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Pandemic effects: do innovation activities of German firms suffer from Long-COVID?

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Pandemic effects: do innovation activities of German firms suffer from Long-COVID?

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Abstract

The COVID-19 pandemic has affected firms in many economies. Exploiting treatment heterogeneity, we use a difference-in-differences design to causally identify the short-run impact of COVID-19 on innovation spending in 2020 and expected innovation spending in subsequent years. Based on a representative sample of German firms, we find that negatively affected firms substantially reduced innovation expenditure not only in the first year of the pandemic (2020) but also in the two subsequent years, indicating 'Long–Covid' effects on innovation. In 2020, innovation expenditure fell by 4.7 % due to the pandemic. In 2022, innovation spending was even 5.4 % lower compared to the counterfactual scenario without the pandemic. Firms with higher pre-treatment digital capabilities show higher innovation resilience during the pandemic. Moreover, COVID-19 leads to a decrease in innovation spending not only in firms that were strongly negatively affected by the pandemic, but also in those firms that experienced a positive demand shock from the pandemic, presumably to increase production capacity.

Keywords: COVID-19, innovation, difference-in-differences, economic crisis, resilience

JEL Classification: O31, O33

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1 Introduction

The COVID-19 pandemic was a shock that exogenously hit societies and economies around the world in early 2020. Most countries imposed immediate measures and restrictions to cope with the pandemic and to prevent healthcare systems from breaking down. Governments highly restricted face-to-face meetings and communication as well as national and international travel with adverse impacts on supply chains, working from home became compulsory in many cases, and the selling of goods and services was limited or even prevented by lockdowns (Brodeur et al. 2021).

As a result, the pandemic and its countermeasures negatively impacted many economies. Many firms experienced a sharp decline in revenues (Bloom et al. 2021a; Paunov and Planes-Satorra 2021), and a recession occurred, with GDP falling by 3.6% worldwide in 2020.[1] To combat the crisis and continue business, firms had to adjust their strategies and procedures, including reallocating resources and reorganizing internal processes and innovation activities, which constitute an important strategic choice variable under these circumstances (Aghion et al. 2012; Bloom 2007).

In this paper, we causally identify to what extent the pandemic has changed firms' innovation efforts. Most empirical evidence from previous crises shows that innovation activity is pro-cyclical, 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 that is not directly comparable to previous economic crises. First, the pandemic caused substantial disruptions of internal processes due to temporary lockdowns and mandatory teleworking. Lack of or limited access to R&D laboratories and, as a result, to tools such as equipment and research materials impede internal R&D activities. Second, labor shortages occurred 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 have affected not only a firm's production but also the material needed for innovation activities. Finally, COVID-19 led to a disproportionate increase in financial restrictions and 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 stringent 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.

At the same time, the COVID-19 restrictions immediately forced many firms to invest in the development of new products and processes and to change their business model. Besides examples such as new health-related products and devices, this relates especially

[1] In Germany, the country of observation in our study, GDP actually contracted by even 4.6% in 2020.

to new online offerings, the digital delivery of services, and the introduction of new forms of remote work and online communication.

A unique feature of the COVID-19 pandemic is that, while it caused a global recession, some firms have also experienced a very unexpected economic boom in their markets resulting from increased demand for their products that were needed to address the crisis, like vaccines, other health protection devices, and IT service providers.

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, and it extends the sparse primary evidence of the immediate impact of COVID-19 on firms' innovation behavior (for summaries, see Brodeur et al. 2021; Allen 2022; Fink et al. 2022) in three important dimensions. First, it focuses on the impact of the COVID-19 pandemic on innovation activities of German firms, looking both at immediate responses (in 2020) and medium-term prospects of innovation activities in the years 2021 and 2022. Second, we further exploit the treatment heterogeneity and investigate heterogeneous innovation responses of both firms that were negatively hit by the pandemic and those that benefited from the pandemic. Finally, we examine the role that digital capabilities play in the size of the treatment effect, more specifically, whether firms' innovation activities have been more resilient during the crisis if they had already possessed substantial digital capabilities before the pandemic.

Our study uses information from two waves of the Mannheim Innovation Panel (MIP), which is the German contribution to the European-wide Community Innovation Survey (CIS). We employ a difference-in-differences (DiD) design to causally identify the short-run impact of COVID-19 on innovation in 2020 and the impact on expected innovation spending in the following years. 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.

Our analysis reveals five important findings. First, firms that are negatively affected by the COVID-19 pandemic show an immediate and strong negative response in R&D activities in 2020. The growth rate of R&D expenditure of negatively affected firms is 12.9 %-points lower than in the control group of non-affected firms. Innovation expenditure, which includes complementary expenditure in addition to R&D, even grows by about 17.6 %-points less. Despite a strong innovation response, it is nevertheless lower than the change in physical capital, with a decline in the growth rate of 29 %-points. The order of these effects suggests that anticipated adjustment costs, which are largest in R&D, outweigh the reversibility value of investments, which are largest in fixed investment.

Second, our results reveal Long-COVID effects. The immediate decline is followed by long-lasting adverse effects on innovation activities in the following years. Firms negatively affected by the COVID-19 pandemic have 2.3 %-points lower growth in planned innovation spending in 2021. Even two years later in 2022, the same firms are still suffering from the pandemic by experiencing a nearly 1 %- point lower innovation spending growth. As a result, firms negatively hit by COVID-19 did not recover in terms of innovation spending by 2022. Instead, we observe a substantial decline in innovation spending between the pre-crisis year 2019 and the post-crisis year 2022.

Third, 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 less digitalized firms. Thus, firms' existing digital capabilities were highly beneficial for performing innovation activities during 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).

Fourth, we also find evidence for opportunity cost arguments that have been brought forward in growth theory. Firms that have been positively affected by the COVID-19 pandemic experienced nearly 20 and 26 %-points lower growth in their R&D and innovation activities, respectively, compared to unaffected firms, in favor of extending short-term revenues and production capabilities. This result confirms Aghion and Saint-Paul (1998)'s argument that firms increase production and reduce innovation activities when demand for their products rises.

Finally, our results show that the short- and medium-term innovation consequences of the COVID-19 pandemic are substantial at the macroeconomic level. The pandemic has led to a short-term decline in innovation spending of EUR 8.8 billion or 4.7 % in Germany in 2020 compared with the counterfactual situation without COVID. The loss in innovation spending further grew to 5.4 % in 2022.

The remainder of the paper is structured as follows: Section 2 discusses the expected effects of the COVID-19 pandemic on innovation in some more conceptual detail. Section 3 presents the data, while Section 4 outlines the econometric methodology. The estimation results are presented in Section 5, and Section 6 concludes.

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 US firms' revenues fell by 29 % in the first quarter of 2020.

Second, lockdowns and restrictions on international transport routes disrupted global supply chains and created shortages of raw materials and intermediate products (Bonadio et al. 2021; Bartik et al. 2020). This supply shock 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 that in 2020, 45 % of German manufacturing firms faced supply problems for intermediate products. 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 cushion their decline in income. Firms needed financial resources to weather a period of low or no revenues and higher costs and to finance important business strategy changes (De Vito and Gómez 2020). Households needed financial resources to compensate for their income decline due to job losses or short-time work. This increased demand for credit met with tight financial markets (Li et al. 2020; Zhang et al. 2020). However, intensive policy interventions partially dampened negative consequences of liquidity constraints as Elenev et al. (2022) and Dörr et al. (2022) describe.

Fourth, firms had to change organizational routines to cope with the pandemic. Due to the health risks associated with face-to-face contacts and the implementation of social distancing measures, firms have had to reorganize relations among their employees and 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 continue business operations while complying with social distancing measures. Such steps included acquiring protective equipment or implementing remote work capabilities (Kraus et al. 2020). Due to the high demand for such solutions, supply shortages, and tense financial markets, these types of reorganization measures became costly for already struggling firms.[2]

In addition to these direct economic impacts, the COVID-19 pandemic led to an abnormally huge increase in economic uncertainty. Firms had no experience about how long the exceptional circumstances would last, which government measures would be imposed that may further restrict business operations, and how product, financial, and labor markets would respond to the situation (Bloom et al. 2021b,a). As a result, any corporate planning process was heavily complicated. According to real options theory, firms may therefore have preferred to postpone decisions, i.e. uncertainty has adverse effects on investment decisions (Bloom et al. 2007).

However, the COVID-19 pandemic did not hit all markets negatively. Some industries faced a substantial exogenous increase in demand for their products and services, including medical equipment, health services, IT services, food delivery services, or cleaning services. In addition to possible other positive direct demand shocks, there were also positive indirect demand effects for industries such as financial consultants helping businesses to apply to

[2] Brodeur et al. (2021); Carlsson-Szlezak et al. (2020a,b) focus only on the first three channels, but they neglect the effect of the frictions and costs of reorganizing production processes to comply with social distancing measures, for finding alternative sales channels or introducing new business models. However, Kraus et al. (2020) and Balla-Elliott et al. (2020) show that restructuring measures represented significant costs and obstacles for firms at the beginning of the pandemic.

government support schemes related to the pandemic. Consequently, some firms in the economy also experienced a boom phase in their business cycle despite the general severe recession.

2.2 Impact of the Pandemic on Innovation

The literature on the impact of economic crises on innovation found both positive and negative effects. Positive effects of a recession on innovation tend to occur as a result of lower opportunity costs of innovation spending compared to capital investment (Aghion and Saint-Paul 1998). Since expanding capacity in a situation of decreasing demand is less profitable than investing in the development of new products or more efficient processes, firms will shift available human and financial resources towards innovation. In addition, the peculiarities of the COVID-19 crisis, especially the social distancing measures, may have urged firms to adjust internal processes and external relations. Both could have led to additional innovation activity in the short run by introducing new product and service offerings, adapting delivery modes, and implementing new procedures for maintaining business operations and interaction with customers and suppliers (Paunov and Planes-Satorra 2021).

The negative impacts of a crisis, on the other hand, are often related to liquidity constraints which result from a decrease in cash flow and profits, limiting the financial means of firms to invest in innovation (Himmelberg and Petersen 1994; Aghion et al. 2012; Ouyang 2011; Paunov and Planes-Satorra 2021). In addition, low demand during a crisis urges many firms to postpone the market launch of innovations until demand picks up, which allows innovators to charge higher prices for new products (see Shleifer 1986; Barlevy 2007; Fabrizio and Tsolmon 2014; Paunov and Planes-Satorra 2021). Finally, the higher level of uncertainty during a crisis may also cause firms to postpone their investments in innovation activities until more information is available on how the markets are developing (Bloom 2007, 2009, 2014). As discussed in the previous section, COVID-19 led to a disproportionate increase in both financial restrictions and uncertainty, which is expected to have reduced innovation activity.

Moreover, the specifics of the COVID-19 crisis may have led to further negative innovation effects. First, lockdowns and mandatory working from home rules may have hindered access to research and development laboratories and, consequently, to supplies such as equipment and research materials. Second, disease and quarantine regulations, which led to labor shortages, including among R&D personnel (Paunov and Planes-Satorra 2021), may have hampered the implementation of innovation activities. Third, companies may have discontinued or postponed innovation collaborations because travel restrictions made it much more difficult to work with external collaborators. Finally, the disrupted supply chains may have adversely affected not only the firm's production but also innovation activities.

In summary, we have opposing theoretical arguments on how the pandemic affected innovation investment decisions. The lower opportunity costs of innovation in economic downturns suggest that affected firms would have decided to invest more than before the crisis. However, the theoretical arguments on liquidity constraints, low demand and higher market uncertainty suggest reduced investment of firms that were hit negatively by the COVID-19 shock. Given the specific nature of the COVID crisis, we expect the negative investment incentives to outweigh the positive ones. First, 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. Second, the shift to working from home may have had a detrimental effect on firms' ability to innovate. A lack of face-to-face contacts, for example, may have reduced knowledge exchange and spillovers and, as a result, reduced researchers' creativity and productivity, and hinder collaborative R&D activities (Xiao et al. 2021; DeFilippis et al. 2020). The latter effect can hamper idea generation and innovation activity not only in the short run but also in the longer term, which would imply 'Long COVID' symptoms.

Therefore, we hypothesize

H1: COVID-19 causes a short-run decline in innovation spending of firms that were negatively affected by the pandemic. That is, firms facing high negative economic impacts from the COVID-19 pandemic will experience stronger negative impacts on their innovation activities in the short-run (i.e., in the first pandemic year 2020) than in the counterfactual situation in which they are not affected by the crisis.

H2: COVID-19 lowers innovation spending by negatively affected firms in the medium term (i.e. in the years 2021 and 2022).

For firms in markets that experienced a boom phase due to the pandemic outbreak, the theoretical arguments favoring pro-cyclical versus counter-cyclical investments may have taken on a different weight. On the one hand, firms that experienced a positive demand shock may have expanded their innovation activities, as they were not likely to suffer from liquidity constraints and, if anything, faced less uncertainty, mainly in how long the boom phase would last. On the other hand, positively affected firms might have been hit by total surprise by this 'windfall' demand surge and, therefore, found it attractive to shift resources from long-term innovation activities to immediate production expansion. The reason lies in the high opportunity costs of long-term innovation activities in terms of high foregone short-term profits. Combined with the adverse impact of social distancing on potential idea generation processes and innovation collaborations, as well as the impediment of innovation activities due to supply chain disruptions, we expect that firms facing higher demand also diverted resources from R&D and innovation (towards production). We, therefore, hypothesize the following.

H3: Firms experiencing a positive demand shock due to the COVID-19 pandemic will invest less in R&D and innovation than in the counterfactual situation of not being affected.

2.3 COVID-19 and Digitalization

A specific feature of the COVID-19 pandemic, compared to other economic crisis, is the role of digitalization. Key measures taken by governments to combat COVID-19 included restricted access to the workplace, mandatory work-from-home rules and travel restrictions. These social distancing measures required firms to increasingly rely on digital technologies for both in-house operations and external relations. Most prominently, firms implemented work-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 rely on digital technologies for procurement and marketing, for example by creating or advancing digital connections with suppliers and other business partners as well as digital sales channels Diekhof et al. (2021). The study by the OECD (2021) also confirmed a substantial increase in the use of digital platforms during the first half of 2020.

Advanced digital capabilities from before COVID are likely to mitigate the negative impact of COVID-19. Firms with high digital capabilities at the onset of the pandemic were presumably better prepared to adjust to the new situation and are likely to have shown greater resilience to the negative economic impacts, including a better ability to continue innovating. Bai et al. (2021) show that firms with a higher 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 less digitalized firms had to make costly investments using their scarce financial resources. These investments became especially expensive during the pandemic because of the increased demand for ICT and disrupted global supply chains.

H4: Firms with high digital capabilities at the onset of the COVID-19 pandemic are more resilient in their innovation activities to a negative COVID-19 shock than firms with low digital capabilities.

3 Data

3.1 Mannheim Innovation Panel

We use data from the Mannheim Innovation Panel (MIP), which collects information on innovation inputs and outputs of firms as well as general firm characteristics potentially affecting 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 for collecting 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 sectors.

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 attrition. 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 a possible non-response bias (for more details, see Peters and Rammer 2013).

3.2 Main Outcome Variables

To study the impact of the COVID-19 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. We can thus 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 in a firm's innovation expenditure between 2019 and 2020, measured as the log growth rate $\Delta\ln(\text{inno})_{2020-2019} = \ln(\text{inno})_{2020}$ - $\ln(\text{inno})_{2019}$[3], allows investigating the *short-run* impact of COVID-19 on firms' innovation behaviour (hypothesis H1). Innovation expenditure is defined as all expenditure incurred in the development and introduction of product and process innovations. In addition to spending on intramural and extramural R&D, this also includes spending on prototypes, testing, training, market introduction, and the acquisition of new machinery, software and intellectual property rights.

In addition to innovation expenditure, we use the corresponding change in *R&D expenditure*, $\Delta\ln(\text{R\&D})_{2020-2019}$, 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, $\Delta\ln(\text{invest})_{2020-2019}$.

To test our second hypothesis about the existence of Long COVID effects on innovation, we exploit the fact that the MIP collects data on planned innovation expenditure for for the two subsequent years after the wave's reference year. That is, the 2021 survey includes information on realized innovation expenditure for 2020 and 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 2021 data represents expected expenditure but with a high degree

[3]We omit the index i for convenience. All variables are measured at the firm level.

of certainty.[4] 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 for years in advance due to their strategic importance and the long-term nature of innovation projects.[5]

We use the changes (growth rate) in firms' innovation expenditure between 2020/2021 and 2021/2022, $\Delta\ln(\text{inno})_{2021-2020}$ and $\Delta\ln(\text{inno})_{2022-2021}$, to examine the *medium-term* impact of COVID-19 on firms' innovation behaviour (hypothesis H2). A negative impact of the COVID-19 treatment indicator on both growth rates would indicate that firms' innovation expenditure have not (fully) recovered even three years after the pandemic, a situation which we consider to be a *Long COVID* impact.

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 COVID-19 and its consequences. Firms were asked to indicate, on a six point Likert scale ranging from extremely negative to very positive, how COVID-19 has affected their enterprise *in general* in the year 2020. Figure A1 in the Appendix shows the question and Table 1 presents the distribution of exposure to COVID-19. Though the German economy was strongly negatively hit by the pandemic, 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 the first part of our 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).

In the second part of our empirical study, we then define the firms that were positively affected as the treatment group $Covid^{pos}$ (category 5 and 6), which represent 8.6 % of the sample, and use the non-affected firms (category 3 and 4) as control group, excluding strongly negatively affected firms.

[4]For the five-year period 2015-2019 before, MIP data show a very high correlation between expected and actual innovation spending for a given year of 0.9685.

[5]For the four-year period 2015-2018 prior, the correlation between the 2-year ahead expected and actual innovation spending is 0.912.

Table 1: Distribution of the Degree of COVID-19 Exposure

Category: COVID-19 Exposure	Observations	%
1. Extremly negative	150	6.0
2. Very negative	342	13.6
3. Slightly negative	829	33.0
4. Not affected	976	38.8
5. Positive	171	6.8
6. Very positive	46	1.8
Total	2514	100.0

Notes: Distribution is 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 first examine the relationship between firms' sales growth between 2019 and 2020 and its degree of COVID-19 exposure. We regress the log sales growth rate on dummy variables for each category of COVID-19 exposure, additionally controlling for pre-treatment firm size measured as log number of employees in 2019, $\ln(\text{emp})_{2019}$, and industry fixed effects. The results in column (2) of Table 2 show that the firms' assessment of their general exposure to the COVID-19 shock has a tight connection to their 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 increases monotonically 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 only lead to uncertain future benefits.

In addition to the shock in sales, our measure for the exposure to COVID-19 also reflects well changes in (external) liquidity constraints as we show in column (3) of Table 2. Firms that are extremely or very negatively affected by COVID-19 suffered a significant deterioration in their credit rating, while firms that indicated a very positive exposure to COVID-19 experienced a significant improvement in their credit worthiness.

Table 2: COVID-19 Exposure, Sales Growth and Change in Credit Rating

	Δ ln(sales)$_{2020-2019}$	Δ ln(credit rating)$_{2020-2019}$
COVID-19 Exposure		
1. Extremely negative	-0.573***	-0.0283***
	(-7.61)	(-5.19)
2. Very negative	-0.209***	-0.0177**
	(-7.34)	(-2.45)
3. Slightly negative	-0.091***	-0.004
	(-4.75)	(-1.48)
4. Not affected	reference category	reference category
5. Positive	0.106***	0.000
	(3.11)	(0.010)
6. Very positive	0.276***	0.013*
	(2.72)	(1.91)
ln(emp)$_{2019}$	-0.004	-.002**
	(-0.55)	(-2.48)
Constant	0.055	0.008
	(1.52)	(1.48)
Observations	2,514	2,457

Notes: 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

To test hypothesis H4 about the mitigating role of advanced IT architecture, we include the firm's level of digitalization prior to the COVID-19 pandemic in 2019 in our analysis. We use a question[6] from the 2020 MIP wave, which asked about the importance of eight digitalization modes to the the firm's business model in 2019 on a four-point Likert scale. Digital elements include, among others, using digital platforms to deliver products and services, interacting with customers through digital channels, digitally integrating suppliers, business and other cooperation partners, collecting data from digital sources, and using machine learning and artificial intelligence. We calculate a digitalization index by summing up the eight modes (assigning the value zero for not important and three for highly important). Based on this index, we create an indicator variable $Digi_{2019}$ that equals one if the firm's pre-treatment digitalization index scores above the sample's median 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.

[6]See figure A2 in the Appendix.

3.5 Descriptive Statistics

For the empirical analysis, we omit observations with missing values in any of our main outcome variables $\Delta \ln(\text{R\&D})_{2020-2019}$ and $\Delta \ln(\text{inno})_{2020-2019}$, the treatment indicator (exposure to COVID-19), or the control variables, which we explain in more detail in Section 4. Furthermore, we drop outliers by excluding firms with log-growth rates of R&D and innovation expenditure below -100% and exclude outliers following the method of Belsley et al. (2005) and Bollen and Jackman (1985).[7] This leaves an estimation sample of 2,482 firms for which we have data for both 2019 and 2020.

Table 3 presents key statistics of the distribution of the variables we use in the analysis, differentiated by treatment and control groups, i.e. we compare both negatively and positively affected firms to the control group of unaffected firms. The control group consists of 1,775 observations and is about four times larger than the treatment group of negatively affected firms, and the distributions of most variables differ at least to some extent. The amount of positively affected firms is substantially smaller than the amount of negatively affected firms. The group of positively treated firms has, with 187 observations, not even half the size of the negatively treated group (463 observations).

Negatively treated firms already had lower sales in 2019 and their sales growth rate $\Delta \ln(\text{sales})$ in 2020 is, on average, about 30%-points lower than that of firms in the control group. This pattern is similar for investment ($\ln(\text{invest})_{2019}$, $\Delta \ln(\text{invest})_{2020-2019}$) and already indicates that, for German firms, being negatively affected by COVID-19 correlates with reduced revenues and investment, as Bloom et al. (2021a) showed for the US.

Differently than for revenues and investment, R&D- and innovation expenditure in 2019, $\ln(\text{R\&D})_{2019}$ and $\ln(\text{inno})_{2019}$, do not differ significantly between negatively treated firms and the control group. However, their average growth rates in 2020, $\Delta \ln(\text{inno})_{2020-2019}$ and $\Delta\ \ln(\text{R\&D}_{2020-2019})$ are significantly lower for the treatment group. The growth rates for expected innovation spending for the years 2021 and 2022, as well as their combined three-year growth rate, exhibit a similar pattern.

In the 'positive' treatment group, we see that sales increased on average by about 15 %, while investments grew by as much as 37 %. Both average growth rates are significantly larger than in the control group. In sharp contrast, R&D and innovation expenditure remained almost constant and turn out to be significantly lower than in the control group. However, these differences between treated and control groups, might reflect differences in firm characteristics or industry differences, which argues for a more rigorous econometric causal analysis.

[7] We measure the most influential observations following Belsley et al. (2005) and Bollen and Jackman (1985) for both estimations with R&D expenditure and innovation expenditure as dependent variable, respectively, and remove the 1% of the most influential observations that either positively or negatively affect the regressions.

Table 3: Descriptive Statistics

	Negatively Treated				Control group				Positively Treated			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Δ ln(sales)$_{2020-2019}$	-0.296***	0.663	-4.533	6.174	-0.017	0.395	-5.432	3.934	0.153***	0.510	-3.672	3.958
Δ ln(R&D)$_{2020-2019}$	0.066***	0.458	-0.911	3.932	0.230	1.045	-0.974	9.547	0.019***	0.151	-0.693	0.641
Δ ln(inno)$_{2020-2019}$	0.060***	0.487	-0.943	4.615	0.284	1.161	-0.974	8.923	0.013***	0.150	-0.773	0.671
Δ ln(inno)$_{2021-2020}$‡	0.036*	0.545	-0.979	7.378	0.103	0.780	-0.992	9.393	0.214	1.153	-0.869	7.601
Δ ln(inno)$_{2022-2021}$‡	-0.000**	0.128	-0.915	0.683	0.022	0.299	-0.875	7.601	0.003	0.177	-0.739	1.592
Δ ln(invest)$_{2020-2019}$‡	0.199**	1.210	-0.984	7.901	0.368	1.196	-1.000	10.309	0.368	1.018	-0.944	6.723
sales$_{2019}$	33.822	174.288	0.002	2572.261	40.064	476.344	0.007	18900.000	173.216	1400.839	0.027	17100.000
ln(sales)$_{2019}$	0.874*	2.099	-6.166	7.853	1.056	1.897	-4.948	9.847	1.393**	2.228	-3.608	9.747
R&D$_{2019}$	0.442	2.567	0.000	39.736	0.670	5.063	0.000	132.000	1.225	7.932	0.000	93.100
ln(R&D)$_{2019}$	-6.526	3.797	-9.210	3.682	-6.755	3.773	-9.210	4.883	-6.709	3.991	-9.210	4.534
inno$_{2019}$	0.480*	2.614	0.000	39.736	0.832	6.402	0.000	133.980	1.411	8.219	0.000	93.100
ln(inno)$_{2019}$	-6.389	3.882	-9.210	3.682	-6.608	3.874	-9.210	4.898	-6.588	4.125	-9.210	4.534
invest$_{2019}$	1.444	9.485	0.000	160.000	1.235	8.862	0.000	253.000	2.183	12.648	0.000	145.500
ln(invest)$_{2019}$	-5.007***	3.958	-9.210	5.075	-4.336	3.781	-9.210	5.533	-3.948	3.978	-9.210	4.980
Digi‡	0.508***	0.500	0.000	1.000	0.425	0.494	0.000	1.000	0.433	0.497	0.000	1.000
credit rating‡	455.822***	56.606	100.000	590.000	468.710	52.739	100.000	595.000	479.168***	43.249	311.000	586.000
Observations	463				1775				187			

Notes: Statistics are based on the unweighted sample. ‡: Variables are only available for a subsample. The number of observations for these variables are given in the estimation result tables in Section 5. The column of mean values of the negatively treated and positively treated group, respectively, indicates whether the respective mean value is significantly different from that of the control group based on a mean difference test with unequal variances. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

4 Estimation Approach

4.1 Difference-in-Differences Setup

To causally identify the average impact of a firm negatively affected by COVID-19 on its innovation activities, we employ a two-period (conditional) difference-in-differences estimation approach.[8] This setup allows controlling for unobserved time-constant effects between negatively treated firms and firms in the control group. As shown in equation (1), the baseline model for the outcome variable $log(Y_{it})$, with $t = 2019, 2020, 2021, 2022$, controls for group differences through the time-constant treatment group dummy G_i and common differences over time through a time trend T_t. In our application, the treatment group dummy G corresponds to the treatment indicator $Covid^{neg}$. T_t equals 0 in the pre-treatment year $t = 2019$, and takes the values 1, 2 and 3 in the years $t = 2020, 2021$, and 2022, respectively. The interaction term between these two variables estimates the average treatment effect β_{GT}^{DiD} on the outcome variable $log(Y_{it})$. The vector $X_{i,2019}$ contains a set of control variables from the pre-treatment period. We interact the pre-treatment control variables with the time trend T_t, so that the pre-treatment control variables may have a differential impact on the outcome variable with advancing time since the onset of the COVID shock.

$$log(Y_{it}) = \beta_0 + \beta_T \cdot T_t + \beta_G \cdot G_i + \beta_{GT}^{DiD} \cdot T_t \cdot G_i + X_{i,2019} \cdot T_t \cdot \beta_X + \epsilon_{it}. \tag{1}$$

Taking the first difference of the model in equation (1) eliminates all time-constant terms and leads to our final estimation equation (2)

$$log(Y_{it}) - log(Y_{it-1}) = \beta_T + \beta_{GT}^{DiD} \cdot G_i + X_{i,2019} \cdot \beta_X + \Delta\epsilon_{it}. \tag{2}$$

The left-hand side of equation (2), $log(Y_{it}) - log(Y_{it-1})$, can be interpreted as the log-growth rate of the outcome variable and is measured either as the log- growth rate of R&D expenditure or innovation expenditure. Since the growth in R&D or innovation spending may depend on the initial absolute level of spending, we include the pre-treatment level of the lagged dependent outcome variable, $\ln(\text{R\&D})_{2019}$ or $\ln(\text{inno})_{2019}$, as a control variable in the corresponding estimation. Furthermore, pre-treatment firm size, $\ln(\text{emp})_{2019}$, and industry fixed effects are used as control variables.

[8] We use a corresponding approach to causally identify the impact on innovation of positively treated firms.

4.2 Entropy Balancing

A fundamental assumption of quasi-experimental study designs like ours is that assignment to treatment is quasi-randomly distributed. This means that firms cannot self-select into treatment and are not selected because of specific characteristics. However, we suspect that the selection of firms negatively affected by COVID-19 is not random but rather depends on firm characteristics such as firm size or industry. We therefore employ the entropy matching method proposed by Hainmueller (2012) to simulate close-to-random treatment selection depending on observable firm characteristics.

Entropy balancing is a re-weighting method that improves the balance of covariates between both treatment- and control groups so that the treatment assignment becomes closer to being independent 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. Since all control observations are used for the re-weighting, entropy balancing does not result in a loss of observations and thus information.

The proposed technique re-weights control group observations such that the covariates' distribution moments of both the treatment and control group match. At the same time, the algorithm aims to remain as close as possible to uniform base weights to assure efficient estimates in the following steps (Hainmueller 2012). In our analysis, we require all first, second, and third moments of covariate distributions to match as closely as possible. We employ entropy balancing as a first design step and then use the resulting weights in the estimation of equation (2) with weighted least squares.

4.3 Heterogeneous Treatment Effects

To test our hypothesis H4 that negatively treated firms with high digital capabilities at the onset of the COVID-19 pandemic are more resilient to the negative COVID shock than treated firms with low digital capabilities, we extend our basic difference-in-differences setup to account for differential effects of COVID-19 on innovation spending for highly and low digitalized firms. We interact our treatment indicator $Covid^{neg}$ with the pre-treatment digitalization dummy $Digi_{2019}$ that equals 1 for highly digitalized firms and define the following three dummy variables:

$$\begin{aligned}
G_{Covid\,only} &= 1 \qquad \text{if } Covid^{neg} = 1 \;\&\; Digi_{2019} = 0 \\
G_{Digi\,only} &= 1 \qquad \text{if } Covid^{neg} = 0 \;\&\; Digi_{2019} = 1 \\
G_{Covid\,\&\,Digi} &= 1 \qquad \text{if } Covid^{neg} = 1 \;\&\; Digi_{2019} = 1.
\end{aligned}$$

Modifying equation (2) by including these three dummy variables leads to the estimation equation (3):

$$
\begin{aligned}
log(Y_{it}) - log(Y_{it-1}) = \quad & \beta_T + \beta^{DiD}_{Covid\,only} \cdot G_{Covid\,only} + \beta^{DiD}_{Digi\,only} \cdot G_{Digi\,only} \\
& + \beta^{DiD}_{Covid\,\&\,Digi} \cdot G_{Covid\,\&\,Digi} + X_{i,2019} \cdot \beta_X + \Delta\epsilon_{it}.
\end{aligned} \tag{3}
$$

Equation (3) allows us to estimate the innovation response for each group separately. The effect on the outcome variable of low digitalized firms that are negatively affected by COVID-19 is captured by $\beta^{DiD}_{Covid\,only}$. For highly digitalized firms that are negatively treated, the effect is measured by $\beta^{DiD}_{Covid\,\&\,Digi}$, while $\beta^{DiD}_{Digi\,only}$ captures the impact for highly digitalized firms but not affected by COVID-19. The reference category consists of untreated firms with low digital capabilities.

5 Results

5.1 Short-run Impact of a Negative COVID-19 Shock on Innovation

To estimate the short-run impact of a negative general COVID-19 shock on firms' innovation activities, we estimate the difference-in-differences model explained in Section 4.1 for the change in R&D and innovation expenditure between 2019 and 2020, $\Delta\ln(\text{R\&D})_{2020-2019}$ and $\Delta\ln(\text{inno})_{2020-2019}$. Since the MIP is a voluntary survey with a year-to-year overlap of about 50 %, we estimate the model separately for each year and do not use the full panel data to preserve sample size.[9] But given that our dependent variable is the difference $log(Y_{it}) - log(Y_{it-1})$, our model controls for any unobserved time-invariant individual heterogeneity (fixed effect) in the log level of R&D or innovation expenditure.

We start by estimating a baseline model without any control variables. The results in Table 4 show a strong significant negative impact of COVID-19 on both innovation spending measures. According to column (1), firms that are strongly negatively affected by COVID-19 have a 16.5 %-points lower growth rate in their R&D expenditure than untreated firms. We find an even stronger effect for innovation expenditure, which shows a growth rate that is 22.5 %-points lower.

The introduction of additional control variables in columns (4) to (6) leads to only a slight decline in the estimated treatment effects. We include the pre-treatment level of the respective dependent variable, the logarithm of the number of employees before COVID-19 in 2019 to control for firm size, and industry fixed effects[10]. This reduces the magnitude of the average treatment effect of firms negatively affected by COVID-19 to -13.3 %-points for R&D expenditure and to -18.4 %-points for total innovation expenditure. The coefficient estimate of the constant shows that, in contrast, the control group on average did not significantly change its innovation spending in 2020. The control variables show the

[9] This section on the short-term impact estimates the model for the growth in 2020, while Section 5.3 on medium-term effects estimates the growth in 2021 and 2022, respectively.

[10] We follow the Eurostat classification and distinguish between five manufacturing sectors - high-tech, medium high-tech, medium low-tech, low-tech, and mining, energy and water supply - and two service sectors - knowledge-intensive services and less knowledge-intensive services.

expected signs. Larger firms have a significantly higher growth in R&D and innovation spending, suggesting that they are less financially constrained in their innovation activities. Furthermore, firms with higher pre-treatment spending exhibit significantly lower spending growth.

For comparison, we also estimate the impact of a negative Covid-19 shock on investment in physical capital. Firms negatively affected by COVID-19 reduce their investment in tangible capital by even 23.6 %-points more than the control group, which in turn have already reduced their investments by 39 percent. From column (6) we can thus discern that innovation spending is more resilient than investment in physical capital in times of crisis.

Table 4: Short-run Impact of a Negative COVID-19 Shock 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)
$\ln(\text{emp})_{2019}$				0.037*	0.036*	0.057**
				(1.96)	(1.86)	(1.98)
$\ln(\text{R\&D})_{2019}$				-0.028***		
				(-3.26)		
$\ln(\text{inno})_{2019}$					-0.035***	
					(-4.10)	
$\ln(\text{invest})_{2019}$						-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: All log growth rates measure the change of the corresponding outcome variable between 2019 and 2020. Method: OLS. Industry fixed effects in models (4)-(6) included 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' exposure to COVID-19 is randomly distributed in our sample. Instead, we suspect that the likelihood of a negative exposure to COVID-19 depends on industry and firm characteristics which would bias our treatment effect estimates. To account for selection and mitigate the potential bias, we follow Hainmueller (2012) in our preferred model specification and implement an entropy balancing procedure as a first design step by reweighting our control group observations such that the first three distribution moments (mean, standard deviation, and skewness) of the covariates match as closely as possible. That is, before estimating each model in Table 5, we reweight the control group using as covariates the pre-treatment level of the lagged dependent variable, the number of employees, and industry dummies. Tables A.1-A.3 in the Appendix show, separately for R&D expenditure, innovation expenditure, and investment, the results of the entropy weighting procedure. While before balancing, there are differences across treatment and control groups especially in terms of industry - firms from low-tech manufacturing and less knowledge-intensive services are treated more frequently - there are virtually no more differences between the distribution moments of the covariates of the treatment and control group after each balancing procedure.

We re-estimate the models using weighted OLS with the corresponding entropy weights. Overall, the estimated treatment effects stay robust when accounting for selection as shown in Table 5. The estimates corroborate strong and significantly negative treatment effects. In the model without control variables in column (1), firms that are negatively affected by COVID-19 decreased their R&D spending by 12.9 %-points more than the control group. This is only slightly lower than without entropy balancing (16.5 %-points). Thus, only a rather small part of the treatment effect without entropy balancing is explained by non-random selection on observables.

Growth in innovation spending is 17.6 %-points lower for treated than for control group firms in column (1). When including the same set of control variables in the models as in Table 4, the treatment effects stay virtually unchanged, showing that after balancing treatment and control groups, firm characteristics do not influence the negative impact of COVID-19 on firms' R&D and innovation responses as the covariates are already accounted for by the entropy weighting scheme.

Overall, our findings show that COVID-19 causes a substantial short-run decline in innovation spending of firms that were negatively affected by the pandemic and thus confirm hypothesis H1. Despite the strong negative effect, however, the innovation response is nevertheless smaller than the change in physical capital investment, which is about 29% points. The order of these effects suggests that the anticipated adjustment costs, which are largest for R&D, outweigh the reversibility value of investment, which is largest for investment in physical capital.

Table 5: Short-run Impact of a Negative COVID-19 Shock 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)
$\ln(emp)_{2019}$				0.010	0.023**	-0.004
				(1.06)	(2.34)	(-0.26)
$\ln(R\&D)_{2019}$				-0.006		
				(-1.50)		
$\ln(inno)_{2019}$					-0.015***	
					(-3.47)	
$\ln(invest)_{2019}$						-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: All log growth rates measure the change of the corresponding outcome variable between 2019 and 2020. Method: Weighted OLS using using entropy weights (see Section 4.2). Industry fixed effects in models (4)-(6) included but not reported; heteroscedasticity robust standard errors; t statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01.

5.2 Robustness Test: Placebo Treatment

One crucial assumption in our methodology outlined in Section 4.1 is that trends of our outcome variables are parallel for both the treatment and control groups in the absence of the treatment. Even though this assumption is not testable in the treatment period itself, testing for 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 higher credibility to our results. We, therefore, conduct a placebo treatment test by regressing for three pre-treatment years the growth rates of R&D- and innovation expenditure on the treatment indicator $Covid^{neg}$, the corresponding lagged dependent variable, firm size, and industry fixed effects. If the trends of these outcome variables are parallel in the indicated pre-treatment period for our two groups, we should find a non-significant effect of the placebo treatment $Covid^{neg}$.

The results in Table 6 indicate that the 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 spending for the pre-treatment years 2019, 2018, and 2017, respectively. The results for innovation expenditure in columns (2), (4), and (6) show a similar picture, with the only exception of a significant effect in 2018. However, it is not the year immediately preceding the treatment period and could be due to the high rate of attrition in our data when spanning the sample over more distant time periods, resulting in a much smaller sample size. We therefore find virtually no evidence that the trends of R&D and innovation spending are not parallel, allowing us to interpret our results as causal estimates.

Table 6: Robustness Checks: Placebo Treatment

	(1) Δ ln(R&D) 2019-2018	(2) Δ ln(inno) 2019-2018	(3) Δ ln(R&D) 2018-2017	(4) Δ ln(inno) 2018-2017	(5) Δ ln(R&D) 2017-2016	(6) Δ ln(inno) 2017-2016
$Covid^{neg}$	-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(emp)$_{2018}$	0.219***	0.254***				
	(6.76)	(7.21)				
ln(R&D)$_{2018}$	-0.160***					
	(-8.45)					
ln(inno)$_{2018}$		-0.220***				
		(-11.29)				
ln(emp)$_{2017}$			0.143***	0.272***		
			(4.25)	(6.52)		
ln(R&D)$_{2017}$			-0.132***			
			(-6.12)			
ln(inno)$_{2017}$				-0.285***		
				(-12.71)		
ln(emp)$_{2016}$					0.226***	0.358***
					(6.08)	(7.73)
ln(R&D)$_{2016}$					-0.266***	
					(-11.43)	
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 included 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 Effects on Innovation

In this section, we shift the focus from the short-run impact of a negative COVID-19 treatment to its medium-term impact and test our second hypothesis about the existence of 'Long COVID' effects on innovation. We estimate our model specified in equation (2) using the expected growth in innovation expenditure in the two subsequent years as dependent variables. Table 7 show the results without and with accounting for selection. Columns (1) and (3) use the expected growth in 2021, $\Delta \ln(\text{inno})_{2021-2020}$, while columns (2) and (4) focus on the growth rate in 2022, $\Delta \ln(\text{inno})_{2022-2021}$. Due to some missing values in the 1-year and 2-year ahead expected innovation expenditure, we can estimate our model only for smaller subsamples. To ensure the balance of covariates and to avoid a potential bias due to non-random treatment allocation based on observable characteristics, we perform the same entropy balancing procedure as described in the previous section for the subsamples. We again re-weight the control group observations such that the first three moments of the control variables match those of the treatment group and use these weights in a second step in the estimation of our models.[11]

The results clearly show that a negative COVID-19 treatment in 2020 still significantly affects innovation activities in the two subsequent periods. When we do not account for a potential selection bias, we estimate a COVID-19 treatment effect one year forward of about -4.1 %-points. This effect reduces to -2.3 %-points after entropy balancing, taking potential treatment selection into account, but it remains highly significant at the 1 percent level. This means that, compared to the control group, firms negatively affected by COVID-19 in 2020 not only have 17.9 %-points lower innovation spending growth immediately in the year of the shock but also continue to experience lower spending growth in the following year. This leads to a continued widening of the innovation gap between the control and treatment groups.

Even two years further, in 2022, we observe a significant COVID-19 treatment effect. In both specifications with and without entropy balancing, we find that firms negatively affected by COVID-19 in 2020 still have an almost 1 percentage point lower growth in innovation spending in 2022 than the control group. Taking the short- and medium-run effects together, we estimate that the three-year growth rate of innovation spending in the treatment group between the year before treatment 2019 and 2022 is about 20.5 %-points lower due to COVID-19.

Table 7: Longer-run Impact of a Negative COVID-19 Shock on Innovation

	Not Accounting for Selection (Without Entropy Balancing)		Accounting for Selection (With Entropy Balancing)	
	(1)	(2)	(3)	(4)
	Δ ln(inno) 2021 − 2020	Δ ln(inno) 2022 − 2021	Δ ln(inno) 2021 − 2020	Δ ln(inno) 2022 − 2021
$Covid^{neg}$	-0.041***	-0.010***	-0.023***	-0.009***
	(-3.92)	(-2.97)	(-2.89)	(-3.58)
$\ln(emp)_{2019}$	-0.002	-0.002	-0.000	-0.002*
	(-0.36)	(-0.94)	(-0.18)	(-1.92)
$\ln(inno)_{2019}$	-0.001	0.002**	0.002	0.003***
	(-0.22)	(2.07)	(0.82)	(4.40)
Constant	0.099	0.023	0.072	0.036***
	(0.92)	(1.23)	(1.32)	(4.16)
Observations	1718	1615	1690	1592

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

Both findings for 2021 and 2022 support our hypothesis H2. They clearly highlight that the COVID-19 pandemic not only causes a short-run dip in innovation spending in 2020 but also has significant longer-term consequences for the innovation activities of negatively affected firms. We thus find evidence for 'Long COVID' symptoms. Although we cannot directly test the underlying channel, it is likely that the longer-term decline in

[11] Tables A.4-A.5 in the Appendix present the results of the entropy balancing procedures.

innovation spending is to a large extent a result of a decline in innovative capabilities due to lower knowledge exchange and spillover effects due to the pandemic in 2020. In contrast, demand arguments are likely to play less of a role here, as GDP in Germany already grew significantly again by 2.1 % in 2021.

5.4 Innovation Response to a Positive COVID-19 Shock

The COVID-19 pandemic constitutes a unique situation because apart from having detrimental impacts on a large quantity of firms, it also affected a non-negligible number of firms positively. In our sample, as many as 8.6 % of the firms reported having benefited from the COVID-19 pandemic. We have shown in Section 3.3 that these firms were able to significantly increase their sales and presumably also their cash flow during the pandemic. At the same time, they benefited from an improved credit rating, which reduces potential liquidity constraints. Both effects should increase incentives to innovate. On the other hand, increased demand raises opportunity costs for innovation activities, as Aghion and Saint-Paul (1998) argue. This, ceteris paribus, decreases incentives for innovation activities with potential future benefits in favor of increasing production with short-run benefits. To test which of these effects predominates, we estimate the impact of COVID-19 on innovation spending among positively treated firms in this section. The control group again consists of firms not affected by COVID-19, while we exclude negatively treated firms.

The results in column (1) and (2) of Table 8 suggest that the opportunity cost effect prevails. Positively affected firms significantly reduce their innovation spending in response to the COVID-19 shock. While the estimate of the constant again shows that control group firms do not significantly change their R&D and innovation spending, we find that positively treated firms exhibit, on average, a 19.8 %-points lower growth in R&D spending and a 26.3 %-points lower growth in innovation spending, respectively, compared to the control group.[12] The empirical evidence thus supports hypothesis H3 stating that firms with a positive demand shock due to the COVID-19 pandemic invest less in R&D and innovation than in the counterfactual situation of not being affected. We also find a negative treatment effect on investment in physical capital in column (3), although the effect is only about half as large at 9.7 %-points.

The results show that the COVID-19 pandemic caused an even greater decline in R&D and innovation spending for positively treated firms than for negatively treated firms. At the same time, being positively treated comes with a substantial increase in sales (see Table 2 in Section 3). In columns (4)-(6) of Table 8, we examine whether this increase in sales is due solely to higher prices of output or is also the result of an increase in output by estimating the same model for flexible production inputs, i.e. material costs, labour costs, and the number of employees. A significant impact of the treatment indicator on flexible inputs would suggest that COVID-19 did indeed lead to higher production and would

[12]The strong negative innovation response of positively treated firms also indirectly confirms that our treatment variable is indeed a general burden of COVID-19 and that firms' assessment of their exposure to COVID-19 was not already based on innovation impacts.

further support the opportunity cost argument. The estimates in columns (4)-(6) reveal that a positive COVID-19 shock induced firms to significantly increase their flexible inputs for production. Compared to the control group, firms positively affected by COVID-19 show a 7.1 %-points higher growth in material costs, a 3.7 %-points larger growth in labour costs as well as a 4.9 %-points larger growth in employment.

While we find positive effects for flexible production inputs such as labor and materials, one might have also expected a positive effect on investment in physical capital. But the treatment effect is negative with -9.7 %-points. However, this negative effect is much smaller in magnitude than the one we have identified for negatively treated firms (-23.6 %-points, see Table 4). It thus seems that the high negative effect of uncertainty is somewhat dampened in firms that experienced a positive demand shock. However, even these firms refrain to some extent from making even (reversible) mid-term decisions such as physical investments.

Table 8: Short-run Impact of a Positive COVID-19 Shock on Innovation - Accounting for Selection (Entropy Balancing)

	(1) Δ ln(R&D)	(2) Δ ln(inno)	(3) Δ ln(invest)	(4) Δ ln(material cost)	(5) Δ ln(labor cost)	(6) 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)
$\ln(\text{emp})_{2019}$	0.003	0.012	0.045*	0.081***	0.281***	-0.003
	(0.36)	(1.15)	(1.87)	(5.91)	(10.08)	(-1.00)
$\ln(\text{R\&D})_{2019}$	-0.008*					
	(-1.74)					
$\ln(\text{inno})_{2019}$		-0.016***				
		(-3.13)				
$\ln(\text{invest})_{2019}$			-0.041***			
			(-3.82)			
$\ln(\text{mat. cost})_{2019}$				-0.059***		
				(-6.30)		
$\ln(\text{labor cost})_{2019}$					-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: All log growth rates measure the change of the corresponding outcome variable between 2019 and 2020. Method: Weighted OLS using entropy weights. Industry fixed effects in models (4)-(6) included but not reported; heteroscedasticity robust standard errors; *t* statistics in parentheses; * p<0.1, ** p<0.05, *** p<0.01.

5.5 Moderating Impact of Digitalization

The use of digital tools increased drastically during the pandemic because it, at least partially, allowed firms to continue operating. 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 hypothesis H4 that a high degree of digitalization also enables firms to better continue their innovation activities when hit by the negative COVID-19 shock, we include the pre-pandemic digitalization indicator in our estimation as described in Section 4.3. Table 9 shows the results without and with accounting for selection. Since the two results do not differ substantially, we focus on the results in columns (3) and (4), where we consider potential treatment selection.

The results clearly reveal that the negative treatment effect of firms negatively affected by COVID-19 shown in Section 5.1 is mainly due to those firms that have low digital capabilities at the onset of the COVID-19 outbreak. Compared to the reference group of low digitalized firms not affected by COVID-19, they exhibit a 10.4 %-points lower growth in R&D spending and a 17.1 %-points lower growth in innovation spending, respectively. Both treatment effects are significant at the 1 percent level. In contrast, negatively treated firms with high digital capabilities do not significantly reduce their R&D and innovation spending but rather leave them unchanged. The same result holds for the reference group of non-treated firms with low digital capabilities. In comparison, non-treated firms that score already high on digitalization before the pandemic even significantly raise their R&D expenditure on average by 17.3 %-points and innovation expenditure by 14.0 %-points more than the reference group. This indicates that highly digitalized firms that were not affected by the COVID-19 pandemic are the only group of firms that remained on a positive growth path in terms of their innovation efforts.

In summary, our results confirm hypothesis H4 about the moderating role of digital capabilities during the COVID-19 pandemic. That is, firms with high pre-treatment digital capabilities are more resilient in their innovation activities to a negative COVID-19 shock than firms with low digital capabilities.

Table 9: Short-run Impact of a Negative COVID-19 Shock on Innovation: Moderating Role of Digital Capabilities

	Not Accounting for Selection (Without Entropy Balancing)		Accounting for Selection (With Entropy Balancing)	
	(1)	(2)	(3)	(4)
	Δ ln(R&D)	Δ ln(inno)	Δ ln(R&D)	Δ ln(inno)
$Covid^{neg} = 1$ & $Digi_{2019} = 0$	-0.099***	-0.163***	-0.104***	-0.171***
	(-2.78)	(-4.02)	(-3.19)	(-4.59)
$Covid^{neg} = 1$ & $Digi_{2019} = 1$	-0.012	-0.052	-0.016	-0.069
	(-0.25)	(-0.98)	(-0.33)	(-1.30)
$Covid^{neg} = 0$ & $Digi_{2019} = 1$	0.186***	0.176***	0.173***	0.140**
	(3.21)	(2.76)	(3.33)	(2.46)
$\ln(\text{emp})_{2019}$	0.032*	0.031	0.002	0.006
	(1.67)	(1.57)	(0.11)	(0.38)
$\ln(\text{R\&D})_{2019}$	-0.035***		-0.018***	
	(-3.81)		(-2.62)	
$\ln(\text{inno})_{2019}$		-0.042***		-0.022***
		(-4.56)		(-3.11)
Constant	-0.312**	-0.333**	-0.088	-0.071
	(-2.17)	(-2.08)	(-0.95)	(-0.71)
Observations	2210	2210	2210	2210

Notes: Reference group: Control group firms not affected by COVID-19 with low pre-treatment digital capabilities ($Covid^{neg} = 0$ & $Digi_{2019} = 0$). Results of the entropy balancing procedure are presented in Tables A.6 and A.7 in the Appendix. 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.

5.6 Macroeconomic Implications

The COVID-19 crisis had, without any doubt, major macroeconomic consequences in many dimensions. In this section, we use our regression results to establish such macroeconomic effects for the German economy.

So far, scholars have investigated to what extent the pandemic might have affected innovation by studying indicators such as patent statistics. In a recent book publication edited by Fink et al. (2022), several scholars conducted country-specific investigations and found, by means of descriptive statistics, that the COVID-19 pandemic may have caused a dip in innovation, mostly measured as inventive activity, but that the different economies recovered fairly quickly and even exceed pre-crisis innovation indicators after a short recovery phase.

As the Mannheim Innovation Panel is a representative survey that provides sampling weights, we can extrapolate numbers such as innovation expenditure to the population of firms in the German business sector. In addition, we can also use our econometric estimations to derive a counterfactual scenario showing how the German economy would have developed in terms of innovation spending if the COVID-19 pandemic had not occurred.

Figure 1 shows the development of the extrapolated innovation expenditure in Germany since 2007 in real terms.[13] We deflated nominal figures by the German GDP deflator, 2015 = 100). It can be seen that the innovation expenditure suffered from the global financial crisis in 2008/9. The expenditure dropped from about EUR 140 billion in 2008 to EUR 122 billion in 2009, i.e. the global financial crisis has been associated with a loss of almost EUR 18 billion of innovation potential. However, the innovation expenditure in the German economy recovered very quickly and basically rose since then in real terms up to EUR 165 billion in 2018 and 2019.

When the COVID-19 pandemic broke out in 2020, the innovation expenditure dropped by EuR 8.8 billion to EUR 156.3 billion; initially not quite as sharply as in the financial crisis though. While nominal innovation spending already increased slightly again in 2021 (see Figure A3 in the Appendix), there was a further decline in deflated innovation spending of EUR 1.5 billion to EUR 154.9 billion in 2021, when price increases are into account, which continued in 2022 to even EUR 148.5 billion. In total, the COVID dip between 2019 and 2022 amounts to almost EUR 17 billion, which more or less equals the sharp dip after the global financial crisis in 2008/9. In the recent pandemic, the effect is just spread out over multiple years. Unfortunately, we do not see a subsequent increase in innovation expenditure yet.

To investigate to what extent the COVID crisis caused the shrinking of innovation expenditure in the German business sector, we derive the counterfactual by taking the difference between the (extrapolated) predicted innovation expenditure by our regression models and the predictions in which we set the treatment indicators to a zero value, i.e., we simulate that COVID did not happen. This means that neither the negative nor the positive treatments of the COVID-19 pandemic would have affected the firms in the business sector. We plot the counterfactual as the dashed line between 2019 and 2022 in the graph.

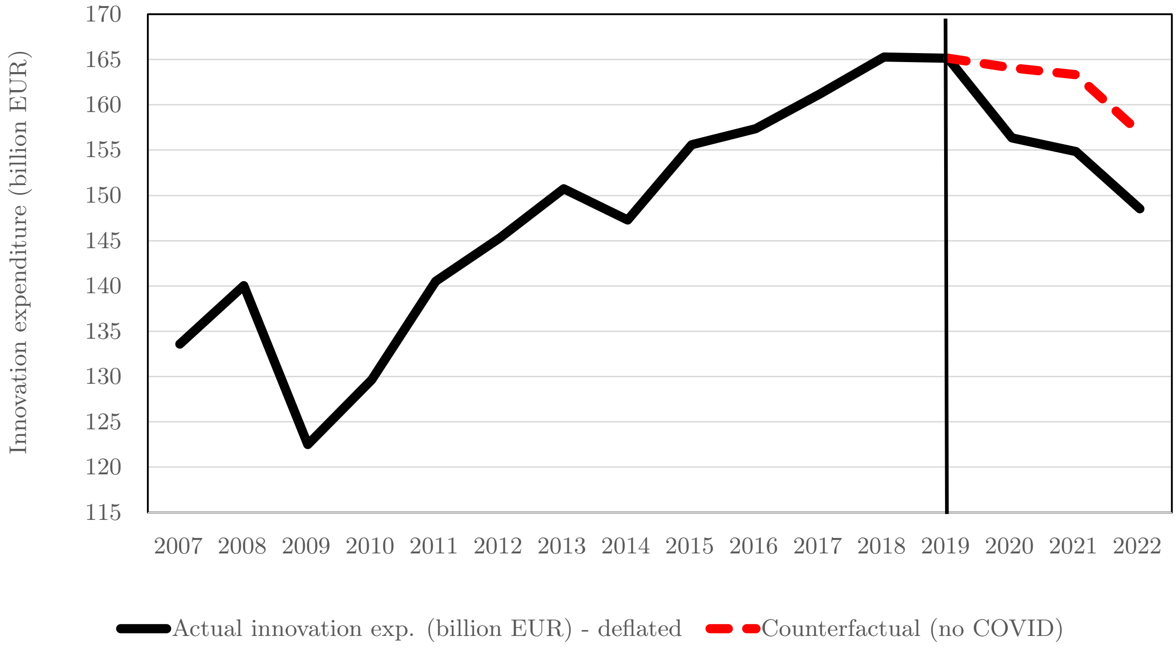
The results show that in the counterfactual situation innovation expenditure would have remained fairly stable in real terms at EUR 164 billion in 2020. This implies that in the short-run COVID-19 caused a decline in innovation spending of 4.7 % in 2020. In 2021, innovation spending would have reached almost the same level of EUR 163 billion. In 2022, however, they would also have fallen, partly due to higher inflation, too. At EUR 157 billion, however, the decline in the counterfactual scenario is much smaller than the actual drop.

In total, the dip between 2019 and 2022 would have amounted only to about EUR 8 billion instead of the actual EUR 17 billion, according to our treatment effect models. In conclusion, the COVID-19 pandemic caused an overall decline in innovation expenditure of EUR 9 billion ($= 17 - 8$), which is about 5.4 %.

To shed more light on the role of digitization, we perform a second counterfactual

[13] Figure A3 in the Appendix shows the underlying development of the nominal innovation expenditure. Source: The corresponding waves of the Mannheim Innovation Panel. Cf. for the official reported innovation expenditure: https://www.zew.de/en/publications/zew-expertises-research-reports/research-reports/innovations/mannheim-innovation-panel-the-annual-german-innovation-survey

Figure 1: Macro-level Impact of COVID-19 on Deflated Innovation Spending



Notes: Actual innovation expenditure and innovation expenditure in the counterfactual scenario of no COVID are deflated using the GDP deflator for Germany.

analysis and compare actual innovation spending with predicted spending in a situation where a negative COVID-19 shock occurs, but firms have high digital capabilities. At the macro level, this would have mitigated the decline in innovation spending in the short-run to 4.4% instead of 4.7%.

6 Conclusion

The COVID-19 pandemic unexpectedly 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 a strong decline in revenues for a considerable number 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 during the COVID-19 pandemic. We provide evidence on firms' short-run and medium-run reactions to a negative shock by COVID-19. We contrast these findings with the innovation response of firms that benefited from the crisis. In addition, we analyze the role of digitalization in firms' innovation investment responses to the pandemic.

Exploiting treatment heterogeneity, we use a DiD design, completed with an entropy balancing to account for potential non-random selection into treatment, to causally identify the short-run impact of COVID-19 on innovation spending in 2020 and expected innovation spending in subsequent years for German firms.

Our results show that negatively affected firms (about 20 % of firms in manufacturing and business service sectors) decrease their R&D expenditure substantially by 12.9 %-points more than in the counterfactual situation of not being negatively hit by the pandemic. The corresponding treatment effect for total innovation expenditure amounts to -17.6 %-points. Our evidence suggests that the procyclical effect results from a negative demand shock and stronger liquidity constraints of treated firms, and - although we could not test this channel directly - the greater uncertainty during the pandemic. The procyclical decline in innovation spending is in line with empirical evidence on innovation behavior during prior crises and recessions (Aghion et al. 2012).

We also find evidence of 'Long-COVID effects'that were not seen, for example, in the recession of 2008/2009. Firms that were negatively hit by the pandemic in 2020 still have a 2.3 and 0.9 %-points lower growth in innovation spending one and two years later, respectively. Precisely because innovation is a key driver of firm performance, it is likely that a continued decrease in innovation activities of already negatively affected firms will further impair their competitiveness in the long-run.

We furthermore find that innovation activities of negatively treated firms that had already invested in building up high 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 digitalized treated firms.

For the smaller subset of firms that were positively affected by the pandemic (about 9 % of firms), our results suggest a strong decline in innovation efforts as well. Growth in R&D spending is almost 20 %-points lower and in innovation spending by about 26 %-points lower due to COVID-19 than in the counterfactual of not being affected. We provide additional evidence that positively treated firms shift scarce resources from innovation to expanding near-term production capacity. This countercyclical innovation behavior is thus consistent with the opportunity cost argument (Aghion and Saint-Paul 1998).

Taking the treatment effect results to the aggregate level, we find that the COVID-19 pandemic causes a substantial dip in innovation spending of about 4.7 % in the short run, which increases to 5.4 % after three years of the COVID outbreak. The causal analysis reveals a much stronger negative impact of COVID-19 on innovation than previous empirical evidence mainly based on descriptive analyses of inventive activity would suggest (Fink et al. 2022). This is likely due in part to the fact that inventive activity observed in 2020 is the result of earlier innovation efforts. It remains an open question whether we will also observe a lagged decline in patent activity.

Our results paint an overall pessimistic picture of the impact of the COVID-19 pandemic on the innovation activities of German firms. We show that negatively affected firms not only curtailed their innovation activities in the short-run but also do not expect to return to pre-crisis innovation levels three years later. Moreover, even firms that benefited from the pandemic reduced their innovation activities. Our results suggest a need for policies aimed at fostering innovation activities of treated firms, considering that innovation is a key component of economic growth and international competitiveness.

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A Appendix

A.1 Figures

Figure A1: Question on Exposure to COVID-19 (MIP)

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

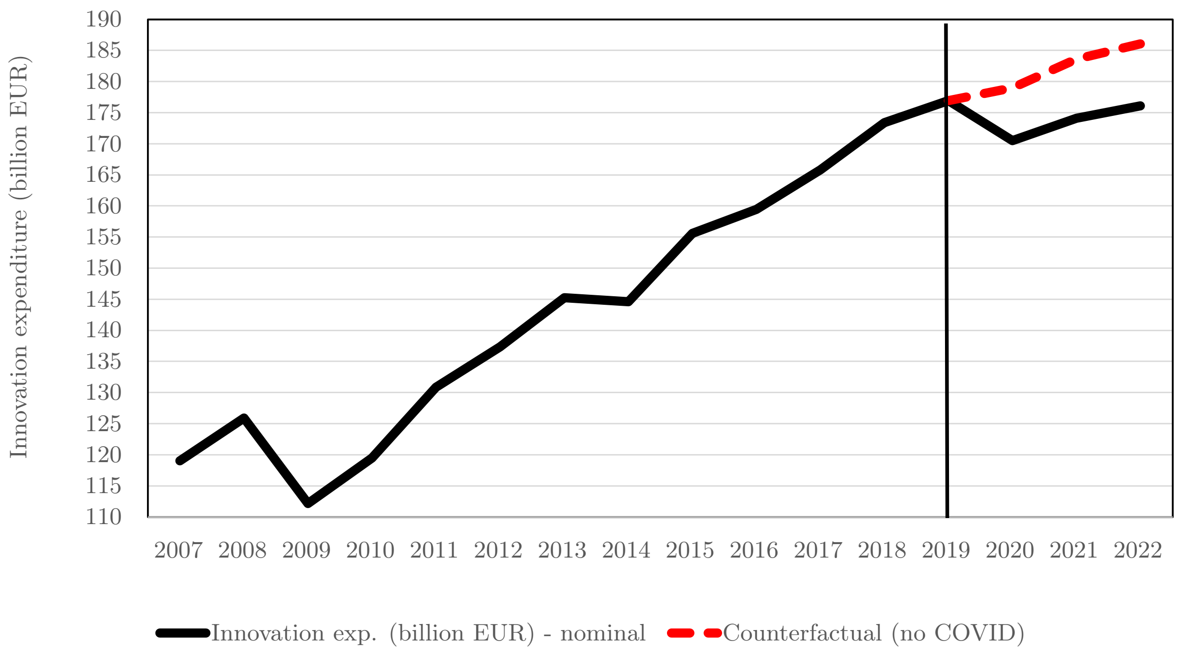
extremely negative	*very negative*	*negative*	*marginally/not at all*	*positive*	*very positive*
☐ 1	☐ 2	☐ 3	☐ 4	☐ 5	☐ 6

Figure A2: Question on Digitalization (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

Figure A3: Macro-level Impact of COVID-19 on Nominal Innovation Spending



A.2 Tables

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

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
			Pre-Balancing			
$\ln(\text{R\&D})_{2019}$	-6.681	14.502	0.982	-6.723	14.380	1.047
$\ln(\text{emp})_{2019}$	3.171	2.860	0.791	3.206	2.297	0.697
M: High-tech	0.053	0.050	4.002	0.061	0.058	3.656
M: Medium high-tech	0.133	0.116	2.161	0.111	0.099	2.473
M: Medium low-tech	0.133	0.116	2.161	0.148	0.126	1.983
M: Low-tech	0.165	0.138	1.804	0.091	0.083	2.841
M: Mining, energy, water	0.014	0.014	8.347	0.117	0.103	2.384
S: Knowledge-intensive	0.236	0.181	1.242	0.280	0.202	0.978
S: Less knowledge-intensive	0.255	0.190	1.127	0.147	0.126	1.990
			Post-Balancing			
$\ln(\text{R\&D})_{2019}$	-6.681	14.502	0.982	-6.682	14.474	0.983
$\ln(\text{emp})_{2019}$	3.171	2.860	0.791	3.171	2.855	0.791
M: High-tech	0.053	0.050	4.002	0.053	0.050	4.003
M: Medium high-tech	0.133	0.116	2.161	0.133	0.115	2.162
M: Medium low-tech	0.133	0.116	2.161	0.133	0.115	2.162
M: Low-tech	0.165	0.138	1.804	0.165	0.138	1.805
M: Mining, energy, water	0.014	0.014	8.347	0.014	0.014	8.165
S: Knowledge-intensive	0.236	0.181	1.242	0.236	0.180	1.243
S: Less knowledge-intensive	0.255	0.190	1.127	0.254	0.190	1.128

Notes: M and S denote manufacturing and service sectors. The industry breakdown follows the definition by Eurostat.

Table A.2: Entropy Balancing for 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
M: High-tech	0.053	0.050	4.002	0.061	0.058	3.656
M: Medium high-tech	0.133	0.116	2.161	0.111	0.099	2.473
M: Medium low-tech	0.133	0.116	2.161	0.148	0.126	1.983
M: Low-tech	0.165	0.138	1.804	0.091	0.083	2.841
M: Mining, energy, water	0.014	0.014	8.347	0.117	0.103	2.384
S: Knowledge-intensive	0.236	0.181	1.242	0.280	0.202	0.978
S: Less knowledge-intensive	0.255	0.190	1.127	0.147	0.126	1.990
			Post-Balancing			
$\ln(\text{inno})_{2019}$	-6.573	15.116	0.931	-6.574	15.087	0.932
$\ln(\text{emp})_{2019}$	3.171	2.860	0.791	3.172	2.855	0.791
M: High-tech	0.053	0.050	4.002	0.053	0.050	4.003
M: Medium high-tech	0.133	0.116	2.161	0.133	0.115	2.162
M: Medium low-tech	0.133	0.116	2.161	0.133	0.115	2.162
M: Low-tech	0.165	0.138	1.804	0.165	0.138	1.805
M: Mining, energy, water	0.014	0.014	8.347	0.014	0.014	8.160
S: Knowledge-intensive	0.236	0.181	1.242	0.236	0.180	1.243
S: Less knowledge-intensive	0.255	0.190	1.127	0.254	0.190	1.128

Notes: See Table A.1.

Table A.3: Entropy Balancing for Investment Regression

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

Notes: See Table A.1.

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

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

Notes: See Table A.1.

Table A.5: Entropy Balancing for 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
M: High-tech	0.033	0.032	5.190	0.061	0.057	3.665
M: Medium high-tech	0.107	0.096	2.542	0.109	0.097	2.509
M: Medium low-tech	0.127	0.111	2.239	0.141	0.121	2.066
M: Low-tech	0.167	0.140	1.783	0.090	0.082	2.855
M: Mining, energy, water	0.013	0.013	8.471	0.117	0.103	2.386
S: Knowledge-intensive	0.234	0.180	1.256	0.282	0.202	0.972
S: Less knowledge-intensive	0.308	0.214	0.833	0.155	0.131	1.902
	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
M: High-tech	0.033	0.032	5.190	0.033	0.032	5.191
M: Medium high-tech	0.107	0.096	2.542	0.107	0.096	2.543
M: Medium low-tech	0.127	0.111	2.239	0.127	0.111	2.240
M: Low-tech	0.167	0.140	1.783	0.167	0.139	1.784
M: Mining, energy, water	0.013	0.013	8.471	0.014	0.013	8.385
S: Knowledge-intensive	0.234	0.180	1.256	0.234	0.179	1.256
S: Less knowledge-intensive	0.308	0.214	0.833	0.308	0.213	0.834

Notes: See Table A.1.

Table A.6: Entropy Balancing for R&D Expenditure Regression with Heterogeneous Treatment

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(\text{R\&D})_{2019}$	-6.513	14.487	0.861	-6.753	14.196	1.061
$Digi_{2019}$	0.508	0.250	-0.031	0.425	0.244	0.304
$\ln(\text{emp})_{2019}$	3.177	2.803	0.779	3.197	2.287	0.686
M: High-tech	0.054	0.052	3.927	0.061	0.057	3.686
M: Medium high-tech	0.144	0.123	2.030	0.114	0.101	2.435
M: Medium low-tech	0.135	0.117	2.135	0.148	0.126	1.983
M: Low-tech	0.166	0.138	1.799	0.091	0.083	2.848
M: Mining, energy, water	0.013	0.013	8.574	0.114	0.101	2.426
S: Knowledge-intensive	0.229	0.177	1.292	0.282	0.202	0.971
S: Less knowledge-intensive	0.248	0.187	1.165	0.148	0.126	1.983
	Post-Balancing					
$\ln(\text{R\&D})_{2019}$	-6.513	14.487	0.861	-6.514	14.460	0.861
$Digi_{2019}$	0.508	0.250	-0.031	0.508	0.250	-0.030
$\ln(\text{emp})_{2019}$	3.177	2.803	0.779	3.177	2.798	0.779
M: High-tech	0.054	0.052	3.927	0.054	0.051	3.928
M: Medium high-tech	0.144	0.123	2.030	0.144	0.123	2.031
M: Medium low-tech	0.135	0.117	2.135	0.135	0.117	2.136
M: Low-tech	0.166	0.138	1.799	0.165	0.138	1.800
M: Mining, energy, water	0.013	0.013	8.574	0.014	0.014	8.370
S: Knowledge-intensive	0.229	0.177	1.292	0.229	0.176	1.293
S: Less knowledge-intensive	0.248	0.187	1.165	0.248	0.187	1.166

Notes: See Table A.1.

Table A.7: Entropy Balancing for Innovation Expenditure Regression with Heterogeneous Treatment

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

Notes: See Table A.1.

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