammer (2013) for more details).

3.2 Main Outcome Variables

To study the impact of the Corona pandemic on firms' innovation behaviour, we make use of the two most recent survey waves, collected in 2020 and 2021, each of which includes information for the previous year. As a result, we can exploit information on firms' *innovation expenditure* prior to the pandemic in 2019 (pre-Covid) and in the first year of the pandemic in 2020 (post-Covid). The change (log growth rate) in firm's innovation expenditure between 2019 and 2020, Δ ln(inno$_{2019-2020}$), allows us to investigate the *short run* impact of COVID-19 on firms' innovation behaviour (hypothesis H1). Innovation expenditure is defined as firm's spending on intramural and extramural R&D, prototypes, testing, training, market introduction and on the acquisition of new machines, software and IPR, all related to the development and introduction of product and process innovation. In addition to innovation expenditure, we use the change in *R&D expenditure*, Δ ln(R&D$_{2019-2020}$), as a second alternative innovation indicator to measure the short-term effect of Covid-19 on innovation. Finally, we compare the short-term COVID-19 response of innovation expenditure with the Covid-19 response of investment in physical capital, Δ ln(invest$_{2019-2020}$).

Importantly for our second research question about the existence of Long Covid effects on innovation, the MIP also collects data on planned innovation expenditure for the two years following the reference year of a survey. That is, the 2021 survey collects data on realized innovation expenditure for 2020 and data on planned innovation expenditure in 2021 and 2022. Since the 2021 survey was conducted in the spring and summer, at a time when many companies have already set their innovation budgets for the respective year, the planned figures for 2021 are expected expenditures, but are likely to be associated with a high degree of certainty. The expenditure data for 2022 are naturally subject to a higher degree of uncertainty, but it should be taken into account that companies often tend to set their innovation budgets longer in advance due to their strategic importance and the long-term nature of innovation projects. The changes (growth rate) in firm's innovation expenditure between 2020/2021 and 2021/2022, Δ ln(inno$_{2020-2021}$) and Δ ln(inno$_{2021-2022}$), are used to examine the *medium-term* impact of COVID-19 on firms' innovation behaviour (hypothesis H2). Our final outcome variable is the change (growth rate) in firm's innovation expenditure between 2019 and 2022, Δ ln(inno$_{2019-2022}$). A negative impact of the Covid-19 treatment indicator on this growth rate indicates that firm's innovation expenditures have not (fully) recovered even three years after the pandemic, a situation which we call *Long Covid* of the innovation system.

3.3 Covid-19 Treatment

As emphasized before, COVID-19 was an exogenous shock to economies worldwide that unexpectedly emerged early 2020. The 2021 MIP included a special section on Corona and its consequences. Firms were asked to indicate how COVID-19 affected their enterprise in general in the year 2020 on a six point Likert scale from extremely negative to very positive. Figure A1 in the Appendix shows the question and Table 1 shows the distribution of COVID-19 affectedness. Though the German economy was strongly negatively hit by COVID-19, we can observe an important treatment heterogeneity among firms. That is, not all firms were equally negatively affected, others remained by and large unaffected and some also benefited from COVID-19. We exploit this treatment heterogeneity to define our treatment and control group.

In our main analysis, the treatment group $Covid^{neg}$ is defined as all firms that were very or extremely negatively hit by the COVID-19 pandemic in 2020 (category 1 and 2). This represents about 19.6% of all firms in the sample. The control group consists of all firms that were not affected at all or only slightly negatively affected (category 3 and 4). We thus exclude firms from the control group that were positively affected by COVID-19 (category 5 and 6). The main focus of our study is the innovation response of firms that were negatively treated by COVID-19. However, in section 5.5, we reverse the perspective and additionally compare the innovation response of positively treated firms $Covid^{pos}$ with control firms.

Table 1: Distribution of COVID-19 Affectedness

	Number	Percentage
Extremly negativ	150	6.0
Very negative	342	13.6
Slightly negative	829	33.0
Not affected	976	38.8
Positive	171	6.8
Very positive	46	1.8
Total	2514	100.0

Notes: The statistics in this table are based on the unweighted sample.

The treatment indicator is based on a subjective assessment by the companies. To show the credibility of the assessment and thus of our treatment indicator, we examine the relationship between firms' sales growth between 2019 and 2020 and its degree of COVID-19 affectedness. We regress the sales growth rate on dummy variables for each category of COVID-19 affectedness and additionally control for pre-treatment firm size measured as log number of employees in 2019, $ln(\text{emp}_{2019})$, and industry fixed effects. The results in Table 2 show that the firm's assessment of its general affectedness by COVID-19 has a tight connection with sales growth in 2020. Firms that are extremely negatively affected have on average about 57% lower sales growth compared to non-affected firms. The size of the negative effect monotonically declines with the stated impact of COVID-19, for example sales decline only by 20.9% for firms that stated to be very negatively affected. Furthermore, the effect becomes significantly positive and monotonically increasing for the firms with a positive COVID-19 treatment. Sales grow by 10.6% for positively affected and even almost 28% for very positively affected firms on average. This result confirms previous findings in the literature and clearly shows that firms negatively affected by COVID-19 have to cope with a substantial decline in sales, possibly leading to a shift in management strategies toward more short-term damage reduction rather than pursuing innovations that might only lead to uncertain future benefits.

Table 2: COVID-19 Affectedness and Sales Growth

	Δ ln(sales)
Affected by COVID-19	
Extremely negative	-0.573***
	(-7.61)
Very negative	-0.209***
	(-7.34)
Slightly negative	-0.091***
	(-4.75)
Positive	0.106***
	(3.11)
Very positive	0.276***
	(2.72)
$\ln(emp_{2019})$	-0.004
	(-0.55)
Constant	0.055
	(1.52)
Observations	2,514

Notes: Reference group: not affected at all. Industry fixed effects included in all models but not reported; heteroscedasticity robust standard errors, t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

3.4 Digitalization Indicator

We include the firm's level of digitalization prior to the COVID-19 pandemic in 2019 in our analysis in order to analyze the potentially mitigating role of digitalization. We use a question[3] in the MIP 2020 wave that asked about the importance of eight digital elements in 2019 for the firm's business model on a four-point Likert scale. Digital elements included, among others, the use of digital platforms, interaction through digital channels with customers, data collection from digital sources, and machine learning and artificial intelligence application. We calculate a digitalization index by summing up the eight elements (assigning the value zero for not important and three for highly important).From this index, an indicator variable is generated that equals one if the firm's digitalization index scores above the median in the sample and zero else. Its distribution in table 3 shows that firms in the treatment group are, on average, slightly more digitalized than control group firms.

[3]See figure A2 in the Appendix.

3.5 Descriptive Statistics

For the empirical analysis, we drop observations with missing values in either our main outcome variables Δ ln(R&D$_{2019-2020}$) and Δ ln(inno$_{2019-2020}$), the treatment indicator $COVID^{neg}$ and control variables which we explain in more detail in section 4. Furthermore, we drop outlier by excluding firms with log-growth rates of innovation expenditure below -100% and exclude outliers following the method of Belsley et al. (2005) and Bollen and Jackman (1985). [4] We are left with an estimation sample of 2482 firms for whom we have data for both 2019 and 2020.

Table 3 presents key statistics of the distribution of the variables used in the analysis while differentiating between the treatment- and control groups. The control group consists of 1,988 observations and is about four times larger than the treatment group, and the distributions of most variables differ at least to some extent. Revenues *ln(revenues*$_{2019}$ of firms in the treatment group already had lower revenues in 2019 and their revenue log growth rate Δ *ln(revenues)* in 2020 is on average about 30% lower than than for firms in the control group. This pattern is similar for investment (*ln(investment*$_{2019}$, Δ *ln(investment)*) and already indicates that being negatively affected by COVID-19 correlates with reduced revenues and investment, as Bloom et al. (2021a) showed for US firms. Differently than for revenues and investment, R&D- and innovation expenditures in 2019 (ln(R&D$_{2019}$, ln(inno. exp.$_{2019}$) are on average similar between the two groups. However, their average growth rates (Δ *ln(inno. exp.*$_{2020-2021}$, Δ *ln(R&D*$_{2020-2021}$) for the treatment group are substantially lower for 2020. Expected innovation expenditure growth rates for the years 2021 and 2022, as well as their combined three-year growth rate, exhibit a similar pattern.

[4] We measure the most influential observations following Belsley et al. (2005), and Bollen and Jackman (1985) for both estimations with R&D expenditures and innovation expenditures as dependent variables and drop 1% of the most influential observations affecting the regression either positively or negatively.

Table 3: Descriptive Statistics

	Treatment Group:				Control Group:			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Δ ln(sales)	-0.296	0.663	-4.533	6.174	-0.017	0.395	-5.432	3.934
Δ ln(R&D)	0.066	0.458	-0.911	3.932	0.230	1.045	-0.974	9.547
Δ ln(invest)‡	0.199	1.210	-0.984	7.901	0.368	1.196	-1.000	10.309
Δ ln(inno$_{2019-2020}$)‡	0.060	0.487	-0.943	4.615	0.284	1.161	-0.974	8.923
Δ ln(inno$_{2020-2021}$)‡	0.036	0.545	-0.979	7.378	0.103	0.780	-0.992	9.393
Δ ln(inno$_{2021-2022}$)‡	-0.000	0.128	-0.915	0.683	0.022	0.299	-0.875	7.601
Δ ln(inno$_{2019-2022}$)‡	0.051	0.590	-0.943	6.909	0.184	0.954	-0.980	9.210
Neg. COVID	1.000	0.000	1.000	1.000	0.000	0.000	0.000	0.000
ln(sales$_{2019}$)	0.874	2.099	-6.166	7.853	1.056	1.897	-4.948	9.847
sales$_{2019}$	33.822	174.288	0.002	2572.261	40.064	476.344	0.007	18900.000
ln(R&D$_{2019}$)	-6.526	3.797	-9.210	3.682	-6.755	3.773	-9.210	4.883
ln(R&D$_{2019}$)	0.442	2.567	0.000	39.736	0.670	5.063	0.000	132.000
ln(inno$_{2019}$)	-6.389	3.882	-9.210	3.682	-6.608	3.874	-9.210	4.898
inno$_{2019}$	0.480	2.614	0.000	39.736	0.832	6.402	0.000	133.980
ln(invest$_{2019}$)	-5.007	3.958	-9.210	5.075	-4.336	3.781	-9.210	5.533
ln(invest$_{2019}$)	1.444	9.485	0.000	160.000	1.235	8.862	0.000	253.000
Observations	463				1775			

Notes: The statistics in this table are based on the unweighted sample; ‡: Variables are only available for a subsample. Observation numbers for these variables are given in the estimation results tables in section 5.

4 Estimation Approach

4.1 Difference-in-Differences Setup

To estimate the average impact of a firm negatively affected by COVID-19 on its innovation activities, we employ a two-period difference-in-differences estimation approach. This setup allows us to control for unobserved time-constant effects between strongly negatively affected and not strongly negatively affected firms. The baseline model, as shown in equation 1 controls for group differences through the treatment group dummy G_i and common differences over time through a time dummy T_t. The interaction between those two estimates the average treatment effect β_{DiD} on the outcome variable $log(Y_{it})$. The vector X_i contains a set of control variables from the pre-treatment period.

$$log(Y_{it}) = \beta_0 + \beta_T \cdot T_t + \beta_g \cdot G_i + \beta_{DiD} \cdot T_t \cdot G_i + X_{i,2019} \cdot T_t \cdot \beta_x + \epsilon_{it} \tag{1}$$

Taking the first difference of the model in equation (1) eliminates all time-constant terms and leads to our estimation equation

$$log(Y_{it}) - log(Y_{it-1}) = \beta_0' + \beta_{DiD} \cdot G_i + X_{i,2019} \cdot \beta_x + \Delta\epsilon_{it}. \tag{2}$$

In our application, the treatment group dummy G corresponds to our treatment indicator Covid^{neg}. We estimate equation (2) using OLS. The left-hand side of (2) can be interpreted as a log-growth rate of the outcome variable.

Since innovation inputs are highly persistent over time, we include the pre-treatment level of the lagged dependent outcome variable (in logs) as Control variable in each estimation. We additionally control for the firm's size by including the pre-treatment number of employees (in logs) in the analysis.

4.2 Entropy Balancing

A fundamental assumption of quasi-experimental study designs like ours is that treatment assignment is quasi-randomly distributed. This means that firms cannot select themselves into treatment and are not selected because of specific characteristics. However, we suspect firm selection into being negatively affected by COVID-19 not to be random and rather to depend on firm characteristics such as firm size or industry. We, therefore, employ an entropy matching method proposed by Hainmueller (2012) to simulate close-to-random treatment selection dependent on observable firm characteristics. Entropy balancing is a reweighing method improving covariate balance between both treatment- and control groups allowing treatment assignment to become closer to being assigned independently of covariates (Hainmueller and Xu 2013). In contrast to commonly employed matching techniques, entropy balancing systematically improves the balancing of potentially high-dimensional covariate vectors by matching distribution moments directly in finite samples. It does not result in loss of observations and, consequently, information and produces a smooth set of weights. The proposed technique reweights control group observations such that covariate distribution moments of both the treatment and control group match. The algorithm aims to remain as close as possible to uniform base weights to assure efficient estimates in the following steps (Hainmueller 2012). We then use the resulting weights to estimate equation (2) with weighted least squares. In our analysis, we require all first, second, and third moments of covariate distributions to match as closely as possible. Section 5 provides further information.

4.3 Heterogeneous Treatment Effects

The digital capabilities of firms might have mitigated the impact of COVID-19. To investigate to which extent this was the case, we extend our basic difference-in-differences setup to allow for different effects of COVID-19 on innovation activity for highly digitalized firms. This essentially means that we modify equation (2) to include three dummy variables, whereas D_{t-1} is a dummy for being highly digitalized in 2019 before the COVID-19 pandemic:

$$\begin{aligned}
G_{COVID\ only} &= 1 \quad && \text{if } Covid_t^{neg} = 1 \;\&\; Digi_{t-1} = 0 \\
G_{Digi\ only} &= 1 \quad && \text{if } Covid_t^{neg} = 0 \;\&\; Digi_{t-1} = 1 \\
G_{COVID\&Digi} &= 1 \quad && \text{if } Covid_t^{neg} = 1 \;\&\; Digi_{t-1} = 1
\end{aligned}$$

This allows to estimate the impact on each group separately and changes the estimation equation to

$$log(Y_{it}) - log(Y_{it-1}) = \beta_0' + \beta_{DiD}^{COVID\ only} \cdot G_{COVID\ only} + \beta_{DiD}^{Digi\ only} \cdot G_{Digi\ only} + \beta_{DiD}^{COVID\&Digi} \cdot G_{COVID,Digi} + X_i \cdot \beta_x + \Delta\epsilon_{it}. \tag{3}$$

The effect of being negatively affected by COVID-19 on the outcome variable for not highly digitalized firms equals $\beta_{DiD}^{COVID\ only}$. For highly digitalized firms, the effect equals $\beta_{DiD}^{Digi\ only}$ and for highly digitalized firms that are affected by COVID-19 $\beta_{DiD}^{COVID\&Digi}$. The construction of the digitalization dummy variable is explained in section 3.

5 Results

5.1 Short-run Impact of the COVID-19 Pandemic on Innovation

Focusing on the influence that a generally negative impact of COVID-19 had on innovation activities of firms, we estimate the difference-in-differences model explained in section 4 on innovation process input variables. We start by estimating a baseline model without any control variables. The results in Table 4 show a clear negative impact of COVID-19 on both innovation inputs. Firms strongly negatively affected by COVID-19 decrease their R&D expenditure growth rate by 16.5% compared to not-affected firms in column 1. We find an even stronger effect of a 22.5% reduction on the broader measure of innovation expenditure growth, which includes additional expenditures on, e.g., design and software development in column 2. Compared to firm investment in general, negatively affected firms reduce innovation inputs more strongly as innovation growth only decreases by 16.8% (see column 3). This comparison shifts when introducing additional control variables. We include the logarithm of the number of employees before COVID-19 in 2019 to control for firm size, industry dummies, and the firm's lagged level innovation input variable, respectively. This reduces the estimated effect of being negatively affected by COVID-19 on R&D expenditures to 13.3% and innovation expenditure to 18.4%. However, the effect on general investment growth increases to 23.6%, surpassing the effects on innovation inputs. However, not affected firms reduce investment growth in 2020 by 39.0% as estimated by the constant in our model, which confirms that firm investment generally tends to be more volatile than innovation inputs Filippetti and Archibugi (2011). Therefore, firms that were strongly negatively affected by COVID-19 reduced their R&D expenditure growth on average by 34.5%, innovation expenditure growth by 42.2.7%, and investment growth by 62.6%.

Table 4: Short-run Impact of COVID-19 Pandemic on Innovation

	(1) Δ ln(R&D)	(2) Δ ln(inno)	(3) Δ ln(invest)	(4) Δ ln(R&D)	(5) Δ ln(inno)	(6) Δ ln(invest)
COVID^{neg}	-0.165***	-0.225***	-0.168**	-0.133***	-0.184***	-0.236***
	(-5.05)	(-6.30)	(-2.05)	(-4.35)	(-5.50)	(-2.90)
ln(emp$_{2019}$)				0.037*	0.036*	0.057**
				(1.96)	(1.86)	(1.98)
ln(R&D$_{2019}$)				-0.028***		
				(-3.26)		
ln(inno$_{2019}$)					-0.035***	
					(-4.10)	
ln(invest$_{2019}$)						-0.092***
						(-5.92)
Constant	0.230***	0.284***	0.368***	-0.212	-0.238	-0.390*
	(9.29)	(10.31)	(10.52)	(-1.57)	(-1.56)	(-1.80)
Observations	2238	2238	1433	2238	2238	1433

Notes: Industry fixed effects in models 4-6 but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

It is unlikely that firms' affectedness by COVID-19 is randomly distributed in our sample. Instead, we suspect the likelihood of a negative impact of COVID-19 to depend on several firm characteristics. To mitigate a possible bias in our estimates, we follow Hainmueller (2012) and implement an entropy balancing procedure, reweighing our control group observations such that the first three distribution moments (mean, standard deviation, and skewness) of several covariates match as closely as possible. Before the estimation of each model in Table 5 and 8, we reweight the control group using the level of the dependent variable in 2019, the number of employees, and industry dummy variables. Tables A.1-A.3 in the appendix show the results for each entropy weighting procedure separately, the only difference being the exchanged level of the dependent variable. There are virtually no differences between covariates' distribution moments of treatment and control group anymore after each balancing procedure.

We continue to estimate the same models as above while including the estimated observation weights. The estimated effects of being strongly negatively affected by COVID-19 on innovation inputs only change in size of some estimates, but the qualitative results stay robust. Firms strongly negatively affected by COVID-19 decreased their R&D expenditure growth immediately by 12.9%; 3.6pp lower than the estimate from the base specification without entropy balancing. Innovation expenditure growth is decreased to 17.6% instead of 22.5%. Investment growth, in turn, increased from 16.8% to 29,4% with entropy balancing, a level much closer to the effect in the model with control variables. When including the same set of control variables, the results stay virtually unchanged, showing that after balancing treatment- and control groups, firm characteristics do not influence the negative impact of COVID-19 on firms' immediate innovation responses.

Table 5: Short-run Impact of COVID-19 Pandemic on Innovation - Accounting for Selection (Entropy Balancing)

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(R&D)	Δ ln(inno)	Δ ln(invest)	Δ ln(R&D)	Δ ln(inno)	Δ ln(invest)
COVID^{neg}	-0.129***	-0.176***	-0.294***	-0.129***	-0.176***	-0.294***
	(-7.06)	(-8.39)	(-6.94)	(-7.07)	(-8.41)	(-7.01)
$\ln(\text{emp}_{2019})$				0.010	0.023**	-0.004
				(1.06)	(2.34)	(-0.26)
$\ln(\text{R\&D}_{2019})$				-0.006		
				(-1.50)		
$\ln(\text{inno}_{2019})$					-0.015***	
					(-3.47)	
$\ln(\text{invest}_{2019})$						-0.026***
						(-3.94)
Constant	0.115***	0.149***	0.244***	0.042	-0.031	-0.035
	(7.59)	(8.44)	(8.40)	(0.68)	(-0.42)	(-0.15)
Observations	2180	2180	1373	2180	2180	1373

Notes: Industry fixed effects in models 4-6 but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

5.2 Robustness Checks

One crucial assumption in our methodology outlined in 4 is that trends of our outcome variables are parallel for both the treatment and control groups in the absence of treatment. Even though this assumption is not testable in the treatment period itself, testing parallel trends in the pre-treatment period is possible. If trends in the pre-treatment period are found to develop in parallel, it is likely that this is also the case in later periods, giving credibility to our results. We, therefore, conduct a placebo treatment test by regressing our model on R&D- and innovation expenditure growth rates only in years from our pre-treatment period. If trends of these variables for our groups are parallel in the specified year, we should not find a significant effect of the placebo treatment.

The results in Table 6 indicate that pre-treatment trends of both outcome variables generally run in parallel. Columns 1, 3, and 5 in Table 6 reveal no significant effect of our treatment on R&D expenditure for the pre-treatment years 2019, 2018, and 2017, respectively. The results for innovation expenditures in columns 2, 4, and 6 show a similar picture, where we only find a significant effect in 2018. However, this might be driven by the high rate of attrition in our data when spanning the sample over larger time periods, resulting in a strongly smaller sample size. We, therefore, find virtually no evidence for trends of the R&D and innovation expenditures not to be parallel, allowing us to interpret our results as causal estimates.

Table 6: Robustness Checks: Placebo Treatment

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(R&D)	Δ ln(inno)	Δ ln(R&D)	Δ ln(inno)	Δ ln(R&D)	Δ ln(inno)
	2018-2019	2018-2019	2017-2018	2017-2018	2016-2017	2016-2017
COVID^{neg}	-0.021	0.003	0.129	0.255**	-0.007	0.056
	(-0.33)	(0.03)	(1.47)	(2.08)	(-0.09)	(0.42)
ln(R&D$_{2018}$)	-0.160***					
	(-8.45)					
ln(emploees$_{2018}$)	0.219***	0.254***				
	(6.76)	(7.21)				
ln(inno$_{2018}$)		-0.220***				
		(-11.29)				
ln(R&D$_{2017}$)			-0.132***			
			(-6.12)			
ln(emploees$_{2017}$)			0.143***	0.272***		
			(4.25)	(6.52)		
ln(inno$_{2017}$)				-0.285***		
				(-12.71)		
ln(R&D$_{2016}$)					-0.266***	
					(-11.43)	
ln(emploees$_{2016}$)					0.226***	0.358***
					(6.08)	(7.73)
ln(inno$_{2016}$)						-0.350***
						(-15.21)
Constant	-1.896***	-2.546***	-1.653***	-3.164***	-2.915***	-4.332***
	(-6.87)	(-8.23)	(-6.14)	(-10.75)	(-8.91)	(-12.20)
Observations	1688	1688	1347	1347	1456	1456

Notes: Industry fixed effects in all models but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

5.3 Long-COVID of Innovation Activities

Shifting the focus from the immediate impact of a firm's affectedness by COVID-19 to its impact on expected innovation expenditures in the following years. Table 7 shows the results for the same model with the log growth rate of expected future innovation expenditures as dependent variables. The independent variable of the first two columns is the expected innovation expenditure log growth rate between 2020 and 2021 and between 2021 and 2022, respectively. A negative impact of COVID-19 in 2020 still influences expected innovation activities in the two subsequent periods. It reduces the expected log growth rate in 2021 by 4.1% and by 1.0% in 2022. These results indicate that firms negatively affected by COVID-19 did not just reduce their innovation activities immediately after the shock but continued to restrict their activities further compared to non-negatively affected firms for at least two more years. We estimate the overall impact of being negatively affected by COVID-19 on the firms' innovation expenditures over the combined log growth rate of innovation expenditures of the three-year period from 2019 to 2022 in column 3. Overall, firms reduced their (expected) innovation expenditure growth in this period by 11.4%.

Table 7: Longer-run Impact of COVID-19 Pandemic on Innovation

	(1) Δ ln(inno) 2020 − 2021	(2) Δ ln(inno) 2021 − 2022	(3) Δ ln(inno) 2019 − 2022
COVID^{neg}	-0.041***	-0.010***	-0.114***
	(-3.92)	(-2.97)	(-6.72)
$\ln(\text{emp}_{2019})$	-0.002	-0.002	0.015
	(-0.36)	(-0.94)	(1.21)
$\ln(\text{inno}_{2019})$	-0.001	0.002**	-0.001
	(-0.22)	(2.07)	(-0.11)
Constant	0.099	0.023	-0.063
	(0.92)	(1.23)	(-0.82)
Observations	1718	1615	1673

Notes: Industry fixed effects but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

We employ the same entropy balancing procedure as in the previous section to counteract a potential bias due to non-random treatment allocation. We again reweight the control group observations such that the first three moments of the control variables match the treatment groups' and use these observation weights in a second step in the estimation of our models. Tables A.4-A.6 in the Appendix show the results of the entropy balancing procedure. The results in Table 8 show that after our balancing procedure the estimated impact stays qualitatively the same as without entropy balancing. We still find similar highly significant effects from being negatively affected by COVID-19 pandemic on expected innovation activities. However, the effect for 2021 in column 1 is almost cut in half (2.3%), while the effect in 2022 only slightly decreases by 0.1pp to -0.9%. The overall effect on innovation expenditure growth from 2020 to 2022 declines from 11.4% to 8.9%. As for previous results, including control variables in the estimation in columns 4-6 does not cause any change in the estimated effect and only increases the estimates' precision slightly.

Table 8: Longer-run Impact of COVID-19 Pandemic on Innovation - Accounting for Selection (Entropy Balancing)

	(1)	(2)	(3)
	Δ ln(inno)	Δ ln(inno)	Δ ln(inno)
	2020 − 2021	2021 − 2022	2019 − 2022
COVID^{neg}	-0.023***	-0.009***	-0.089***
	(-2.89)	(-3.58)	(-6.80)
ln(emp$_{2019}$)	-0.000	-0.002*	0.006
	(-0.18)	(-1.92)	(1.17)
ln(inno$_{2019}$)	0.002	0.003***	-0.002
	(0.82)	(4.40)	(-0.54)
Constant	0.072	0.036***	0.001
	(1.32)	(4.16)	(0.02)
Observations	1690	1592	1651

Notes: The models in columns 3 and 4 are estimated using observation weights from the entropy balancing procedure (see 4).Industry fixed effects but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

5.4 Moderating Impact of Digitalization

The use of digital tools increased drastically during the pandemic because it allowed firms to continue to operate at least partially. Therefore, a business model that already included digital elements such as the use of digital platforms or a digital integration of suppliers and cooperation partners before the pandemic likely buffered to some extent the adverse effects of the COVID-19 pandemic (Diekhof et al. 2021). To test if a high degree of digitalization also allowed firms to continue innovation activities, we include the pre-pandemic digitalization level in our estimation as described in section 4. The model's results using unweighted observations in columns 1 and 2 of Table 9 for an immediate impact show that not highly digitalized firms affected by COVID-19 decreased R&D- and innovation expenditure growth by 9.9% and 16.3% respectively. Firms not affected by COVID-19 but with a high level of digitalization had a 18.6% higher R&D- and 17.6% higher innovation expenditure growth rate during the COVID-19 pandemic in 2020 than firms that were not negatively affected and were not highly digitalized. Firms that were highly digitalized and were affected negatively by COVID-19 decreased their R&D expenditure growth rate only by 1.2%. They also only decreased their innovation expenditure growth rate by 5.2%. However, these effects are not significantly different from zero. These differences of being negatively affected by COVID-19 are significantly different for highly digitalized and not highly digitalized firms are significantly different from each other at the 10% level for R&D- and innovation expenditure. The results for the reweighted sample in columns 3 and 4 again only differ slightly in size but stay qualitatively the same[5]. The effect of being negatively affected by COVID-19 on not highly digitalized firms increases slightly for both R&D expenditures and increases innovation, and the effects for both outcomes for highly

[5]We present the results of the entropy balancing procedure in Tables ?? and ?? in the appendix.

digitalized firms decrease slightly. However, the effects of being negatively affected still differ significantly for digitalized and non-digitalized firms.

Table 9: Digitalization: Short-run Impact

	(1) Δ ln(R&D)	(2) Δ ln(inno)	(3) Δ ln(R&D)	(4) Δ ln(inno)
COVID^{neg} $= 1$ & Digi$= 0$	-0.099***	-0.163***	-0.104***	-0.171***
	(-2.78)	(-4.02)	(-3.19)	(-4.59)
COVID^{neg} $= 0$ & Digi$= 1$	0.186***	0.176***	0.173***	0.140**
	(3.21)	(2.76)	(3.33)	(2.46)
COVID^{neg} $= 1$ & Digi$= 1$	-0.012	-0.052	-0.016	-0.069
	(-0.25)	(-0.98)	(-0.33)	(-1.30)
ln(emploees$_{2019}$)	0.032*	0.031	0.002	0.006
	(1.67)	(1.57)	(0.11)	(0.38)
ln(R&D exp.$_{2019}$)	-0.035***		-0.018***	
	(-3.81)		(-2.62)	
ln(inno. exp.$_{2019}$)		-0.042***		-0.022***
		(-4.56)		(-3.11)
ln(investment$_{2019}$)				
Constant	-0.312**	-0.333**	-0.088	-0.071
	(-2.17)	(-2.08)	(-0.95)	(-0.71)
Observations	2210	2210	2210	2210

Notes: Industry fixed effects in all models but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

5.5 Innovation Response of Positively Treated Firms

The COVID-19 pandemic constitutes a unique situation because apart from having detrimental impacts on a large quantity of firms, it also affected a substantial amount positively. In our sample over 200 firms or 8.6% reported to have benefited from the COVID-19 pandemic situation. We showed in section 3 that these firms increased their sales substantially in response to higher demand. Increased demand rise opportunity costs for innovation activities as Aghion and Saint-Paul (1998) argue. This decreases innovation activities for potential future benefits in favor of increasing production for short-run benefits. We, therefore, repeat our analysis for positively affected firms, keeping not affected firms as the control group, and excluding negatively impacted ones.

Our results in Table 10 suggest that positively affected firms reduce their innovation activities and investments significantly in response to the COVID-19 shock. We find a 19.8% reduction in R&D expenditures and a 26.3& reduction in innovation expenditures, as well as a 9.7% decrease in investments in 2019 in columns 1-3. These results show an even stronger effect of the COVID-19 pandemic on innovation activities of positively affected firms than of negatively affected ones. At the same time, being positively affected comes with a substantial increase in sales (see Table 2 in section 3). Columns 4-6 in Table

10 investigate if this solely occurred through their output's price inflation or also through substantially increased production by estimating the same model for flexible production inputs. Column 4 in Table 10 shows that positively affected firms increased, on average, their material production input cost by 7.1%. However, they also increased their labor cost by 3.7%, while significantly increasing employment by an average of 4.9%.

Table 10: Positively Affected Firms: Entropy Balancing

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(R&D)	Δ ln(inno)	Δ ln(invest)	Δ ln(material cost)	Δ ln(labor cost)	Δ ln(emp)
COVID^{pos}	-0.198***	-0.263***	-0.097**	0.071***	0.037*	0.049***
	(-7.31)	(-8.54)	(-2.00)	(2.70)	(1.71)	(5.14)
ln(emp$_{2019}$)	0.003	0.012	0.045*	0.081***	0.281***	-0.003
	(0.36)	(1.15)	(1.87)	(5.91)	(10.08)	(-1.00)
ln(R&D$_{2019}$)	-0.008*					
	(-1.74)					
ln(inno$_{2019}$)		-0.016***				
		(-3.13)				
ln(invest$_{2019}$)			-0.041***			
			(-3.82)			
ln(material cost$_{2019}$)				-0.059***		
				(-6.30)		
ln(labor cost$_{2019}$)					-0.232***	
					(-9.70)	
Constant	0.086	0.034	-0.191	-0.530***	-1.143***	-0.058*
	(1.22)	(0.42)	(-1.34)	(-5.45)	(-10.91)	(-1.82)
Observations	1969	1969	1272	1381	1515	1911

Notes: Industry fixed effects in all models but not reported; Heteroscedasticity robust standard errors; t statistics in parentheses, * p<0.1, ** p<0.05, *** p<0.01

6 Conclusion

The COVID-19 pandemic spread over the globe in early 2020 and had severe economic consequences. The direct health and behavioral consequences combined with imposed pandemic countermeasures led to strong declines in revenue for a majority of firms and resulted in a deep recession. Firms had to react to this crisis by reorganizing internal processes - including innovation activities - while being under substantial financial distress.

This paper investigates how resilient firms' innovation activities were in COVID-19 pandemic. We provide evidence on firms' short- and medium-run reactions to a negative impact by COVID-19. We additionally analyze the role digitalization plays in firms' innovation responses to the pandemic. Furthermore, we shed light on the innovation response of firms positively impacted by COVID-19. We employ data from two waves of the Mannheim Innovation Survey, a representative survey for German firms, constituting the German contribution to the European Commission's Community Innovation Survey (CIS). We complement our difference-in-differences framework with balancing moments of our treatment and control groups using an entropy balance approach to minimize a potential non-random selection into treatment bias.

Our results show that negatively affected firms decrease their R&D expenditures significantly by 12.9% and innovation expenditure by 17.6% more than firms in the control group. Moreover, we find evidence of a Long-COVID effect on the German innovation system. Firms negatively impacted by the pandemic in 2020 still expect to reduce their innovation expenditures by 2.3% in 2021 and 0.9% in 2022. We furthermore find that innovation activities from firms that already possessed a high level of digital capabilities, such as a digital integration of suppliers and customers or the use of digital platforms, are more resilient to the negative COVID-19 shock compared to less digitized treated firms. A subset of firms were generally positively affected by the pandemic situation, mainly because of the increased demand of their products. For example, medical equipment suppliers and providers of digital working solutions increased their revenues substantially in 2020. Our results suggest that even firms that were generally positively affected by the COVID-19 pandemic reduced their R&D- and innovation activities, while shifting attention to extending short-run production capabilities.

Our finding draw an overall pessimistic picture of the impact of the COVID-19 pandemic on innovation activities of German firms. We show that not only negatively affected firms not only cut their innovation activities in the short-run but also do not expect to return to pre-crisis innovation levels by the end of 2022. However, also firms profiting from the pandemic reduce their innovation activities. Our results suggest a need for policies aimed at fostering innovation activities, considering that innovation is a key component of economic growth and international competitiveness.

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A Appendix

Table A.1: Entropy Balancing: R&D Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(R\&D_{2019})$	-6.681	14.502	0.982	-6.723	14.380	1.047
$\ln(emp_{2019})$	3.171	2.860	0.791	3.206	2.297	0.697
high-tech	0.053	0.050	4.002	0.061	0.058	3.656
medium high-tech	0.133	0.116	2.161	0.111	0.099	2.473
medium low-tech	0.133	0.116	2.161	0.148	0.126	1.983
low-tech	0.165	0.138	1.804	0.091	0.083	2.841
knowledge-intensive services	0.236	0.181	1.242	0.280	0.202	0.978
less Knowledge-intensive services	0.255	0.190	1.127	0.147	0.126	1.990
other manufacturing	0.014	0.014	8.347	0.117	0.103	2.384
	Post-Balancing					
$\ln(R\&D_{2019})$	-6.681	14.502	0.982	-6.682	14.474	0.983
$\ln_{lb} ges$	3.171	2.860	0.791	3.171	2.855	0.791
high-tech	0.053	0.050	4.002	0.053	0.050	4.003
medium high-tech	0.133	0.116	2.161	0.133	0.115	2.162
medium low-tech	0.133	0.116	2.161	0.133	0.115	2.162
low-tech	0.165	0.138	1.804	0.165	0.138	1.805
knowledge-intensive services	0.236	0.181	1.242	0.236	0.180	1.243
less Knowledge-intensive services	0.255	0.190	1.127	0.254	0.190	1.128
other manufacturing	0.014	0.014	8.347	0.014	0.014	8.165

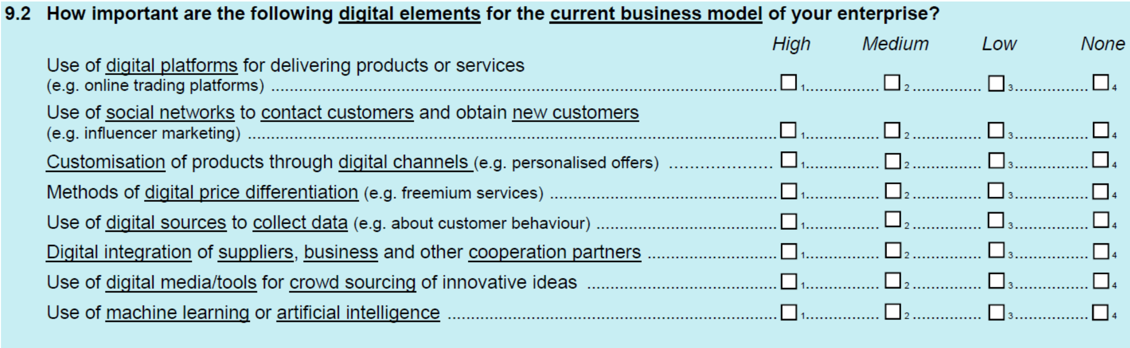
Notes:

Figure A1: COVID-19 question MIP

12.1 How did the Covid-19 Pandemic affect your enterprise in the year 2020?

extremely negative ☐1 …… *very negative* ☐2 …… *negative* ☐3 …… *marginally/not at all* ☐4 …… *positive* ☐5 …… *very positive* ☐6

Figure A2: Digital Concepts Question MIP



9.2 How important are the following digital elements for the current business model of your enterprise?

	High	Medium	Low	None
Use of digital platforms for delivering products or services (e.g. online trading platforms)	☐ 1	☐ 2	☐ 3	☐ 4
Use of social networks to contact customers and obtain new customers (e.g. influencer marketing)	☐ 1	☐ 2	☐ 3	☐ 4
Customisation of products through digital channels (e.g. personalised offers)	☐ 1	☐ 2	☐ 3	☐ 4
Methods of digital price differentiation (e.g. freemium services)	☐ 1	☐ 2	☐ 3	☐ 4
Use of digital sources to collect data (e.g. about customer behaviour)	☐ 1	☐ 2	☐ 3	☐ 4
Digital integration of suppliers, business and other cooperation partners	☐ 1	☐ 2	☐ 3	☐ 4
Use of digital media/tools for crowd sourcing of innovative ideas	☐ 1	☐ 2	☐ 3	☐ 4
Use of machine learning or artificial intelligence	☐ 1	☐ 2	☐ 3	☐ 4

Table A.2: Entropy Balancing: Innovation Expenditure Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(\text{inno}_{2019})$	-6.573	15.116	0.931	-6.606	15.069	0.992
$\ln(\text{emp}_{2019})$	3.171	2.860	0.791	3.206	2.297	0.697
high-tech	0.053	0.050	4.002	0.061	0.058	3.656
medium high-tech	0.133	0.116	2.161	0.111	0.099	2.473
medium low-tech	0.133	0.116	2.161	0.148	0.126	1.983
low-tech	0.165	0.138	1.804	0.091	0.083	2.841
knowledge-intensive services	0.236	0.181	1.242	0.280	0.202	0.978
less Knowledge-intensive services	0.255	0.190	1.127	0.147	0.126	1.990
other manufacturing	0.014	0.014	8.347	0.117	0.103	2.384
	Post-Balancing					
$\ln(\text{inno}_{2019})$	-6.573	15.116	0.931	-6.574	15.087	0.932
$\ln_{lb} ges$	3.171	2.860	0.791	3.172	2.855	0.791
high-tech	0.053	0.050	4.002	0.053	0.050	4.003
medium high-tech	0.133	0.116	2.161	0.133	0.115	2.162
medium low-tech	0.133	0.116	2.161	0.133	0.115	2.162
low-tech	0.165	0.138	1.804	0.165	0.138	1.805
knowledge-intensive services	0.236	0.181	1.242	0.236	0.180	1.243
less Knowledge-intensive services	0.255	0.190	1.127	0.254	0.190	1.128
other manufacturing	0.014	0.014	8.347	0.014	0.014	8.160

Notes:

Table A.3: Entropy Balancing: Investment Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(invest$_{2019}$)	-5.338	16.077	0.455	-4.277	14.381	0.003
ln(emp$_{2019}$)	3.099	2.801	0.650	3.206	2.245	0.555
high-tech	0.046	0.044	4.312	0.063	0.059	3.584
medium high-tech	0.148	0.126	1.986	0.107	0.095	2.551
medium low-tech	0.139	0.120	2.084	0.142	0.122	2.055
low-tech	0.156	0.132	1.895	0.080	0.074	3.094
knowledge-intensive services	0.245	0.186	1.188	0.305	0.212	0.845
less Knowledge-intensive services	0.236	0.181	1.242	0.140	0.120	2.075
other manufacturing	0.021	0.021	6.665	0.120	0.105	2.343
	Post-Balancing					
ln(invest$_{2019}$)	-5.338	16.077	0.455	-5.334	16.039	0.453
ln(emp$_{2019}$)	3.099	2.801	0.650	3.100	2.790	0.650
high-tech	0.046	0.044	4.312	0.046	0.044	4.316
medium high-tech	0.148	0.126	1.986	0.147	0.126	1.989
medium low-tech	0.139	0.120	2.084	0.139	0.120	2.087
low-tech	0.156	0.132	1.895	0.156	0.132	1.898
knowledge-intensive services	0.245	0.186	1.188	0.244	0.185	1.190
less Knowledge-intensive services	0.236	0.181	1.242	0.236	0.180	1.245
other manufacturing	0.021	0.021	6.665	0.022	0.022	6.441

Notes:

Table A.4: Entropy Balancing: Expected Innovation Expenditure 2020-2021 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno$_{2019}$)	-7.035	14.199	1.285	-6.772	14.816	1.109
ln(emp$_{2019}$)	3.097	2.816	0.898	3.175	2.350	0.752
high-tech	0.037	0.036	4.903	0.059	0.056	3.732
medium high-tech	0.117	0.104	2.379	0.116	0.103	2.392
medium low-tech	0.127	0.111	2.247	0.140	0.120	2.077
low-tech	0.160	0.135	1.850	0.092	0.084	2.818
knowledge-intensive services	0.241	0.183	1.213	0.277	0.201	0.994
less Knowledge-intensive services	0.296	0.209	0.892	0.153	0.130	1.928
other manufacturing	0.012	0.012	8.832	0.117	0.103	2.381
	Post-Balancing					
ln(inno$_{2019}$)	-7.035	14.199	1.285	-7.035	14.164	1.286
ln(emp$_{2019}$)	3.097	2.816	0.898	3.097	2.809	0.898
high-tech	0.037	0.036	4.903	0.037	0.036	4.904
medium high-tech	0.117	0.104	2.379	0.117	0.104	2.380
medium low-tech	0.127	0.111	2.247	0.126	0.111	2.247
low-tech	0.160	0.135	1.850	0.160	0.135	1.850
knowledge-intensive services	0.241	0.183	1.213	0.241	0.183	1.213
less Knowledge-intensive services	0.296	0.209	0.892	0.296	0.209	0.893
other manufacturing	0.012	0.012	8.832	0.013	0.013	8.698

Notes:

Table A.5: Entropy Balancing: Expected Innovation Expenditure 2021-2022 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(\text{inno}_{2019})$	-7.283	12.817	1.434	-6.928	14.568	1.230
$\ln(\text{emp}_{2019})$	3.022	2.655	0.881	3.168	2.391	0.774
high-tech	0.033	0.032	5.190	0.061	0.057	3.665
medium high-tech	0.107	0.096	2.542	0.109	0.097	2.509
medium low-tech	0.127	0.111	2.239	0.141	0.121	2.066
low-tech	0.167	0.140	1.783	0.090	0.082	2.855
knowledge-intensive services	0.234	0.180	1.256	0.282	0.202	0.972
less Knowledge-intensive services	0.308	0.214	0.833	0.155	0.131	1.902
other manufacturing	0.013	0.013	8.471	0.117	0.103	2.386
	Post-Balancing					
$\ln(\text{inno}_{2019})$	-7.283	12.817	1.434	-7.283	12.783	1.434
$\ln(\text{emp}_{2019})$	3.022	2.655	0.881	3.022	2.648	0.882
high-tech	0.033	0.032	5.190	0.033	0.032	5.191
medium high-tech	0.107	0.096	2.542	0.107	0.096	2.543
medium low-tech	0.127	0.111	2.239	0.127	0.111	2.240
low-tech	0.167	0.140	1.783	0.167	0.139	1.784
knowledge-intensive services	0.234	0.180	1.256	0.234	0.179	1.256
less Knowledge-intensive services	0.308	0.214	0.833	0.308	0.213	0.834
other manufacturing	0.013	0.013	8.471	0.014	0.013	8.385

Notes:

Table A.6: Entropy Balancing: Expected Innovation Expenditure 2019-2022 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(\text{inno}_{2019})$	-7.382	12.459	1.531	-6.987	14.263	1.264
$\ln(\text{emp}_{2019})$	2.994	2.600	0.902	3.152	2.360	0.776
high-tech	0.042	0.040	4.587	0.060	0.056	3.715
medium high-tech	0.099	0.090	2.679	0.111	0.098	2.484
medium low-tech	0.122	0.107	2.313	0.143	0.122	2.044
low-tech	0.179	0.148	1.670	0.089	0.081	2.890
knowledge-intensive services	0.234	0.180	1.257	0.275	0.199	1.009
less Knowledge-intensive services	0.301	0.211	0.866	0.157	0.132	1.887
other manufacturing	0.013	0.013	8.661	0.119	0.105	2.357
	Post-Balancing					
$\ln(\text{inno}_{2019})$	-7.382	12.459	1.531	-7.383	12.426	1.532
$\ln(\text{emp}_{2019})$	2.994	2.600	0.902	2.994	2.594	0.902
high-tech	0.042	0.040	4.587	0.042	0.040	4.588
medium high-tech	0.099	0.090	2.679	0.099	0.090	2.679
medium low-tech	0.122	0.107	2.313	0.122	0.107	2.313
low-tech	0.179	0.148	1.670	0.179	0.147	1.671
knowledge-intensive services	0.234	0.180	1.257	0.234	0.179	1.257
less Knowledge-intensive services	0.301	0.211	0.866	0.301	0.211	0.867
other manufacturing	0.013	0.013	8.661	0.013	0.013	8.546

Notes:

Table A.7: Entropy Balancing: Digitization Heterogeneous Treatment Effect R&D Expenditure Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(R\&D_{2019})$	-6.513	14.487	0.861	-6.753	14.196	1.061
Digi	0.508	0.250	-0.031	0.425	0.244	0.304
$\ln(emp_{2019})$	3.177	2.803	0.779	3.197	2.287	0.686
high-tech	0.054	0.052	3.927	0.061	0.057	3.686
medium high-tech	0.144	0.123	2.030	0.114	0.101	2.435
medium low-tech	0.135	0.117	2.135	0.148	0.126	1.983
low-tech	0.166	0.138	1.799	0.091	0.083	2.848
knowledge-intensive services	0.229	0.177	1.292	0.282	0.202	0.971
less Knowledge-intensive services	0.248	0.187	1.165	0.148	0.126	1.983
other manufacturing	0.013	0.013	8.574	0.114	0.101	2.426
	Post-Balancing					
$\ln(R\&D_{2019})$	-6.513	14.487	0.861	-6.514	14.460	0.861
Digi	0.508	0.250	-0.031	0.508	0.250	-0.030
$\ln(emp_{2019})$	3.177	2.803	0.779	3.177	2.798	0.779
high-tech	0.054	0.052	3.927	0.054	0.051	3.928
medium high-tech	0.144	0.123	2.030	0.144	0.123	2.031
medium low-tech	0.135	0.117	2.135	0.135	0.117	2.136
low-tech	0.166	0.138	1.799	0.165	0.138	1.800
knowledge-intensive services	0.229	0.177	1.292	0.229	0.176	1.293
less Knowledge-intensive services	0.248	0.187	1.165	0.248	0.187	1.166
other manufacturing	0.013	0.013	8.574	0.014	0.014	8.370

Notes:

Table A.8: Entropy Balancing: Digitization Heterogeneous Treatment Effect Innovation Expenditure Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(inno_{2019})$	-6.374	15.141	0.798	-6.605	14.966	0.986
Digi	0.508	0.250	-0.031	0.425	0.244	0.304
$\ln(emp_{2019})$	3.177	2.803	0.779	3.197	2.287	0.686
high-tech	0.054	0.052	3.927	0.061	0.057	3.686
medium high-tech	0.144	0.123	2.030	0.114	0.101	2.435
medium low-tech	0.135	0.117	2.135	0.148	0.126	1.983
low-tech	0.166	0.138	1.799	0.091	0.083	2.848
knowledge-intensive services	0.229	0.177	1.292	0.282	0.202	0.971
less Knowledge-intensive services	0.248	0.187	1.165	0.148	0.126	1.983
other manufacturing	0.013	0.013	8.574	0.114	0.101	2.426
	Post-Balancing					
$\ln(inno_{2019})$	-6.374	15.141	0.798	-6.375	15.114	0.798
Digi	0.508	0.250	-0.031	0.508	0.250	-0.030
$\ln(emp_{2019})$	3.177	2.803	0.779	3.177	2.799	0.780
high-tech	0.054	0.052	3.927	0.054	0.051	3.928
medium high-tech	0.144	0.123	2.030	0.144	0.123	2.032
medium low-tech	0.135	0.117	2.135	0.135	0.117	2.136
low-tech	0.166	0.138	1.799	0.165	0.138	1.801
knowledge-intensive services	0.229	0.177	1.292	0.229	0.176	1.293
less Knowledge-intensive services	0.248	0.187	1.165	0.248	0.187	1.166
other manufacturing	0.013	0.013	8.574	0.014	0.014	8.365

Notes: