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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. Their innovative behavior in the initial- and subsequent years is crucial to economic recovery. We investigate its impact on firms' innovation activities by analyzing adversely affected firms' innovation responses. In our analysis, we focus on a sample of German firms drawn from a representative survey. We show that firms substantially reduce R&D and innovation expenditure in the first and the following two years. Moreover, firms' pre-pandemic digital capabilities are able to reduce this negative response significantly.

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, combined with measures to prevent health care systems from breaking down, has negatively affected economies worldwide. Since the pandemic's beginning, firms had to cope with temporary lockdowns, social distancing measures, labor shortages, and disrupted supply chains (Brodeur et al. 2021). A majority of firms experienced a sharp decline in revenues while facing an increasingly uncertain environment and a distressed financial market (Bloom et al. (2021a); Paunov and Planes-Satorra (2021)). Therefore, in an effort to stay in business until the end of the crisis, firms had to adjust their strategies, resulting in the reallocation of resources surviving in the short-run (Aghion et al. (2012); Bloom (2007)). Evidence from previous crises shows that, firms may respond to higher uncertainty and worsened market prospects by reducing innovation activities (Aghion et al.; Archibugi et al.; Hud and Hussinger; Hud and Rammer; Laperche et al.; Paunov and Planes-Satorra). However, the COVID-19 pandemic constitutes a unique situation and is therefore not directly comparable to previous economic crises. International communication was highly restricted with adverse impacts on supply chains, working from home became compulsory, and the distribution of goods and services was limited or even prevented by lockdowns. This all complicated business activity, including innovation activity (Paunov and Planes-Satorra 2021). Nevertheless, innovation is a primary driver of economic growth (Bravo-Biosca et al. 2013) and is highly important for firms to stay internationally competitive. Therefore, a reduction in innovation activities during the pandemic can impact firms negatively in the coming years.

This paper focuses on the impact of the COVID-19 pandemic on innovation activities of German firms, looking both on immediate responses (in 2020) and consequences on short-term prospects of innovation activities in the years 2021 and 2022. 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 the two most recent waves of the Mannheim Innovation Panel (MIP), a representative survey of German firms. The MIP represents the German contribution to the Community Innovation Survey (CIS), a European-wide survey on firm innovation behavior guided by the Oslo Manual. Our final sample consists of 2,448 firms from the manufacturing and service sectors that we observe over both survey waves.

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 about 15.5% more than the control group. Innovation expenditures growth (which includes additional expenditures in innovation that are not only R&D related.) is lowered by about 21.6%, compared to a 31% decrease in investment growth. However, further results show that this immediate response is followed by long-lasting adverse effects on innovation activities in the following years. We find that negatively impacted firms also planned to reduce their innovation expenditure growth rate in 2021 even further by 5%. Even in 2022, the same firms still plan to continue reducing their innovation expenditures compared to 2021 by 0.8%. Negatively affected firms decreased their three-year (expected) innovation expenditure growth rate from 2019 to 2022 in total by 10.8%. Firms existing digital capabilities were highly beneficial in the COVID-19 pandemic Pierri and Timmer (2020). We confirm the results of prior studies on firm performance benefits of digital capabilities during the COVID-19 pandemic for innovation activities. Our results show that highly digitalized firms that are negatively affected by the pandemic do not reduce their innovation activities as strongly as not highly digitalized firms.

These results show that COVID-19 negatively influenced innovation behavior as an immediate response in 2020 and is in line with empirical evidence on the 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

The COVID-19 pandemic directly affected firms worldwide through four main channels (Brodeur et al. 2021; Carlsson-Szlezak et al. 2020a,b)[1]. First, consumption reduced greatly, leading to large direct demand shocks in most sectors that diffused through most of the economy (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, global supply chain disruptions created shortages of raw- and intermediate production materials (Bonadio et al. 2021; Bartik et al. 2020b). 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.

[1]Brodeur et al. (2021); Carlsson-Szlezak et al. (2020a,b) focus on 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.

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.

Lastly, firms had to invest in organizational changes to cope with the pandemic. Because 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 high demand for such solutions, supply issues, and tense financial markets, these types of reorganization became costly for already struggling firms.

The recovery of economies worldwide from the negative impacts of the COVID-19 pandemic, among others, depends on the efficient removal of supply chain issues and expected recovery of demand (Bartik et al. 2020a). It also depends on government recovery packages targeting groups of firms that contribute substantially to economic growth but were more prone to be negatively affected by the pandemic (Coad et al. 2022) and especially on firms' innovation activities (Ebersberger and Kuckertz 2021; Roper and Turner 2020).

The Impact of the Pandemic on Innovation

The pressure firms faced during the COVID-19 pandemic, coupled with an increasingly adverse environment for innovation activities, have affected firms' innovation strategies substantially. In a survey among German firms conducted by the German Federal Ministry for Economic Affairs and Climate Action for Economics Affairs and Action (2020), 74% of firms planned to delay or prolong innovation projects. 53% canceled projects, and 7% stopped innovation activities entirely. Reduced revenues, supply chain disruptions, and organizational restructuring processes cut available funds for research projects (Paunov and Planes-Satorra 2021). At the same time, increased uncertainty makes benefits of future-oriented projects like innovation projects more volatile and reduces expected gains (Bloom 2007, 2014). Research on previous crises showed that these mechanisms generally reduce innovation activity in crises (Pellens et al. (2020), Aghion et al. (2012), ?). However, the specific characteristics of the COVID-19 pandemic increase costs of research projects further while simultaneously reducing their productivity. Similar to their production processes, firms also had to implement measures to guarantee their researchers' health, such as acquiring hygiene equipment, reduced laboratory personnel, or mandatory home office (Paunov and Planes-Satorra 2021). Apart from the cost of these measures, they also negatively affected the productivity of innovation processes. Even for tasks that researchers could perform outside of research facilities (Paunov and Planes-Satorra 2021) and Xiao et al. (2021) argue that the lack of face-to-face meetings reduced a researcher's productivity and creativity.

However, even though conditions for research activities worsened during the COVID-19 pandemic, firms in industries providing solutions to cope with the pandemic situation benefited from the pandemic situation. For example, producers of pharmaceuticals and medical products such as vaccines, medical masks, disinfectants, or face shields faced substantially higher demand. Similarly, firms in the information and communication technology sectors (ICT) saw increased demand for their solutions because firms needed to provide mobile work solutions in order to keep operating. However, the effect on these firms' innovation activities from this positive demand shock is ex-ante unclear. While these firms benefited in terms of increased revenues, which allowed them to fund additional innovation activities, the opportunity costs of innovation activities may have increased as allocating resources to enlarging production capacities will offer higher returns (Aghion et al. 2012).

Although innovation activity generally declines during crises, its importance for economic recovery cannot be underestimated. Filippetti and Archibugi (2011) argue that innovation activities allow firms to adapt to the altered economic landscape caused by crises. It allows firms to discover new business areas spurring their growth while increasing job creation (Hausman and Johnston 2014). Therefore, if innovation activity maintains at a lower level for a prolonged time, it can strongly hinder the recovery of economies from the COVID-19 pandemic.

COVID-19 and Digitalization

In order to cope with the consequences of the COVID-19 pandemic, firms rushed to adopt digital technologies. 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)). This shifted work routines substantially DeFilippis et al. (2020) and firms who implemented work-from-home capabilities fared better during the pandemic **?**. In addition, advancing digital sales channels and digital connections to suppliers and other business partners were another priority of digitalization efforts. Diekhof et al. (2021) show that 37% of firms at least temporarily increased their usage of digital sales channels. OECD (2021) report increased usage of digital platforms during the first half of 2020. However, little research focuses on pre-COVID existing digital abilities of firms mitigating the adverse effects of the COVID-19 pandemic. Only Bai et al. (2021) show that firms with high pre-pandemic work-from-home feasibility performed better during the pandemic in terms of higher revenues and stock returns. Firms that 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.

3 Estimation Approach

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

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

We estimate equation (2) using OLS. The left-hand side of (2) can be interpreted as a log-growth rate of the outcome variable.

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 consequencly information, and produces a smooth set of weights. The proposed technique reweights control group observations such that covariate distribution moments of both 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.

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:

$$\begin{aligned} G_{COVID\ only} &= 1 \quad && \text{if } G_t = 1 \ \& \ D_{t-1} = 0 \\ G_{Digi\ only} &= 1 \quad && \text{if } G_t = 0 \ \& \ D_{t-1} = 1 \\ G_{COVID,Digi} &= 1 \quad && \text{if } G_t = 1 \ \& \ D_{t-1} = 1 \end{aligned}$$

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

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

The effect of being negatively affected by COVID-19 on the outcome variable for not highly digitalized firms equals $\beta_{COVID\ only}$. For highly digitalized firms, the effect equals β_{Digi} and for highly digitalized firms that are affected by COVID-19 $\beta_{COVID,Digi}$. The construction of the digitalization dummy variable is explained in section 4.

4 Data

4.1 Data Source

We use data from the Mannheim Innovation Panel (MIP), which is the German contribution to the harmonized Community Innovation Survey (CIS) coordinated by the European Commission. The CIS and the MIP follow the Oslo Manual, a set of international guidelines on innovation surveys in Europe (OECD and Eurostat 2019; **?**). First conducted in 1993, the MIP is an annual, representative survey of firms in Germany with more than five employees in 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 in order to compensate for panel mortality. Since the MIP is a voluntary survey, the response rate is rather low at 25-50% (see **?** for more details) The MIP collects data on innovation inputs and outputs of firms as well as indicators on factors that may affect firms' innovation inputs and outputs. Important for our study, the MIP also collects data on planned innovation expenditure for the two years following the reference year of a survey. For this study, we measure innovation expenditure for four points in time: actual innovation expenditures in 2019, i.e., prior to the pandemic (taken from the MIP survey conducted in 2020), actual innovation expenditures in 2020, i.e., in the first year of the pandemic (taken from the MIP survey conducted in 2021), and planned innovation expenditures for 2021 and 2022 (also taken from the MIP survey conducted in 2021). Data on planned innovation expenditure for 2021 and 2022 were collected during the spring and summer of 2021.

After processing the responses of both waves, we drop observations with log-growth rates of innovation expenditure below -100%. We continue by dropping observations that have any missing values in either the treatment indicator, control variables, or our main outcome variables and exclude outliers following Belsley et al. (2005) and Bollen and Jackman (1985) [2]. We are left with an estimation sample of 2482 firms for whom we have data for both 2019 and 2020.

Outcome- and Control Variables

We focus our analysis on the financial input to innovation (innovation expenditure). Innovation expenditures include all in-house and extramural R&D expenditures as well as expenditure on engineering, design, marketing, training, software, and the acquisition of intangible and other assets that took place for develoioping and implementing product or process innovation. Since innovation inputs are highly persistent over time, we also include logarithms of the lagged dependent variables in each estimation. We additionally control for the firm's size by including the logarithm of the total number of employees in the analysis.

Table 1 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

[2] 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 either regression positively and 1% most influential observations affecting either regression negatively.

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.

Treatment Indicator

The MIP wave conducted in the year 2021 (collecting data for the reference year 2020), included several questions concerning the consequences that COVID-19had for the firms during the year 2020. In one question, firms were asked to indicate how COVID-19 affected their enterprise in general on a six-item Likert scale from extremely negative to very positive.[3] We categorize the answer items to create a treatment indicator equaling one if the answer stated to have been impacted negatively or extremely negatively by the COVID-19 pandemic in 2020. This constitutes about 18.8% of all firms in the sample.

Digitalization of Firms

Advanced digital capabilities are likely to mitigate the negative impact of COVID-19 to some extent. The government measures to combat COVID-19 included travel restrictions, restricted access to the workplace and mandatory rules for working from home. Accessing work resources from outside the firm, digital meeting capabilities, and interaction with customers and suppliers via digital channels could have been important tools for firms to continue operations and mitigate some of the negative impacts of COVID-19. It might have guarded firms against substantial revenue reductions and improved work conditions for innovation activities. We, include the firm's level of digitalization prior to the COVID-19 pandemic in 2019 in our analysis in order to analyze this potentially mitigating role of digitalization. We use a question[4] in the MIP 2020 wave, that asked about the importance ofeight 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 of all digitalization indices in the sample. Its distribution in table 1 shows that firms in the treatment group are, on average, slightly

[3] See figure A1 in the Appendix for the exact question.
[4] See figure A2 in the Appendix for the exact question

more digitalized than control group firms.

Table 1: Descriptive Statistics

	Treatment Group				Control Group			
	Mean	Std. Dev	Min	Max	Mean	Std. Dev	Min	Max
Δ ln(revenues)	-0.297	0.664	-4.533	6.174	0.003	0.412	-5.432	3.958
Δ ln(investment)‡	0.201	1.213	-0.984	7.901	0.364	1.165	-1.000	10.309
Δ ln(R&D)	0.044	0.369	-0.911	3.045	0.234	1.050	-0.974	9.547
Δ ln(inno. exp.$_{2019-2020}$)	0.036	0.381	-0.943	2.733	0.290	1.176	-0.974	8.923
Δ ln(inno. exp.$_{2020-2021}$)‡	0.036	0.545	-0.979	7.378	0.116	0.823	-0.992	9.393
Δ ln(inno. exp.$_{2021-2022}$)‡	-0.000	0.128	-0.915	0.683	0.020	0.290	-0.913	7.601
Δ ln(inno. exp.$_{2019-2022}$)‡	0.051	0.592	-0.943	6.909	0.184	0.966	-0.980	9.210
ln(revenues$_{2019}$)	0.881	2.103	-6.166	7.853	1.101	1.940	-4.948	9.847
ln(investment$_{2019}$)‡	-5.006	3.969	-9.210	5.075	-4.280	3.793	-9.210	5.533
ln(R&D$_{2019}$)	-6.520	3.803	-9.210	3.682	-6.726	3.795	-9.210	4.883
ln(inno. exp.$_{2019}$)	-6.382	3.888	-9.210	3.682	-6.574	3.901	-9.210	4.898
Digi‡	0.507	0.501	0.000	1.000	0.421	0.494	0.000	1.000
N	460				1988			

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.

5 Results

We first examine the relationship between firms' degree of COVID-19 affectedness and their revenue. Therefore, we regress the log growth rate of firm revenue between 2019 and 2020 onto dummy variables for each item of the COVID-19 question in the MIP. The results in table 2 show that the firm's general affectedness by COVID-19 has a tight connection with revenue growth in 2020. Firms that were extremely negatively affected have about 58% lower revenue growth compared to not-affected firms. The size of this effect declines with the stated impact of COVID-19. Revenues of firms that state to have been only negatively impacted by COVID-19 grows only 20.7% slower. However, this relationship continues analogously for positively affected firms, whose revenues grew 10.9% more than not-affected firms, and very positively affected firms who even had a 28% increased log growth rate. This result confirms previous findings in the literature and clearly shows that firms that COVID-19 heavily impacted had to cope with a substantial revenue decline, possibly leading to a shift of management strategies to more short-term damage reduction instead of pursuing innovation that might only lead to uncertain future benefits.

Table 2: Revenue and COVID-19

	(1)
	Δ ln(revenues)
Affected by COVID-19	
Extremely negative	-0.575***
	(-7.19)
Very negative	-0.207***
	(-6.89)
Negative	-0.091***
	(-4.64)
Positive	0.109***
	(3.15)
Very positive	0.280***
	(2.74)
ln(emploees$_{2019}$)	-0.005
	(-0.66)
Constant	0.058
	(1.56)
Observations	2448

Notes: Item 'Marginally/Not at all 'omitted as reference category; 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

Baseline Results

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 3 on innovation process input variables. We first start by estimating a baseline model without any control variables. The results in table 3 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 19% compared to not-affected firms in column 1. We find an even stronger effect of a 25.4% 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 16.4% (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 15.3% and innovation expenditure to 21.1%. However, the effect on general investment growth increases to 24%, surpassing the effects on innovation inputs. However, not affected firms reduce investment growth in 2020 by 29.2% 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 20%, innovation expenditure growth by 36.7%, and investment growth by 63.2%.

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 4 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 impacts expected innovation activities in the two subsequent periods. It reduces the expected log growth rate in 2021 by 6.7% and by 1.2% in 2022, even though the latter is only significant at the 10% level. When introducing the same control variables as in the previous models, the effect on innovation expenditure growth in 2021 decreases by 1.6pp (column 4) but increases in 2022 by 0.4pp while improving the precision of the estimate rendering it significant at the 1% level (column 5). 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 not-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 expenditure over the combined log growth rate of innovation expenditures of the three-year period from 2019 to 2022 in column 3 for the sparse model, introducing control variables in column 6. Overall, firms reduced their (expected) innovation expenditure growth in this period by 14.6% in the sparse and 11.8% in the full model.

Table 3: Base Specification: Immediate Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(R&D exp.)	Δ ln(inno. exp.)	Δ ln(investment)	Δ ln(R&D exp.)	Δ ln(inno. exp.)	Δ ln(investment)
Neg. COVID	-0.190***	-0.254***	-0.164**	-0.153***	-0.211***	-0.240***
	(-6.51)	(-7.99)	(-2.01)	(-5.70)	(-7.07)	(-2.98)
ln(emploees$_{2019}$)				0.042**	0.052**	0.061**
				(2.20)	(2.54)	(2.28)
ln(R&D exp.$_{2019}$)				-0.023***		
				(-2.92)		
ln(inno. exp.$_{2019}$)					-0.032***	
					(-3.97)	
ln(investment$_{2019}$)						-0.087***
						(-6.08)
Constant	0.234***	0.290***	0.364***	-0.047	-0.156	-0.392**
	(9.92)	(10.98)	(11.33)	(-0.30)	(-0.96)	(-2.00)
Observations	2448	2448	1572	2448	2448	1572

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

Table 4: Base Specification: Future Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)
	2020 – 2021	2021 – 2022	2019 – 2022	2020 – 2021	2021 – 2022	2019 – 2022
Neg. COVID	-0.067***	-0.012*	-0.146***	-0.051***	-0.008***	-0.118***
	(-4.55)	(-1.90)	(-7.14)	(-4.59)	(-2.69)	(-7.02)
ln(emploees$_{2019}$)				0.001	-0.000	0.016
				(0.19)	(-0.17)	(1.34)
ln(inno. exp.$_{2019}$)				-0.002	0.002	-0.001
				(-0.74)	(1.48)	(-0.25)
Constant	0.049***	0.015**	0.110***	0.148	0.013	-0.029
	(3.96)	(2.50)	(6.22)	(1.12)	(0.71)	(-0.35)
Observations	1874	1759	1817	1874	1759	1817

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

Entropy Balancing

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 6, 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.6 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 covariats' 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 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 15.5%; 3.5% lower than the estimate from the base specification without entropy balancing. Innovation expenditure growth is decreased by 21.6% instead of 25.4%. Investment growth, in turn, increased from 16.4% to 31% 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 have an impact on innovation activity growth anymore.

The effect of a negative COVID-19 impact on expected innovation expenditure growth stays virtually unchanged. It decreases for 2021 in column 1 to -5%, and only slightly decreases for 2022 to -0.8%, though becoming significant on the 1% level. The overall decrease of innovation expenditure growth declines from 14.6% to 10.8% but stays significant at the 1% level. 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 5: Entropy Balancing: Immediate Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(R&D exp.)	Δ ln(inno. exp.)	Δ ln(investment)	Δ ln(R&D exp.)	Δ ln(inno. exp.)	Δ ln(investment)
Neg. COVID	-0.155***	-0.216***	-0.310***	-0.155***	-0.216***	-0.310***
	(-5.76)	(-7.10)	(-8.05)	(-5.74)	(-7.07)	(-8.16)
$\ln(\text{emploees}_{2019})$				0.008	0.022	-0.010
				(0.69)	(1.52)	(-0.71)
$\ln(\text{R\&D exp.}_{2019})$				-0.006		
				(-1.23)		
$\ln(\text{inno. exp.}_{2019})$					-0.013**	
					(-2.31)	
$\ln(\text{investment}_{2019})$						-0.021***
						(-3.45)
Constant	0.198***	0.251***	0.249***	0.172	0.124	-0.005
	(9.62)	(10.19)	(9.42)	(1.48)	(0.94)	(-0.02)
Observations	2448	2448	1542	2448	2448	1542

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

Table 6: Entropy Balancing: Future Impact

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)	Δ ln(inno. exp.)
	2020 − 2021	2021 − 2022	2019 − 2022	2020 − 2021	2021 − 2022	2019 − 2022
Neg. COVID	-0.050***	-0.008***	-0.108***	-0.050***	-0.008***	-0.108***
	(-4.60)	(-2.74)	(-7.01)	(-4.62)	(-2.76)	(-7.03)
ln(emploees$_{2019}$)				0.003	-0.001	0.015**
				(0.85)	(-0.63)	(2.30)
ln(inno. exp.$_{2019}$)				-0.001	0.003***	-0.005
				(-0.61)	(3.75)	(-1.42)
Constant	0.032***	0.011***	0.073***	0.094	0.030***	-0.024
	(4.31)	(4.30)	(6.24)	(1.27)	(2.93)	(-0.51)
Observations	1874	1759	1817	1874	1759	1817

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

digitalization for Resilience

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 3. The model's results using unweighted observations in columns 1 and 2 of table 7 for an immediate impact show that not highly digitalized firms affected by COVID-19 decreased R&D- and innovation expenditure growth by 11.6% and 20% respectively. Firms not affected by COVID-19 but with a high level of digitalization had a 21% higher R&D- and 14.5% 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 5.5%. However, this effect is not significantly different from zero. They also only decreased their innovation expenditure growth rate by 12.2%. 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% and 5% level for R&D- and innovation expenditure, respectively. 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- and innovation expenditures, and the effect on highly digitalized firms increases. The effect on R&D expenditures becomes significant at the 10% level. However, they are still significantly different from each other.

[5] We present the results of the entropy balancing procedure in tables A.7 and A.8 in the appendix.

Table 7: digitalization: Immediate Impact

	(1)	(2)	(3)	(4)
	Δ ln(R&D exp.)	Δ ln(inno. exp.)	Δ ln(R&D exp.)	Δ ln(inno. exp.)
Neg. COVID == 1 & Digi == 0	-0.116***	-0.200***	-0.119***	-0.204***
	(-3.43)	(-5.05)	(-3.96)	(-5.45)
Neg. COVID == 0 & Digi == 1	0.210***	0.145**	0.203***	0.123**
	(3.46)	(2.32)	(3.58)	(2.11)
Neg. COVID == 1 & Digi == 1	-0.055	-0.122***	-0.058*	-0.133***
	(-1.40)	(-2.75)	(-1.68)	(-3.22)
ln(emploees$_{2019}$)	0.050*	0.036*	0.020	0.009
	(1.91)	(1.80)	(0.95)	(0.74)
ln(R&D exp.$_{2019}$)	-0.038***		-0.023***	
	(-3.78)		(-2.66)	
ln(inno. exp.$_{2019}$)		-0.037***		-0.021***
		(-4.54)		(-3.37)
ln(investment$_{2019}$)				
Constant	-0.248	-0.189	-0.066	0.052
	(-1.29)	(-1.14)	(-0.42)	(0.41)
Observations	2421	2421	2421	2421

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

Covid-19 was an exogenous shock that hit societies and economies around the world in early 2020. This paper investigates how firms that are strongly negatively affected by COVID-19 change their innovation expenditure in the short and long-run. In the short-run, we find that strongly negatively affected firms decrease their R&D expenditures significantly by 15% and innovation expenditure by 21% more than control firms. Moreover, we find evidence of a Long-Covid effect on the German innovation system, as treated firms not only cut their innovation budgets in the short-run, but also do not expect to return to pre-crisis levels by the end of 2022. More digitized treated firms are more resilient to the Covid-19 shock compared to less digitized treated firms.

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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$_{2019}$)	-6.520	14.464	0.865	-6.726	14.400	1.055
ln(employees$_{2019}$)	3.182	2.790	0.775	3.246	2.412	0.774
high-tech	0.052	0.050	4.028	0.060	0.056	3.711
medium high-tech	0.141	0.122	2.059	0.111	0.098	2.482
medium low-tech	0.137	0.118	2.112	0.146	0.125	2.001
low-tech	0.163	0.137	1.824	0.100	0.090	2.674
knowledge-intensive services	0.230	0.178	1.280	0.279	0.201	0.985
less Knowledge-intensive services	0.252	0.189	1.141	0.151	0.129	1.945
other manufacturing	0.013	0.013	8.584	0.111	0.099	2.474
	Post-Balancing					
ln(R&D$_{2019}$)	-6.520	14.464	0.865	-6.522	14.435	0.866
ln(employees$_{2019}$)	3.182	2.790	0.775	3.183	2.785	0.775
high-tech	0.052	0.050	4.028	0.052	0.049	4.030
medium high-tech	0.141	0.122	2.059	0.141	0.121	2.061
medium low-tech	0.137	0.118	2.112	0.137	0.118	2.113
low-tech	0.163	0.137	1.824	0.163	0.136	1.826
knowledge-intensive services	0.230	0.178	1.280	0.230	0.177	1.282
less Knowledge-intensive services	0.252	0.189	1.141	0.252	0.189	1.143
other manufacturing	0.013	0.013	8.584	0.014	0.014	8.323

Table A.2: Entropy Balancing: Inno. Exp. Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno. exp.$_{2019}$)	-6.382	15.116	0.803	-6.574	15.219	0.981
ln(employees$_{2019}$)	3.182	2.790	0.775	3.246	2.412	0.774
high-tech	0.052	0.050	4.028	0.060	0.056	3.711
medium high-tech	0.141	0.122	2.059	0.111	0.098	2.482
medium low-tech	0.137	0.118	2.112	0.146	0.125	2.001
low-tech	0.163	0.137	1.824	0.100	0.090	2.674
knowledge-intensive services	0.230	0.178	1.280	0.279	0.201	0.985
less Knowledge-intensive services	0.252	0.189	1.141	0.151	0.129	1.945
other manufacturing	0.013	0.013	8.584	0.111	0.099	2.474
	Post-Balancing					
ln(inno. exp.$_{2019}$)	-6.382	15.116	0.803	-6.384	15.087	0.804
ln(employees$_{2019}$)	3.182	2.790	0.775	3.183	2.785	0.775
high-tech	0.052	0.050	4.028	0.052	0.049	4.030
medium high-tech	0.141	0.122	2.059	0.141	0.121	2.061
medium low-tech	0.137	0.118	2.112	0.137	0.118	2.113
low-tech	0.163	0.137	1.824	0.163	0.136	1.826
knowledge-intensive services	0.230	0.178	1.280	0.230	0.177	1.282
less Knowledge-intensive services	0.252	0.189	1.141	0.252	0.189	1.143
other manufacturing	0.013	0.013	8.584	0.014	0.014	8.323

Figure A1: COVID-19 question 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: 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.3: Entropy Balancing: Investment Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
$\ln(\text{investment}_{2019})$	-5.225	16.049	0.384	-4.235	14.424	-0.008
$\ln(\text{employees}_{2019})$	3.127	2.758	0.620	3.240	2.332	0.574
high-tech	0.049	0.047	4.189	0.063	0.059	3.588
medium high-tech	0.146	0.125	2.001	0.108	0.096	2.526
medium low-tech	0.138	0.120	2.097	0.137	0.119	2.107
low-tech	0.154	0.131	1.912	0.089	0.081	2.893
knowledge-intensive services	0.244	0.185	1.193	0.306	0.213	0.840
less Knowledge-intensive services	0.240	0.183	1.219	0.140	0.121	2.070
other manufacturing	0.020	0.020	6.799	0.114	0.101	2.426
	Post-Balancing					
$\ln(\text{investment}_{2019})$	-5.225	16.049	0.384	-5.224	15.997	0.384
$\ln(\text{employees}_{2019})$	3.127	2.758	0.620	3.127	2.749	0.620
high-tech	0.049	0.047	4.189	0.049	0.046	4.190
medium high-tech	0.146	0.125	2.001	0.146	0.125	2.001
medium low-tech	0.138	0.120	2.097	0.138	0.119	2.097
low-tech	0.154	0.131	1.912	0.154	0.131	1.912
knowledge-intensive services	0.244	0.185	1.193	0.244	0.185	1.193
less Knowledge-intensive services	0.240	0.183	1.219	0.240	0.182	1.219
other manufacturing	0.020	0.020	6.799	0.020	0.020	6.786

Table A.4: Entropy Balancing: Expected Inno. Exp. 2020-2021 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno. exp.$_{2019}$)	-6.921	14.215	1.185	-6.732	15.073	1.096
ln(employees$_{2019}$)	3.107	2.802	0.876	3.208	2.466	0.833
high-tech	0.036	0.035	4.987	0.059	0.056	3.740
medium high-tech	0.123	0.108	2.299	0.116	0.103	2.395
medium low-tech	0.126	0.110	2.257	0.136	0.118	2.119
low-tech	0.159	0.134	1.868	0.099	0.089	2.691
knowledge-intensive services	0.237	0.181	1.240	0.279	0.201	0.988
less Knowledge-intensive services	0.299	0.210	0.876	0.155	0.131	1.905
other manufacturing	0.012	0.012	8.973	0.112	0.099	2.466
	Post-Balancing					
ln(inno. exp.$_{2019}$)	-6.921	14.215	1.185	-6.922	14.178	1.185
ln(employees$_{2019}$)	3.107	2.802	0.876	3.108	2.795	0.876
high-tech	0.036	0.035	4.987	0.036	0.035	4.988
medium high-tech	0.123	0.108	2.299	0.123	0.108	2.300
medium low-tech	0.126	0.110	2.257	0.126	0.110	2.258
low-tech	0.159	0.134	1.868	0.159	0.134	1.869
knowledge-intensive services	0.237	0.181	1.240	0.236	0.181	1.241
less Knowledge-intensive services	0.299	0.210	0.876	0.299	0.210	0.877
other manufacturing	0.012	0.012	8.973	0.012	0.012	8.796

Table A.5: Entropy Balancing: Expected Inno. Exp. 2021-2022 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno. exp.$_{2019}$)	-7.126	13.188	1.291	-6.877	14.829	1.204
ln(employees$_{2019}$)	3.035	2.621	0.860	3.198	2.489	0.850
high-tech	0.036	0.034	5.013	0.059	0.056	3.731
medium high-tech	0.107	0.096	2.546	0.110	0.098	2.499
medium low-tech	0.136	0.118	2.125	0.138	0.119	2.100
low-tech	0.168	0.140	1.773	0.097	0.088	2.719
knowledge-intensive services	0.227	0.176	1.307	0.283	0.203	0.965
less Knowledge-intensive services	0.304	0.212	0.851	0.158	0.133	1.876
other manufacturing	0.013	0.013	8.618	0.112	0.099	2.465
	Post-Balancing					
ln(inno. exp.$_{2019}$)	-7.126	13.188	1.291	-7.127	13.152	1.292
ln(employees$_{2019}$)	3.035	2.621	0.860	3.035	2.614	0.860
high-tech	0.036	0.034	5.013	0.036	0.034	5.014
medium high-tech	0.107	0.096	2.546	0.107	0.095	2.547
medium low-tech	0.136	0.118	2.125	0.136	0.117	2.125
low-tech	0.168	0.140	1.773	0.168	0.140	1.774
knowledge-intensive services	0.227	0.176	1.307	0.226	0.175	1.307
less Knowledge-intensive services	0.304	0.212	0.851	0.304	0.212	0.852
other manufacturing	0.013	0.013	8.618	0.013	0.013	8.502

Table A.6: Entropy Balancing: Expected Inno. Exp. 2019-2022 Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno. exp.$_{2019}$)	-7.126	13.188	1.291	-6.877	14.829	1.204
ln(employees$_{2019}$)	3.035	2.621	0.860	3.198	2.489	0.850
high-tech	0.036	0.034	5.013	0.059	0.056	3.731
medium high-tech	0.107	0.096	2.546	0.110	0.098	2.499
medium low-tech	0.136	0.118	2.125	0.138	0.119	2.100
low-tech	0.168	0.140	1.773	0.097	0.088	2.719
knowledge-intensive services	0.227	0.176	1.307	0.283	0.203	0.965
less Knowledge-intensive services	0.304	0.212	0.851	0.158	0.133	1.876
other manufacturing	0.013	0.013	8.618	0.112	0.099	2.465
	Post-Balancing					
ln(inno. exp.$_{2019}$)	-7.126	13.188	1.291	-7.127	13.152	1.292
ln(employees$_{2019}$)	3.035	2.621	0.860	3.035	2.614	0.860
high-tech	0.036	0.034	5.013	0.036	0.034	5.014
medium high-tech	0.107	0.096	2.546	0.107	0.095	2.547
medium low-tech	0.136	0.118	2.125	0.136	0.117	2.125
low-tech	0.168	0.140	1.773	0.168	0.140	1.774
knowledge-intensive services	0.227	0.176	1.307	0.226	0.175	1.307
less Knowledge-intensive services	0.304	0.212	0.851	0.304	0.212	0.852
other manufacturing	0.013	0.013	8.618	0.013	0.013	8.502

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

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(R&D exp.$_{2019}$)	-6.529	14.511	0.871	-6.760	14.232	1.070
ln(employees$_{2019}$)	3.161	2.773	0.756	3.199	2.409	0.819
Digi	0.507	0.251	-0.026	0.421	0.244	0.321
high-tech	0.052	0.050	4.017	0.060	0.056	3.720
medium high-tech	0.135	0.117	2.132	0.112	0.099	2.468
medium low-tech	0.138	0.119	2.105	0.148	0.126	1.986
low-tech	0.159	0.134	1.861	0.086	0.079	2.951
knowledge-intensive services	0.231	0.178	1.274	0.287	0.205	0.940
less Knowledge-intensive services	0.262	0.194	1.082	0.155	0.131	1.908
other manufacturing	0.013	0.013	8.564	0.111	0.099	2.476
	Post-Balancing					
ln(R&D exp.$_{2019}$)	-6.529	14.511	0.871	-6.530	14.482	0.872
ln(employees$_{2019}$)	3.161	2.773	0.756	3.161	2.768	0.756
Digi	0.507	0.251	-0.026	0.506	0.250	-0.026
high-tech	0.052	0.050	4.017	0.052	0.050	4.019
medium high-tech	0.135	0.117	2.132	0.135	0.117	2.133
medium low-tech	0.138	0.119	2.105	0.137	0.119	2.106
low-tech	0.159	0.134	1.861	0.159	0.134	1.862
knowledge-intensive services	0.231	0.178	1.274	0.231	0.178	1.275
less Knowledge-intensive services	0.262	0.194	1.082	0.262	0.193	1.084
other manufacturing	0.013	0.013	8.564	0.014	0.014	8.314

Table A.8: Entropy Balancing: Digitization Heterogeneous Treatment Effect Inno. Exp. Regression

	Treatment Group			Control Group		
	Mean	Variance	Skewness	Mean	Variance	Skewness
	Pre-Balancing					
ln(inno. exp.$_{2019}$) ln$_{li}ages$	-6.392	15.159	0.810	-6.394	15.129	0.810
Digi	0.507	0.251	-0.026	0.506	0.250	-0.026
ln(employees$_{2019}$)	3.161	2.773	0.756	3.161	2.768	0.756
high-tech	0.052	0.050	4.017	0.052	0.050	4.019
medium high-tech	0.135	0.117	2.132	0.135	0.117	2.133
medium low-tech	0.138	0.119	2.105	0.137	0.119	2.106
low-tech	0.159	0.134	1.861	0.159	0.134	1.862
knowledge-intensive services	0.231	0.178	1.274	0.231	0.178	1.275
less Knowledge-intensive services	0.262	0.194	1.082	0.262	0.193	1.084
other manufacturing	0.013	0.013	8.564	0.014	0.014	8.314
	Post-Balancing					
ln(inno. exp.$_{2019}$)	-6.392	15.159	0.810	-6.610	15.061	1.000
Digi	0.507	0.251	-0.026	0.421	0.244	0.321
ln(employees$_{2019}$)	3.161	2.773	0.756	3.199	2.409	0.819
high-tech	0.052	0.050	4.017	0.060	0.056	3.720
medium high-tech	0.135	0.117	2.132	0.112	0.099	2.468
medium low-tech	0.138	0.119	2.105	0.148	0.126	1.986
low-tech	0.159	0.134	1.861	0.086	0.079	2.951
knowledge-intensive services	0.231	0.178	1.274	0.287	0.205	0.940
less Knowledge-intensive services	0.262	0.194	1.082	0.155	0.131	1.908
other manufacturing	0.013	0.013	8.564	0.111	0.099	2.476