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RESEARCH ARTICLE

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The impact of the EU General data protection regulation on product innovation

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ABSTRACT
In May 2018, a new regulation, the General Data Protection Regulation (GDPR), on data protection came in the European Union into force. It requires firms to update their data protection strategy and may complicate the use of data related to individuals, with potentially adverse effects on product innovation. This study provides evidence on the likely impacts of the GDPR on innovation. We employ a conditional difference-in-differences research design and estimate firm fixed-effects models based on data from the German innovation survey. We find that the GDPR led to a substantial shift from radical to incremental product innovation. Our finding indicates that the GDPR stimulated firms to re-organise their data management in a more profound way than they would have done in the absence of the regulation, opening up opportunities for improving existing products. The additional resources needed for complying with the GDPR limited their capacity for developing entirely new products.

KEYWORDS
General data protection regulation; innovation; community innovation survey; conditional difference-in-differences estimation; new product sales

JEL CLASSIFICATION
O31; O38; C22; L51

1. Introduction

In 2018, the General Data Protection Regulation (GDPR) came into force. The GDPR aims to protect consumers and give them more control of their data. The GDPR applies to organisations that control and process data of EU citizens regardless as to where the organisation is located. The regulation is aimed at not only tackling increasing public concern regarding the protection of personal data, but also to instil consumer trust in the digital economy and providing space for the digital economy to grow (ITU, World Bank 2020). Indeed, the GDPR aims to secure competition in markets related to personal data. The GDPR is particularly relevant to firms operating large digital platforms (Geradin, Karanikioti, and Katsifis 2021), but affects all other firms that collect or process personal data of EU citizens. Depending on firm size and business activity, the GDPR requires firms, among others, to demonstrate a lawful and transparent use of personal data, maintain a list of data processing activities, guarantee data protection and accountability,

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respect privacy rights and inform individuals about the use of their data, including data deletion upon request.[1]

While the GDPR applies to all firms, not all firms are affected by the GDPR in their innovation activities. Firms serving consumers and relying on user data to develop and specify products and services to specific user requirements are likely to have to adapt their innovation processes to be compliant with the GDPR. In contrast, a firm that processes timber and sells timber products to other firms will not experience much if any consequences for their innovative efforts from the GDPR. For firms with data-driven business-models, complying to the GDPR may increase costs (e.g. re-organising data security processes), but it may also generate benefits (e.g. increase in consumer trust).

Based on this firm heterogeneity in GDPR affectedness, a debate regarding the effect of the GDPR on innovation emerged. On the one hand, firms in the EU may lose market shares in global online markets (Goldberg, Johnson, and Shriver 2019) while firms from outside the EU may strengthen their market power (Peukert et al. 2022), with likely adverse effects on innovation in EU based firms. Furthermore, the GDPR may decrease the attractiveness for venture capital to invest in (Jia, Jin, and Wagman 2021; Kircher and Foerderer 2021), complicating the financing of innovation, because the compliance with GDPR creates additional cost requiring the adjustment of their business models as well as reducing their longer-term profitability (Jia, Jin, and Wagman 2021). On the other hand, Arcuri (2020) and Cisco (2019, 2020) observe increasing values of EU firms and the demand for their products. Much of this debate rests on conceptual arguments (see Krämer 2021; Niebel 2021; Richardson 2019; von Grafenstein 2019; Wallace and Castro 2018) or focuses on case studies such as digital platforms (Florez Ramos and Blind 2020; Pietronudo et al. 2022) or apps (Janssen et al. 2022). There are only few empirical studies yet that analyse whether and how the GDPR did change innovation across different industries and types of firms (see the recent review by Johnson 2022). Our analysis attempts to fill this gap by investigating the short-term impact of the introduction of the GDPR on innovation in German firms in the three years after the regulation came into force. In particular, we analyse which type of innovation is stimulated or hindered, considering firms from.

Following Jia et al. (2021), Chen et al. (2022a), Kircher and Foerderer (2021), and Lefrere et al. (2022), we employ a conditional difference-in-differences research design based on fixed-effects panel regressions in order to identify changes in innovation performance prior and after the introduction of the GDPR in firms. A critical issue in this respect is to separate firms into those 'treated' by GDPR and a control group. Since the GDPR concerns all firms that control and process data of EU citizen's, there is most likely not a single firm in Germany (or any other EU country) not affected by the regulation also argued by Johnson (2022). The situation is different for innovation, however. Many firms may pursue innovation activities that do not involve the use of personal data, e.g. developing a new chemical molecule or a new technology to process or handle materials. We use information on whether data protection regulation affected the firm's innovation activities (positively, negatively or not at all) in order to allocate firms to treated and non-treated groups. Innovation performance is measured through new product sales as well as cost reduction resulting from process innovation. We use firm-level panel data from the German Community Innovation Survey (CIS) covering a period prior to the GDPR introduction (2011 to 2017) as well as the first three years after its

[1]See GDPR compliance checklist: https://gdpr.eu/checklist/.

introduction (2018 to 2020). As we are able to analyse only a short time span since the GDPR came into force, our results are limited to short-run, direct impacts of the new regulation. Medium to long-run impacts as well as indirect effects are beyond the scope of this paper.

Our empirical results reveal that the GDPR had no significant impact on firms' innovation total output, but it significantly shifted the focus of product innovation. Sales from incremental innovations rose by 1.8 percentages points, while sales from radical innovations fell by 0.9 percentage points. This finding is driven by small and young firms, firms in B2B markets, in service sectors and in knowledge-intensive industries. Further analysis of the firms affected by the GDPR in their innovation activities suggest that the GDPR forced firms to re-organise their data management in a more profound way that they would have done in the absence of the regulation, opening-up opportunities for improving existing products through a more thoroughly or smarter use of data. On first sight, the GDPR seems to have created a kind of win-win-situation in the sense of the Porter hypothesis (which was formulated for the context of environmental regulation, see Porter and van der Linde 1995) by stimulating more incremental product innovation. This result confirms the expectations put forward by other authors (see Niebel 2021). However, the additional resources needed for complying with the GDPR limited the capacity for developing entirely new products, which may result in negative long-term innovation impacts of the GDPR.

The remainder of the paper is structured as follows. Section 2 reviews the limited literature and derives our research questions. Section 3 explains the empirical strategy and describes the data while section 4 presents the results of our analysis. Section 5 discusses the implications of our findings with respect to how data protection regulation may interfere with innovation strategies of firms. The concluding section 6 which are then discussed in the following chapter including the limitations of our approach. We close with the main conclusions, but also first policy implications.

2. GDPR and innovation

The discussion around the impact of data protection regulation – or privacy regulation as it is often called in the US literature – on innovation is layered. On a broad level, it is situated in the discussion regarding the impact of regulation on innovation. On the one side, regulation is seen as a restriction to firms' decision on how to operate business activities – either through raising costs or by complicating or impeding certain activities, resulting in negative impacts on innovation. On the other side, regulation is perceived to be able to also have a positive effect on innovation, such as by stimulating innovative adaptations to a new situation or market opportunities created by a regulation. Within this sphere of thought, the 'Porter hypothesis' stands out as describing under which conditions a regulation – in this case an environmental one – can be beneficial for firms' innovation and competitiveness while at the same time meeting the regulator's goals (Porter and van der Linde 1995). For environmental regulation and innovation, the empirical evidence is mixed. The review by Ambec et al. (2013) supports that at least in the long run environmental innovation push firms' innovation. The broader review by Blind (2016) concludes that the impact of regulation on innovation is ambivalent.

With respect to privacy regulation, Goldfarb and Tucker (2012) argue that a trade-off exists between privacy and innovation in general referring to numerous studies focusing on the online-advertising and health-care sectors. In particular related to the GDPR, Martin et al. (2019) confirm its ambivalent role for innovation. On the one hand, it spurs privacy-related innovation as well as increased demand for 'regulation-exploiting innovation' to support data protection and compliance e.g. compliance management software or encryption capabilities. However, Martin et al. (2019) claim that the GDPR can lead firms to abandon products, but also limit their access to input data, which might be needed for artificial-intelligence applications. Indirectly, the competition increasing impact of the GDPR because of the required interoperability and transferability of data might foster also innovation in the long-run.

The empirical literature on the impact of the GDPR is still in its infancy. Some studies point to a positive effect on competition, eventually triggering innovation (Niebel 2021). However, whereas Arcuri (2020) claims – without considering a control group – that the value of European-listed financial firms has increased after the implementation of the GDPR, other studies applying a more rigorous approach come to less favourable results. First, Peukert et al. (2022) reveal that after the GDPR became effective, the majority of more than 100,000 websites especially relevant for the collection of personal data substantially reduced their interactions with web technology providers irrespective of whether the GDPR legally binds them (see also Goldberg, Johnson, and Shriver 2019). Eventually, the market concentration in web technology services increased (see also a similar study by Johnson, Shriver, and Goldberg 2022), benefitting already market-dominant firms and leading to less competition, which might, in the long run, harm innovation in particular of European firms. Similarly, Chen et al. (2022b), but also Koski and Valmari (2020) show that, in particular, small but not large firms exposed to the GDPR experienced declines both in turnover and even more profits, questioning the innovation-enhancing competition impact again. However, the burden for innovation by increased compliance costs (e.g. Blind 2012) related to GDPR is not disadvantaging European based firms, as shown by Godinho de Matos and Adjerid (2022) and Lefrere et al. (2022).

Whereas the above studies allow us to derive only indirect implications of the GDPR for innovation, the investigations explicitly focusing on the innovation dimensions are limited, and the evidence on positive or negative impacts is mixed (see the recent review by Johnson 2022). Janssen et al. (2022) show that the GDPR has slowed innovation by triggering the exit of about a third of available apps. However, Krämer (2021) expects the GDPR to create incentives for innovation among platform providers because of the competition enhancing impact of the required interoperability and portability of data, e.g. between Spotify and Apple Music (Florez Ramos and Blind 2020). However, this competition and innovation triggering impact has not been realised except for specific cases, like a digital platform the health sector (Pietronudo et al. 2022). At the firm level, Martin et al. (2019) capture the responses of a limited set of start-ups to data protection regulation, including the GDPR. The GDPR was found to have unleashed innovation-stimulating effects on start-ups – contradicting the above-reported empirical evidence on the over-proportionate burden on SMEs, where there were also suggestions of innovation-constraining effects. However, these were less apparent and often were to be expected (e.g. socially problematic innovations). In total, the innovation-stimulating results were found for start-ups particularly relevant to broaden the above-summarised discussion regarding the GDPR's impact on SMEs. Finally, not only is the current situation of start-ups being perceived as essential drivers for innovation, but also their future is impacted by the GDPR. For example, Jia et al.

(2021) find a negative effect in terms of less venture capital invested in the EU compared to the US after the implementation of the GDPR or in US-based start-ups being active in the EU (Kircher and Foerderer 2021).

In summary, the empirical evidence highlights the regulatory burden of the GDPR, which eventually disadvantaged SMEs. Consequently, this negative implication on competition might hamper innovation. However, current research cannot support the claim of over-proportionate compliance costs for European firms. Research explicitly focusing on innovation is limited, revealing positive examples among start-ups but negative implications on the supply of new Apps.

Based on the limited and ambivalent insights from the existing literature, this paper aims to contribute to the debate on data protection regulation and innovation by empirically exploring the link between GDPR and innovation using a large-scale data base. Specifically, we want to investigate whether firms that are affected in their innovation activities by the GDPR show changes in their innovation outputs (introduction of new products and processes, economic returns from these innovations in terms of sales and cost reduction) compared to firms that did not experience positive or negative consequences of the GDPR for their innovative efforts. We deliberately refrain from deriving hypotheses since we still know too little about the actual implications of the changes in privacy regulation on firms' innovation strategies. The explorative results presented in this paper are intended to enlarge our knowledge in this respect and Our empirical analysis is guided by three broad research questions:

(1) Did GDPR lead to more or less innovation output?
(2) What type of innovation was stimulated by the GDPR?
(3) Were different types of firms affected differently by the GDPR, e.g. by size, age, markets and industry?

3. Empirical strategy and data

3.1. Conditional difference-in-differences (CDiD)

The main purpose of this paper is to identify whether and how the GDPR changed innovation in firms. In order to separate the contribution of the GDPR from other changes within firms and in the firms' environment that took place at the same time, we follow other studies (Chen et al. 2022; Jia, Jin, and Wagman 2021; Kircher and Foerderer 2021) and employ a difference-in-differences (DiD) research design. The key idea is to compare firms whose innovation activities are affected by the GDPR ('treated firms') with firms whose innovation activities are not affected by the new regulation ('non-treated firms'), e.g. because they innovate in a way and develop innovations that do not involve the use of personal data. Since these two groups may be quite different in nature, we condition the comparison to non-treated firms that are similar to the group of treated firms, resulting in a conditional DiD approach (CDiD). For this purpose, matching techniques are employed and explained in more detail below. In order to separate the GDPR impact from other factors that drive a firm's innovation results, we use a firm fixed-effects panel regression model and control for variations in inputs to innovation within a firm over time. Firm fixed-effect estimations imply that all characteristics of a firm that do not (or only slightly) vary within the observation period, such as the firm's competitive strategy, its management capability and its basic resource endowment, are captured by the firm fixed effects and need not be controlled for by separate variables. Including measures for innovation input, which are likely to vary over time, ensures that the contribution of these investments for developing and commercialising innovations to innovation output are separated from effects of the GDPR.

A critical point of our CDiD approach is to separate treated from non-treated firms. Since the GDPR concerns all firms that control and process data of EU citizen's, there is most likely not a single firm in Germany (or any other EU country) not affected by the regulation in their general business, in organising internal data management, and in communicating with customers, suppliers and other business partners. The situation is different for innovation, however. With respect to developing innovations, many firms may pursue innovation activities that do not involve the use of personal data, e.g. developing a new chemical molecule or a new technology to process or handle materials. In terms of using innovations by customers or end users, there are also many examples that do not involve the processing of personal data, e.g. intermediary products or machinery and equipment used by other firms.

In order to allocate firms to the treated and non-treated groups, one would need detailed information about the role and nature of data for the firms' business strategy and innovative attempts. Such information is not exogenously available, however, since one cannot observe from outside whether and how a firm uses which type of data to produce, offer and sell products and services. Firms usually do not disclose such information about their internal processes. We therefore rely on firm managers, by asking them whether data protection regulation affects their firm's innovation activities (see the section on data source below for more details). This survey-based information can be considered highly reliable since managers are those who are best aware of whether certain regulations do affect their operations and their ability to implement certain changes.

3.2. Model set-up

We evaluate the impact of the GDPR on innovation by looking at the result of the firms' innovation efforts (innovation output), rather than the input side (e.g. innovation expenditure). Innovation output, i.e. the sales generated by new products and the unit cost reduction obtained from new processes, is a more precise measure of GDPR impacts as it also considers likely consequences of the GDPR in commercialising and marketing innovations, as well as consequences on data management and protection when using new products or new processes.

We estimate a firm fixed-effects panel model that analyses the impact of being affected by the GDPR on innovation output (*INOUT*) while controlling for other variables **Z** that may affect *INOUT* and including time dummies δ_t, firm fixed-effects γ_i, a constant α and a firm-specific and time-specific error term ε (*i* indicating firms and *t* indicating years):

$$INOUT_{it} = a + b_1 GDPR_{it} + b_2 GDPR\_pre_{it} + \chi \mathbf{Z}_{it-1} + \delta_t + \gamma_i + \varepsilon_{it} \quad (1)$$

The treatment variable *GDPR* takes unit value for $t \geq 2018$ (and zero otherwise) if a firm reported that its innovation activities were (positively or negatively) affected by data protection regulation. A critical assumption of the DiD methodology is that the treated and not treated firms follow the same trend before the treatment takes place; i.e. that treated firms showed the same development in innovation output prior to the introduction of the GDPR as non-treated firms did. In order to test this assumption, we include 'pre-treatment' dummy variable which takes unit value for $t \leq 2017$ (and zero otherwise) in case a firm reported to be affected by the GDPR in its innovation activities (*GDPR_pre*). In case the GDPR has an impact on innovation output, we will find a statistically significant coefficient β_1, while β_2 should be insignificant in order to support the common trend assumption. In addition, we test the common trend assumption for each year of our observation period 2011 to 2020. The results are shown in Figure A1 in the Appendix and reveal that in none year prior to 2018, treated and non-treated differ significantly in terms on any of the innovation output measures used in this study.

While the GDPR came into force in May 2018, it was approved already in 2016, and proposed by the European Commission in 2012. Firms may hence have adapted to the regulation earlier than 2018. We test this hypothesis by running a variant of model [1] in which *GDPR* takes the value 1 from the year 2016 on, while *GDPR_pre* takes the value one for $t < 2016$. In addition, we run a Placebo test by assuming that the GDPR came into force already in 2014 (i.e. at a time when little details on the proposed regulation have been known to businesses).

In addition to the common trend assumption, the DiD approach also rests on the common shock assumption (Dimick and Ryan 2014; Ryan, Burgess, and Dimick 2015), i. e. that treated and non-treated firms are subject to the same exogenous factors that may affect innovation results. We made an attempt to test this assumption by analysing the role of time-variant drivers of innovation output (as time-invariant are already captured by firm-fixed effects) for treated and untreated firms separately. We used different tangible and intangible investments (expenditure on R&D, non-R&D innovation, software & database, marketing & branding, training, fixed assets) as predictors of innovation output that vary significantly over time and may be subject to exogenous shocks such as changes in financing cost, demand shocks or shocks on labour markets. Information on expenditure for these capital goods is directly taken from the German CIS (see Roth, Sen, and Rammer 2022). We found that the estimated coefficients for most expenditure categories are not statistically significant between treated and untreated, except for software and database (higher positive effect for treated) and marketing (lower positive effect for treated). In order to take likely differences in the role of exogenous factors for innovation output between treated and not-treated firms into account, we include these expenditure variables as controls in our main FE estimations. In addition, the control vector **Z** includes size (to capture changes in the general resource availability), the share of graduated employees (to capture changes in human capital) and the export share.[2] Since investing in innovation inputs and realising innovation output from this investment takes time, all control variables are measured for t-1.

In a further attempt to render treated and not-treated firms comparable, and to make the common trends assumptions more credible, we combine the DiD estimator with a

[2]We also tested further control variables such as the credit rating that a firm has been assigned (which captures access to external funding through loans) and capital expenditures for fixed assets per full-time employee (representing the firm's efforts to update or extend its technical equipment, including machinery and ICT hardware). Since these control variables did not exert a statistically significant effect on innovation output, and their inclusion did not alter the coefficients for our key model variables, but reduced the number of observations and hence the representativeness of the data, we did not consider these additional controls in the final estimations.

matching estimator and restrict the control group to firms which are similar to the group of treated firms ('conditional DiD' - CDiD, see Bergemann, Fitzenberger, and Speckesser 2009; Heckman et al. 1998). There are different balancing methods available for implementing a CDiD approach. Nearest neighbour matching assigns to each treated firm a control group firm that shows the most similar values for the chosen matching variables (based on the estimated propensity score). An alternative method is entropy balancing, which stochastically assigns weights to control group firms in a way that the moments (mean, variance, skewness) of the matching variables in the pre-treatment period are the same for the control group sample as those in the treatment group (Hainmueller 2012). Entropy balancing is a more flexible approach particularly in the case when the treated group includes firms for which no similar non-treated firms are available in the sample. We use firm size, age, innovation activities, human capital and industry as matching variables. Table A1 in the Appendix reports the marginal effects of the matching variables on the probability that a firm reports to be affected in its innovation activities by the GDPR. Table A2 reveals that the entropy balancing produced the identical moments for the matching variables in the control group and the treated group, whereas there were significant differences prior to the matching, particularly with respect to innovation activity, human capital and industry composition. The weights from the entropy balancing matching are assigned to each control group firm when estimating [1]. Treated firms enter the estimation with a unit value for the weight.

3.3. Data source

Our empirical analysis rests on a unique data source on the role of privacy regulation for a firm's innovation activities. The data have been collected through the German part of the European Commission's Community Innovation Survey (CIS) conducted in the year 2019 and obtaining information for the reference year 2018 ('CIS 2018'). The harmonised questionnaire of the CIS 2018 contained a question on the role of legislation and regulation for the innovation activities of firms, separating positive impacts (initiating or facilitating of innovation activities) and negative ones (preventing or hampering innovation activities). The harmonised questionnaire distinguished the following areas of legislation/regulation: product safety and consumer protection, environmental protection, intellectual property, taxation, employment law, and worker safety and social affairs. In the German questionnaire for the CIS 2018, another area 'data protection' was added. Figure 1 shows the design of the question used in the German CIS 2018.

As for most other questions on innovation activities, the question on legislation and regulation referred to a three year reference period (2016 to 2018), following the recommendations of the Oslo Manual (OECD 2018). Though the survey form did not make explicit reference to the GDPR (as it did not make reference to any specific legislation or regulation), the introduction of the GDPR in May 2018 was the only major legislative event during the reference period 2016 to 2018. As the GDPR overruled all major prior privacy regulation in Germany, we can safely assume that firms were referring to the GDPR when reporting positive or negative innovation consequences of data protection regulation.

Differently to most other national CIS, the German CIS is designed as an annual panel survey and called the Mannheim Innovation Panel (MIP). It surveys the same sample of

8.1 During 2016 to 2018, has legislation or regulation affected your enterprises' R&D/innovation activities in any of the following ways?

(Tick all that apply) *Legislation/regulation on …*	*R&D/innovation activities were …* *initiated/ facilitated*	 *prevented/ hampered*	*No effect on R&D/innovation activities*
Product safety, consumer protection	☐₁	☐₁	☐₁
Environmental protection, climate protection	☐₁	☐₁	☐₁
Intellectual property	☐₁	☐₁	☐₁
Data protection	☐₁	☐₁	☐₁
Employment law	☐₁	☐₁	☐₁
Worker safety, social affairs	☐₁	☐₁	☐₁
Taxation	☐₁	☐₁	☐₁

Figure 1. Question on the role of legislation and regulation on innovation in the German CIS 2018. Source: MIP, survey year 2019.

firms (with a panel sample refreshment every second year) and collects data beyond the standard set of CIS variables, including more information on financial variables (see Peters and Rammer 2013 for more details on the MIP). The panel nature of the survey allows us to analyse innovation activities of firms before and after the introduction of the GDPR and enables the implementation of the CDiD research design.

3.4. Measurement of model variables

Innovation output is measured for both product and process innovation. For product innovation, we use the share of sales obtained from product innovation (*INS_P*), which can be split into sales from new-to-the-market ('radical') innovations (*INS_M*) and sales from innovations that were only new to the firm ('incremental innovation' or 'imitations') (*INS_F*). This information can be directly obtained from the CIS questionnaire and is collected on an annual bases in the German CIS.[3] The sales share indicator on product innovation output has widely been used in the literature (see Klingebiel and Rammer 2014; Laursen and Salter 2006; Leiponen and Helfat 2010; Mairesse and Mohnen 2002). Note that both incremental and radical innovation have to meet a minimum threshold of novelty, which is that the new or improved product has to differ significantly from the products offered by the firm before. With respect to likely product innovation effects of the GDPR, this definition implies that only products that represent a substantial departure from the firm's previous product portfolio qualifies as innovations.

For process innovation output, we use the share of unit cost reduction owing to process innovation (*INS_C*). This indicator has less widely been used in the literature since it is not part of the standards set of innovation indicators collected in the CIS. Some countries, including Germany, have included this indicator in their national surveys (see Rammer 2023), which has produced reasonable results in different research settings (see for example Piening and Salge 2015; Rammer 2023; Rammer, Fernández, and Czarnitzki 2022).

[3]The sales share information is obtained from two separate questions. First, firms were asked on the share of sales from product innovations (introduced in the past three years) in total sales (without making any reference to the level of novelty of the innovation). In a following question, firms were asked whether any of the product innovations introduced during the past three years was new to the market that the firm serves (i.e. no other firm has offered the same or a similar product on the market that the firm serves). In case a firm responded yes, it was asked to provide the share in total sales of these new-to-market innovations. The share of sales from incremental innovations is calculated as the difference of the sales share of all product innovations and the sales share of new-to-market innovations.

The treatment variable *GDPR* takes unit value if a firm reported that data protection regulation constitutes an obstacle for innovation (by preventing or hampering innovation activities) or supported innovation (by initiating or facilitating innovation activities). For more detailed analysis on the GDPR impact, we build two further variables that indicate whether the regulation act as an obstacle (*GDPR_OB*) or as a supporter (*GDPR_SU)*. All treatment variables can take unit value only from the year of GDPR introduction in 2018 and have the value zero for all years prior to 2018. For firms not affected by the GDPR, treatment variables have zero values in all years.

Innovation inputs are measured by the volume of innovation expenditures (in constant prices using the GDP deflator) per full-time employee, distinguishing two types of expenditure: R&D expenditures (*RD*) and other innovation expenditures (*NRD*). *RD* identifies the amount of resources that are devoted to generating new knowledge, whereas *NRD* refers to the resources used for implementing new knowledge in new products and processes, such as design, market introduction and other preparatory work. Digitalisation efforts (*DIG*) are measured as expenditures for software and databases per full-time employee. *DIG* includes both in-house costs and purchase of software programmes, software licences, software programming services and databases. Marketing expenditures (*MKT*) are measured as expenditures for advertising and other reputation or brand value building activities per full-time employee. All financial data is converted into constant prices using the GDP deflator.

A firm's general resource endowment is measured by the logarithm of the number of full-time employees (*EMP*) and by human capital intensity (*HC*, measured as the share of graduated employees). In addition, we include the firm's export share (sales to customers abroad in total sales, *EXP*) in order to control for likely effects on business activities abroad on the way the GDPR affects innovation. Such effects may occur due to national differences in the implementation of the GDPR. Note that by estimating fixed-effects models, we already account for firm-specific effects on innovation output that arises from a firm's capabilities and accumulated assets.

Measuring both the dependent and the independent variables through the same survey may cause a common method bias, i.e. that variables are correlated because of respondent-specific factors (e.g. some respondents consider their firm as being highly innovative and over-report both inputs and outputs of innovation activities) or instrument-specific factors (e.g. the way survey questions are presented drive responses in the same direction). For the present survey, we are confident that such a bias is unlikely for several reasons. First, we use panel data which have been collected through annual surveys over a ten year time period (from 2011 to 2020). The dependent variable, innovation output, and the control variables hence come only in one year from the same survey from which the key independent variable – the relevance of the GDPR for the firm – is taken (which is the survey for the reference year 2018). In this survey, the question on innovation output has been asked in the first part of the survey form (Section 2), while the question on the relevance of the data protection regulation came much later (in section 8) and was unrelated to the question on innovation output. At the same time, the innovation survey covers a large number of topics. In the survey for the reference year 2018, there were 15 major topics, including one topic on factors that may affect innovation activities containing two questions, one being the question with the item on data protection regulation. To the best of our knowledge, it is most unlikely that the survey instrument caused a correlation between the responses to innovation output (measured at up to then different points in time) and the responses to the relevance of data protection regulation for the firm's innovation activities.

The model variables are measured for the time period 2011 to 2020. The starting year is determined by the fact that this was the first year that the MIP collected data on software and database expenditure, which is considered a major input for innovation activities linked to data usages. The last year 2020 is the most recent year available at the time of analysis. The unit of observation is the firm, defined as a legal unit, or as an enterprise group in case of multiple legal units are owned by the same parent company. In case a firm significantly changes its operations over time due to mergers, acquisitions or sale of major parts of the firm, this firm will be split in two separate firms. The total number of firm x year observations for model estimations is 28,814 for product innovation output (representing 6,190 different firms) and 28,687 for process innovation output (representing 6,172 different firms), implying that on average, a firm provided information for 4.7 years within the 10-year time window of this study. Table 1 shows the definition and descriptive statistics of all model variables.

The key variable of interest, GDPR, shows a mean value of 14.0% for the entire observation period 2011–2020. When restricted to the period 2018–2020 (which is the period for which GDPR can take positive values), 36.4% of all firms in the sample reported to be affected in their innovation activities by the GDPR (32.3% reported negative and 4.2% positive consequences, with only 0.1% reporting both consequences). When comparing the descriptive statistics of the model variables for treated firms and control group firms (the latter weighted based on the entropy balancing results, see Table 2), we find higher shares of product and process innovators among the treated group as well as higher sales shares from product

Table 1. Definition of model variables and descriptive statistics.

Variable	Definition	# obs.	Mean	SD	Min	Max
INS_P	Share of sales from product innovation	28,814	0.0671	0.1653	0.0	1.0
INS_F	Share of sales from product innovation that were only new to the firm	28,814	0.0523	0.1410	0.0	1.0
INS_M	Share of sales from product innovation that were new to the firm's market	28,814	0.0148	0.0731	0.0	1.0
INS_C	Share of unit cost reduction owing to process innovation	28,687	0.0088	0.0384	0.0	1.0
GDPR	1 if firm reported that data protection regulation has affected innovation activities, 0 otherwise	28,814	0.1396	0.3466	0	1
RD	R&D expenditures (at 2015 prices) per full-time employee (million Euro)	28,814	0.0023	0.0073	0.0	0.0
NRD	Non-R&D innovation expenditures (at 2015 prices) per full-time employee (million Euro)	28,814	0.0018	0.0063	0.0	0.1
DIG	Software and database expenditures (at 2015 prices) per full-time employee (million Euro)	28,814	0.0011	0.0021	0.0	0.0
MKT	Marketing expenditures (at 2015 prices) per full-time employee (million Euro)	28,814	0.0012	0.0026	0.0	0.0
EXP	Share of export sales in total sales	28,814	0.1176	0.2257	0.0	1.0
EMP	No. of full-time employees (log)	28,814	3.1326	1.5029	−0.7	12.0
HC	Share of gradated employees	28,814	0.2350	0.2776	0.0	1.0

Source: MIP.

Table 2. Mean of model variables by treatment group (weighted based on entropy balancing).

	max(GDPR) = 1	max(GDPR) = 0	Difference[b]	GDPR = 1 for $t \geq 2018$	GDPR = 0 for $t \geq 2018$	Difference[b]
IN_P[a]	0.3812	0.3202	***	0.4132	0.3405	***
IN_F[a]	0.3395	0.2818	***	0.3742	0.3002	***
IN_M[a]	0.1407	0.1238	***	0.1373	0.1238	
IN_C[a]	0.1604	0.1082	***	0.2080	0.1375	***
INS_P	0.0986	0.0823	***	0.1044	0.0873	***
INS_F	0.0769	0.0638	***	0.0840	0.0666	***
INS_M	0.0217	0.0185	***	0.0204	0.0207	
INS_C	0.0143	0.0092	***	0.0170	0.0108	***
RD	0.0032	0.0030	**	0.0037	0.0035	
NRD	0.0025	0.0021	***	0.0017	0.0015	
DIG	0.0014	0.0012	***	0.0016	0.0014	***
MKT	0.0015	0.0013	***	0.0014	0.0012	***
EXP	0.1188	0.1323	***	0.1199	0.1472	***
EMP	3.1648	3.1512		3.1440	3.1623	
HC	0.2619	0.2772	***	0.2848	0.2924	

[a]Dummy variables indicating whether a firm introduced product innovation (IN_P), only new-to-firm product innovation (IN_F), new-to-market product innovation (IN_M), or cost reducing process innovation (IN_C).
[b]Significance level of difference between treated and non-treated: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: MIP.

innovation (*INS_P*) and incremental innovations (*INS_F*) as well as higher unit cost reduction from process innovation (*INS_C*). This result holds both for the entire period and the period after the GDPR has been introduced. For the sales share of radical innovation (*INS_M*), we find higher values for treated firms for the entire period, but not for the post-introduction period. For most of the control variables, the mean values for the group of treated firms are slightly higher compared to the control group, except for the export share and the human capital variable.

4. Estimation results

4.1. Base model

The estimation results of the firm fixed-effects panel regressions (Table 3) show that the impact of the GDPR on innovation varies significantly by type of innovation output. For total sales from product innovations (*INS_P*), as well as for cost reduction from process innovation (*INS_C*), we do not find a statistically significant impact of the regulation. However, the results indicate that sales with incremental product innovation (*INS_F*) significantly increased due to the introduction of the GDPR, while sales with radical innovation (*INS_M*) declined. Both effects are significant at the 5% confidence level and also significant in magnitude. The sales share of new-to-firm innovations went up by 1.8 percentage points, which represents 17% of the average sales share of these innovation in the 2018–2020 period in firms affected by the regulation (which is at 10.4%). For the new-to-market innovations, the decrease of the sales share by 0.9 percentage points represents about 40% of the average sales share of these innovations in the group of treated firms in 2018 to 2020 (which is at 2.0%). This result implies that the GDPR has shifted innovation

Table 3. Results of CDiD estimations on the effect of GDPR on innovation output.

	INS_P	INS_F	INS_M	INS_C
	(1)	(2)	(3)	(4)
GDPR	0.010	0.018***	−0.009**	0.003
	(0.007)	(0.006)	(0.004)	(0.002)
GDPR_pre	0.001	0.004	−0.003	0.002
	(0.007)	(0.006)	(0.004)	(0.002)
RDINP in *t*-1	0.237	−0.402	0.639	−0.012
	(0.523)	(0.485)	(0.469)	(0.134)
NRDINP in *t*-1	1.020***	0.539**	0.481	0.213*
	(0.352)	(0.236)	(0.297)	(0.109)
DIG in *t*-1	− 0.016	1.137	−1.154*	−0.109
	(1.625)	(1.520)	(0.608)	(0.457)
EXP in *t*-1	0.002	0.006	−0.004	−0.005
	(0.021)	(0.019)	(0.014)	(0.005)
MKT	0.933	0.992	−0.059	0.186
	(1.118)	(1.040)	(0.587)	(0.283)
EMP	0.003	0.004	−0.002	0.001
	(0.006)	(0.006)	(0.004)	(0.002)
HC	0.013	0.005	0.009	0.004
	(0.014)	(0.015)	(0.010)	(0.005)
Constant	0.074***	0.048**	0.026**	0.007
	(0.021)	(0.020)	(0.012)	(0.006)
No. observations	28,814	28,814	28,814	28,687
No. firms	6,190	6,190	6,190	6,172
R-squared	0.016	0.013	0.010	0.007
Year dummies	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

towards a lower level of novelty. The GDPR hence facilitated the marketing of incremental changes and the imitation of product innovations that have been introduced by other firms before. At the same time, it complicated more radical innovation.

The common trend assumption for the pre-treatment period holds as *GDPR_pre* is not statistically significant in any of the four models. This is also confirmed by a more detailed analysis for each year (reported in Figure A1 in the Appendix), which shows than in each year before 2018, innovation output does not differ statistically significant between treated and non-treated firms. For the control variables, we find a significant positive impact of non-R&D innovation expenditures on the sales share from all product innovation, incremental product innovation and on cost reduction owing to process innovation. We do not find a significant positive effect of R&D expenditures in our fixed-effect models. This is likely due to the fact that R&D expenditures do not vary strongly over time but rather represent a structural feature of a firm. In a firm fixed-effect estimation, these structural features are absorbed by the firm fixed-effect. Variations in R&D expenditures do not translate into short-term changes in innovation output. We also do not find a significant contribution of expenditures on software and databases or on marketing on innovation outcome. The same holds for size, export share and human capital. All in all, the variations in the control variables have little effects on variations in innovation outcome, suggesting that it is unobserved firm heterogeneity (captured by firm fixed-effects) such as management capacity, organisational capabilities, employee skills or accumulated knowledge, which drives the observed variance in innovation outcome among firms, but not short-term changes in input variables.

4.2. Treatment in 2016 and placebo test

In order to analyse the robustness of the findings presented above, we test whether an assumed introduction of the GDPR in the year 2016 (i.e. the year in which the GDPR was approved) produces similar or different results. The estimation results (reported in Table A3 in the Appendix) show no statistically significant effects for the four innovation output variables, suggesting that firms did not adapt to the new regulatory situation prior to its legal enforcement. This finding is in line with the results of a representative survey conducted at the end of 2017 among firms in knowledge-intensive service industries in Germany, which shows that only 37% aimed to fully comply with the GDPR by May 2018, whereas 31% expected only partial compliance by this date (Erdsiek 2018). 11% planned to start the compliance process only by May 2018, and 21% did not expect to deal with GDPR issues by this date. Given that knowledge-intensive service industries make more intense use of data in their business activities than many other industries, one may assume a lower share of firms actively considering GDPR impacts prior to 2018.

In addition, we run a Placebo test by assuming the GDPR had been implemented in 2014 already. The results (shown in Table A4 in the Appendix) are very much the same as those for an assumed introduction year 2016 and support the robustness of our main findings.

4.3. Split models

In order to identify differences in the impact of the GDPR on innovation across types of firms, we run split models by size, age and industry. With respect to size, we separate the sample into very small firms (less than 20 employees), small to medium-sized firms (20 to less than 100 employees) and medium-sized to large firms (100 or more employees), based on the average number of employees of a firm during the observation period 2011 to 2020. For firm age, we distinguish young firms (up to 15 years), medium old firms (16 to 30 years) and old firms (more than 30 years), based on the firm's average age during the observation period. In terms of industry, we consider three classifications. According to the dominant group of customers, we separate B2B industries (firms mainly supplying other firms) and B2C industries (firms mainly supplying consumers). B2B and B2C industries are classified at the 4-digit level of NACE[4] rev. 2 based on information collected in the 2016 wave of the MIP, when firms were asked to report about their dominant group of customers. As a second classification, we distinguish manufacturing industries (incl. mining; NACE sections B and C) and services (including energy and water supply, recycling, construction, trade; NACE sections D to N). Finally, we separate knowledge intensive and not knowledge intensive industries based on the R&D intensity of manufacturing sectors (following the OECD classification, see Galindo-Rueda and

[4]NACE is the European variant of the International Standard Industrial Classification (ISIC) of the United Nations.

Table 4. Results of CDiD estimations on the effect of GDPR on innovation output for split models.

	GDPR				
	INS_P	*INS_F*	*INS_M*	*INS_C*	No. of observations/
Split model	*(1)*	*(2)*	*(3)*	*(4)*	no. of firms[a]
<20 employees	0.001	0.018*	−0.016***	0.002	14,068
	(0.010)	(0.009)	(0.006)	(0.003)	[3,100]
20–99 employees	0.019*	0.022*	−0.003	0.005*	9,831
	(0.011)	(0.011)	(0.005)	(0.003)	[2,029]
100+ employees	0.015	0.012	0.002	−0.000	4,915
	(0.013)	(0.012)	(0.005)	(0.004)	[1,061]
<16 years	0.002	0.032**	−0.030***	0.002	7,307
	(0.016)	(0.015)	(0.010)	(0.004)	[1,779]
16–30 years	0.006	0.010	−0.004	0.003	13,141
	(0.009)	(0.010)	(0.005)	(0.003)	[2,786]
>30 years	0.025***	0.021**	0.004	0.004	8,366
	(0.009)	(0.009)	(0.005)	(0.003)	[1,625]
B2B industries	0.015	0.030***	−0.015***	0.002	16,671
	(0.009)	(0.009)	(0.006)	(0.003)	[3,639]
B2C industries	0.002	0.003	−0.001	0.003	12,143
	(0.010)	(0.010)	(0.004)	(0.003)	[2,551]
Manufacturing	0.010	0.014	−0.003	0.000	13,133
	(0.010)	(0.009)	(0.005)	(0.003)	[2,812]
Services	0.009	0.021**	−0.012**	0.004	15,681
	(0.009)	(0.009)	(0.005)	(0.003)	[3,378]
Knowledge-intensive	0.016	0.036***	−0.020***	0.002	11,835
industries	(0.012)	(0.011)	(0.007)	(0.003)	[2,614]
Not knowledge-intensive	0.005	0.003	0.002	0.004*	16,979
industries	(0.007)	(0.007)	(0.003)	(0.002)	[3,576]

Robust standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
[a]Number of observations for *INS_F*, *INS_F* and *INS_M* (number of observations for *INS_C* differ slightly), number of firms in squared brackets.

Verger 2016) and the share of graduated employees in service industries (classifying 2-digit industries with more than 30% of graduates as knowledge-intensive).

The full estimation results of the split models are reported in Tables 5 to A5 in the Appendix. The results for our key variable of interest, *GDPR* are summarised in Table 4. The split models reveal that the main finding from the base model – a positive effect of GDPR on incremental innovation and a negative one on radical innovation – only holds for specific groups of firms. The positive impact of the GDPR on incremental innovation is found for smaller firms, as well as for young and very old firms. The negative impact on radical innovation is statistically significant only for the groups of very small and young firms. With respect to industries, the shift from radical to incremental innovation output resulting from the GDPR is confined to B2B industries, services and knowledge-intensive industries. For the group of firms older than 30 years, we find a strong positive impact of the GDPR on total new product sales, resulting from the fact that this group does not show a negative impact on radical innovation. We also find some weakly positive GDPR effects on unit cost reduction from process innovation for medium-small firms and for firms in not knowledge-intensive industries.

Table 5. Results of CDiD estimations on the effect of GDPR on innovation output: split between the qualitative and quantitative part of innovation outcome variables.

	Innovation yes/no (all firms)				Innovation output share (only firms with the respective type of innovation)			
	IN_T	*IN_F*	*IN_M*	*IN_C*	*INS_P*	*INS_F*	*INS_M*	*INS_C*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GDPR	0.048***	0.060***	0.010	0.035***	0.003	0.008	−0.035	0.013
	(0.017)	(0.018)	(0.012)	(0.013)	(0.016)	(0.018)	(0.022)	(0.015)
GDPR_pre	0.008	0.014	0.018	−0.001	−0.008	−0.008	−0.024	0.032**
	(0.017)	(0.017)	(0.012)	(0.013)	(0.017)	(0.018)	(0.023)	(0.015)
RD	1.976***	0.319	2.278***	1.149*	−0.376	−0.652	0.675	0.535
	(0.736)	(0.949)	(0.800)	(0.627)	(0.648)	(0.786)	(0.858)	(0.673)
NRD	1.892***	2.112***	1.242**	0.853*	1.386***	0.320	0.625	0.608***
	(0.561)	(0.577)	(0.534)	(0.511)	(0.493)	(0.474)	(0.722)	(0.224)
DIG	−1.614	−0.413	−2.127	1.337	−1.291	−0.014	−4.212*	−0.296
	(3.051)	(3.243)	(2.761)	(2.475)	(2.046)	(2.033)	(2.377)	(1.166)
EXP	0.010	0.015	0.028	0.024	0.025	0.036	−0.027	0.021
	(0.046)	(0.048)	(0.038)	(0.040)	(0.034)	(0.037)	(0.047)	(0.016)
MKT	4.009	1.320	1.495	0.186	−0.454	1.460	−0.315	0.176
	(2.631)	(2.823)	(2.489)	(1.586)	(1.716)	(2.037)	(1.668)	(1.640)
EMP	0.023*	0.017	0.020**	0.006	−0.016	−0.008	−0.092**	0.018
	(0.014)	(0.015)	(0.009)	(0.012)	(.018)	(0.016)	(0.039)	(0.012)
HC	0.008	0.013	−0.019	−0.004	.048	0.015	0.045	0.012
	(0.035)	(0.036)	(0.026)	(0.025)	(.032)	(0.039)	(0.043)	(0.026)
Constant	0.261***	0.237***	0.042	0.130***	.283***	0.238***	0.503***	−0.014
	(0.049)	(0.051)	(0.036)	(0.042)	(0.066)	(0.061)	(0.146)	(0.048)
No. observ.	28,814	28,814	28,814	28,687	7,654	6,777	2,893	2,966
No. firms	6,190	6,190	6,190	6,172	3,109	2,958	1,300	1,611
R-squared	0.038	0.030	0.013	0.020	0.013	0.007	0.049	0.089
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: MIP.

4.4. Model variants

As the innovation output variables contain many observations with the value zero (for all firms with no product innovation in case of sales shares, and for all firms with no process innovation in case of unit cost reduction), we estimated an alternative model variant that splits the innovation output variables into a dichotomous part (i.e. a dummy variable that indicates whether a firm had product innovation *IN_P*, new-to-market product innovation *IN_M*, only new-to-firm product innovation *IN_F*, or cost reducing process innovation *IN_C*) and a continuous variable (*INS_P*, *INS_M, INS_F* and *INS_C*), restricting the estimations on *INS_P, INS_M, INS_F* and *INS_C* to firms that have introduced the respective type of innovation (i.e. for *INS_P* if *IN_P* > 0, etc.). For all models, fixed-effect OLS regressions are used, including the dichotomous dependent variables. Descriptive statistics of the variables for these model variants are reported in Table A6 in the Appendix. Estimation results are reported in Table 5.

The results for the innovation-initiating effects (columns 1 to 4 in Table 5) reveal that the GDPR led to an increase in the firms' propensity to introduce incremental product innovation (by 6.0 percentage points) and cost reducing process innovation (by 3.5 percentage points), while it had no effect on the propensity to introduce radical product innovations. The propensity to introduce any type of product innovation also increased (by 4.8 percentage points), since most firms focus their product innovation activity on incremental innovation. When looking at the continuous part of the innovation outcome variables (columns 5 to 8 in Table 5), we find no statistically significant effects of the GDPR. These results indicate that the innovation impact of the GDPR is related to the firms' decisions how to innovate, but does not affect the success of innovations once introduced on the market or implemented in the firm.

As a second model variant, we split the treatment variable *GDPR* into two dummy variables, indicating whether firms reported to be positively or negatively affected in their innovation activities by the new regulation. The dummy variable *GDPR_OB* represents firms that reported that the GDPR was an obstacle for innovation, and *GDPR_SU* represents firms that reported that the GDPR initiated or facilitated innovation. The estimation results are shown in Table 6.

Table 6. Results of CDiD estimations on the effect of GDPR on innovation output: GDPR as obstacle vs. As support for innovation.

	INS_P	INS_F	INS_M	INS_C
	(1)	(2)	(3)	(4)
GDPR_OB	0.004	0.016**	−0.012**	0.003*
	(0.007)	(0.007)	(0.005)	(0.002)
GDPR_SU	0.039**	0.055***	−0.017	0.003
	(0.016)	(0.015)	(0.013)	(0.006)
GDPR_OB_pre	−0.004	0.001	−0.005	0.001
	(0.007)	(0.006)	(0.004)	(0.002)
GDPR_SU_pre	0.022	0.025	−0.003	0.011*
	(0.019)	(0.017)	(0.012)	(0.006)
RDINP in *t*-1	0.245	−0.397	0.642	−0.007
	(0.522)	(0.486)	(0.469)	(0.134)
NRDINP in *t*-1	1.015***	0.533**	0.483	0.213*
	(0.353)	(0.237)	(0.297)	(0.109)
DIG in *t*-1	−0.016	1.131	−1.147*	−0.083
	(1.623)	(1.521)	(0.609)	(0.449)
EXP in *t*-1	0.002	0.006	−0.005	−0.005
	(0.021)	(0.019)	(0.014)	(0.005)
MKT	0.972	1.039	−0.066	0.178
	(1.117)	(1.039)	(0.586)	(0.284)
EMP	0.003	0.004	−0.002	0.001
	(0.006)	(0.006)	(0.004)	(0.002)
HC	0.014	0.005	0.009	0.004
	(0.014)	(0.015)	(0.010)	(0.005)
Constant	0.076***	0.047**	0.029**	0.006
	(0.021)	(0.020)	(0.012)	(0.006)
No. observations	28,814	28,814	28,814	28,687
No. firms	6,190	6,190	6,190	6,172
R-squared	0.016	0.014	0.010	0.008
Year dummies	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: MIP.

Not surprisingly, the results of these estimations reveal that the negative impact of the GDPR on radical innovation is limited to firms reporting that the regulation prevented or complicated their innovation activities. For this group, the sales share of new-to-market innovations goes down by 1.2 percentage points. At the same time, these firms show an average increase in the sales share of incremental innovation by 1.6 percentage points. In addition, the GDPR slightly increased unit cost reduction from process innovation in this group (0.3 percentage points), though this effect is only weakly significant. For firms whose innovation activities were stimulated or facilitated by the GDPR, we find a high positive impact on incremental innovation (+5.5 percentage points sales share), while the negative effect on radical innovation is not statistically significant. In this small fraction of all firms, also total sales of product innovations went up as a result of the GDPR (by 3.9 percentage points).

5. Discussion

The introduction of the GDPR in 2018 resulted in a considerable shift of innovation activities in firms that were affected by the GDPR in their innovative efforts towards more incremental product innovation and away from radical innovation. At first sight, this is an astonishing result since the regulation does not include provisions that would directly stimulate a certain type of innovation or impede another one. We read these findings as an indirect effect of the regulation that was not intended by those who designed the regulation. Following the Porter Hypothesis that expects a shift towards radical innovation following more rigorous environmental regulation, a similar shift may have been expected for implementing a more rigorous data protection regulation (Niebel 2021).

The positive impact on incremental innovation might have at least partially compensated the additional cost and burden that firms had to take for complying with the regulation. A key consequence of the GDPR was that firms had to review and often revise their IT process and data management in order to meet the demands of the regulation, e.g. informing individuals of the type of data processed by the firm, and implementing routines to delete personal data upon request. For doing so, it is likely that changes to existing routines throughout the firm were necessary, involving the communication and cooperation across different business functions and the setup of cross-departmental teams to implement the changes and adapt IT systems and data flows. Whilst all this required additional resources and produced additional cost, it also provided new opportunity for improving IT routines and updating products, services and processes, i.e. incremental innovations, based on a better or more comprehensive use of data.

That such changes occurred in many firms at the time the GDPR came into force is revealed by a survey that was conducted in early 2020 on the consequences of the GDPR in the ICT industry and in knowledge-intensive services in Germany. These sectors are likely to be more strongly affected by the GDPR since many business models in these sectors rely on the use of data (Lindgren 2016). The survey[5] shows that 68% of all firms had to increase the efforts required to comply with the regulation, 61% reported that operations became more complex due to the requirements of the GDPR, 59% experience

[5]ZEW Sector Report on the Information Economy, May 2020 edition (https://ftp.zew.de/pub/zew-docs/brepikt/202001BrepIKT.pdf).

Table 7. Share of firms with IT and data capabilities in 2018, by type of product innovation and GDPR affectedness.

	Incremental product innovators			Radical product innovators		
As a percentage of all firms of the respective group	Not affected	Affected	Sig.	Not affected	Affected	Sig.
In-house computer programming	37.9	52.3	***	55.9	66.6	***
Purchase of computer software	48.7	62.5	***	54.9	68.0	***
In-house database work	33.6	49.1	***	50.0	61.5	***
Purchase of databases	3.4	10.1	***	7.5	12.4	**
Big data analysis	8.2	17.9	***	16.9	27.9	***
Use of artificial intelligence methods	8.5	15.7	***	15.9	25.2	***
Use of social networks as knowledge source	24.9	38.0	***	31.6	49.0	***
Use of open platforms/open source software as knowledge source	26.2	37.3	***	29.5	47.2	***
No. of observations	928	986		437	441	

Sig.: level of significance of difference between firms affected and not affected by the GDPR: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: MIP, survey year 2019.

increasing cost for implementing the regulation, and 51% had to engage external consulting services. At the same time, 36% of all firms report that the review of their IT and data management systems led to improvements of IT routines, and 29% reported a higher level of standardisation of IT routines as a result of compliance efforts.

Our argument that the GDPR helped to unfold potentials for improving existing products and better aligning them to customer needs through a more effective use of data is supported by the fact that product innovators affected by the GDPR in their innovation activities show significantly higher IT and data capabilities compared to product innovators not affected. This results holds both for the group of incremental and the group of radical product innovators (see Table 7). However, the latter group is characterised by even higher capabilities compared to the former. While we do not have direct evidence from our survey that product innovators affected by the regulation actually entered into new product development activities, our data show that there was certainly the opportunity and the capability to do so both for incremental and radical innovation. This is supported by the fact that the shift towards incremental innovation mainly occurred in small and young firms, firms serving B2B markets as well as firms in services and knowledge-intensive industries. Young and small firms are less likely than larger and older organisations to having implemented a regular review of their routines, like data policy. This is in line with Pesch et al. (2021) arguing and providing empirical evidence that older firms benefit more from such routines called formalisation related to radical digital product innovation. In small firms, IT routines have been established on an ad-hoc basis and developed according to short-term needs of the business. Complying with the GDPR could have served as an occasion to more systematically reconsider the existing routines and data management procedures, potentially identifying room for improvements and better using existing data to design and deliver their products and services. Related to business models, the GDPR has different implications (Lindgren 2016). For example, firms in B2B markets may put less focus on data-driven business models compared to firms in B2C markets, e.g. the more impacted telecommunication providers (Godinho de Matos and Adjerid 2022) or tourism sector (Aridor et al. 2020), resulting in a less systematic continuous update of the opportunities that existing data provide for refining their offerings. In services and in knowledge-intensive industries, the positive effect on incremental innovation may be linked to the generally greater opportunities for data-based business models and the integration of data into products and services. This confirms the insights both by Aridor et al. (2020) finding that the increased value of the remaining consumers for an online travel platform overcompensated the due to GDPR requirements lost customers and by Lefrere et al. (2022) revealing that online content providers adapted successfully their products and services to the requirement of the GDPR.

A further support for our hypothesis is provided by an analysis of digital elements used in the firms' business model. The German innovation survey conducted in 2020 contained a question on the importance of eight ways to integrate digital tools into the firm's business model at the time of the survey (i.e. in 2020). We link these data with the information on GDPR affectedness (from the survey conducted in 2019) and separate product innovators into two groups, one showing a shift towards incremental innovation between the two survey waves (i.e. between the reference years 2018 and 2019) based on the sales share of incremental and radical innovation, and the other not showing such a

Table 8. Share of firms using digital elements in the business model in 2020, by shift in product innovation focus and GDPR affectedness.

	Product innovators **without a shift** towards incremental innovation		Product innovators **with a shift** towards incremental innovation		Significance of the difference between two groups			
Firms reporting the digital element to be of high importance, as a percentage of all firms of the respective group	Not affected (1)	Affected (2)	Not affected (3)	Affected (4)	(1):(2)	(3):(4)	(1):(3)	(2):(4)
Use of digital platforms for delivering products/services	15.6	26.9	18.1	30.1	***	***	n.s.	n.s.
Use of social networks for prospecting and customer contact	6.5	13.8	5.4	15.4	***	***	n.s.	n.s.
Customisation of products through digital channels	11.9	11.4	9.7	12.5			n.s.	*
Methods of digital price differentiation	1.4	3.4	0.3	2.2	*	**	n.s.	n.s.
Use of digital sources to collect data	8.8	15.5	10.7	18.0	**	**	n.s.	n.s.
Digital integration of suppliers and other business partners	11.9	16.2	8.7	16.2			n.s.	n.s.
Use of digital tools for crowd sourcing of innovative ideas	2.4	6.6	3.7	5.5	**		n.s.	n.s.
Use of machine learning or artificial intelligence	4.4	8.3	2.0	9.2		***	*	n.s.
No. of observations	294	290	298	272				

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$; n.s.: not significant.
Source: MIP, survey years 2019 and 2020.

shift. 49% of firms with product innovations in both years showed such a shift. Among those product innovators reporting to have been affected by the GDPR, this share is almost the same (48%).

The analysis shows that product innovators affected by the GDPR that shifted towards incremental innovation tend to use digital elements in their business model much broader than product innovators shifting towards incremental innovation, but not being affected in their innovation activities by the GDPR (Table 8). This particularly applies for using digital platforms for delivering products and services, using social networks for prospecting and customer contacts, and using digital sources for collecting data and for crowd sourcing of innovative ideas being in line with the insights of Aridor et al. (2020) and Lefrere et al. (2022), but contradicting Janssen et al. (2022) and Peukert et al. (2022). Compared to product innovators also affected by the GDPR, but not shifting towards incremental innovations, the difference in employing digital elements in business models is not statistically different.

It is also worthwhile to consider some structural differences between firms that are positively or negatively affected by the GDPR in their innovation activities from those that are not affected. First, larger firms are more often affected by the GDPR than smaller firms. This is particularly true for firms reporting positive impacts from the new regulation on their innovation efforts (see Table 10 in the Appendix). The size differences are not linked to differences in firm age, however. Firms positively affected by the GDPR are more often found in ICT and consulting services, whereas negatively affected firms are more frequent in engineering and financial services and trade. The group of firms reporting not to be affected by the GDPR in their innovation activities shows higher industry shares in a number of non-R&D intensive manufacturing industries (food, textiles, wood/paper, metals) as well as in construction and transport services.

Considering that the GDPR is unchartered territory in terms of not only being the most comprehensive data protection regulation to date, but also a trailblazer as arguably the first ambitious regulation specifically targeted at regulating the digital economy, these findings make sense. A lack of precedence and information means that most likely incremental innovation in ensuring compliance would be initially a more attractive option (Aridor et al. 2020; Lefrere et al. 2022). As time progress and information about the GDPR increase as well as vital court cases shedding further light on key stipulations and the parameters of the GDPR, it would provide the sure footing that could make radical innovation more attractive and less risky.

In case the GDPR represented any stimulus for innovation (which applies to almost 14% of the affected firms), the shift towards incremental innovation was particularly strong. Additional innovation efforts of this group of firms deliberately targeted incremental improvements. This may be linked to the fact that uncertainty about the consequences of the GDPR was high both for innovators and for the users of new products and services for which the GDPR was relevant. Firms hence opted for the safe way and updated or improved their products or services to both comply to GDPR requirements and offer some additional features for users (e.Aridor et al. 2020 or Lefrere et al. 2022). Another additional point could be that under a lower threat of enforcement under the previous data protection regime (see Martin et al. 2019) there was less incentive to comply and adopt basic privacy features, whereas under the GDPR there was more incentive to comply as a result of the expected, but so far in Germany not yet realised significant fines up to €20 million or 4% of total global annual sales in the preceding financial year. Hence, firms became more up-to-date regarding privacy features that was already in existence but had simply not been adopted. The significant role of firms' IT and data capabilities and relevance of digital elements in the business model suggest that many of these innovations represent solutions for the firms' customers to comply with the GDPR, e.g. updated software programmes. Finally, larger and older firms experience stronger increases of innovations that are new to the firm being in line with insights them benefit more from formalisation related to their product innovation (Pesch, Endres, and Bouncken 2021) whereas small and young firms benefit less.

When focusing on the firms reporting that the GDPR complicated their innovation activities, we observe that their losses in turnover with radical innovation are compensated by their higher sales from incremental innovations However, the firms reporting that the GDPR has facilitated their innovation activities are not suffering, but also not benefiting from higher sales with radical innovation, but experiencing positive effects on sales with incremental product innovations as those being hampered by the GDPR.

6. Implications

This paper assessed the impacts of the EU's General Data Protection Regulation (GDPR) that was introduced in 2018 on innovation activities in firms, using unique panel data from the German part of the Community Innovation Survey (CIS). This survey included a question on whether and how data protection regulation affected the firms' innovation activities, which allowed us to separate affected ('treated') firms from non-treated and apply a conditional difference-in-difference (CDiD) research design, although all firms in the EU have to comply with the GDPR. The results of firm fixed-effects panel regressions show that the GDPR caused a shift of innovation activities in firms affected by this new data protection regulation leading to more incremental and less radical innovation. The sales share with product innovation that were only new to the firm went up by 1.8 percentage points while the sales share of new-to-market products fell by 0.9 percentage points.

These effects were not experienced by all firms in the same way. The shift towards incremental product innovation is confined to smaller and young firms as well as firms in services, B2B markets and knowledge-intensive industries. The shift towards incremental innovation emerged both in firms that report the GDPR to be an obstacle for their innovation efforts, as well as in the much smaller group of firms where the GDPR supported innovation activities, although the former group experienced a much stronger reduction in sales of radical innovations. We interpret these findings as an indirect effect of the firms' efforts to comply with the new regulation. These efforts resulted in a thorough review of internal IT routines and data management policies, which required changes to various internal operations that process data. In this context, many firms identified opportunities for updating and improving products, services and processes beyond the changes required to comply with the regulation. These updates and improvements result in additional incremental product innovations and increased the contribution of these innovations to the firms' total sales. At the same time, the resources needed for these changes necessitated by the introduction of the GDPR limited the firms' ability to invest into real new product developments that would eventually result in radical innovations. A significant fraction of firms resigned, at least temporarily, from such innovation activities, resulting in a lower share of sales generated by radical innovations.

A further mechanism that may have resulted in a shift away from radical towards incremental innovation may be related to the data requirements of radical innovation. Rammer et al. (2022) showed that a major technological basis of radical innovation in German industry during the time period investigated in this paper is artificial intelligence (AI). In 2018, almost one-fifth of all sales from radical product innovation can be attributed to the use of AI methods. Since AI required large data sets, often involving data of individuals, the introduction of the GDPR is likely to have complicated the use and analysis of such data, hence delaying (or even impeding) the development of certain radical innovations.

Our results show that the impact of the GDPR – regardless as to whether firms stated it to be an obstacle or stimulator for innovation – was never fully negative. This finding is in line with recent studies by Aridor et al. (2020) or Lefrere et al. (2022), but stands in contrast to other investigations outlining the negative effect of the GDPR on the on market concentration (Peukert et al. 2022) or venture investments (Jia, Jin, and Wagman 2021; Kircher and Foerderer 2021). While complying with the new regulation imposed additional cost on firms and required resources that could not be used for other activities, including the development and commercialisation of innovations, the need to review and adapt IT routines and data management also led to the identification of innovation potentials. In this respect, the GDPR served as a kind of win-win situation in the sense Porter and van der Linde (1995) argued in case of environmental regulation. However, the positive impact on incremental innovation came with a negative one on radical innovation – which may harm firms much more in the long run.

Our findings have significant implications both for firms and policy. With respect to innovation and IT management, the implementation of the GDPR forced firms to review, update and change their IT routines and data management. Whereas such adjustments require resources which might not be available for investment in research and innovation activities necessary for radical innovation, they can foster incremental innovation within the existing product and service portfolio. In addition, some firms could reduce their costs triggered by the implementation of the GDPR. These regulation-induced benefits suggest that there were efficiency potentials in firms that have not been identified by the firms internal controlling and auditing processes. This calls for a review of firm practices on revising IT management, particularly with respect to small and medium-sized firms (which drive the results found in our study). More frequently implemented internal mechanisms or regular external audits related to voluntary certification schemes associated with IT management might be an opportunity to realise increases in revenues from incremental innovations or cost savings.

With respect to policy implications, the GDPR has been criticised that it may hinder innovation particularly in SMEs, as it may put a disproportionate burden on SMEs and deteriorate their competitiveness vis-à-vis large firms, particularly large tech companies in digital markets (Niebel 2021; Peukert et al. 2022). Our results show that the situation is more complex. We do indeed find that the negative impacts of the GDPR on radical innovation are mainly confined to small and young firms. However, we also find that these firms profit from the GDPR as it stimulated additional incremental innovation, although the positive effects are smaller in magnitude (and statistically weaker) than the negative effects for those small and young firms that report the GDPR to be an obstacle for their innovation activities. In order compensate for this overall negative consequences of the regulation, young and small firms should be supported by governments in their efforts to comply with the GDPR. At the same time, we see that those small and young firms, which report GDPR to be facilitating innovation, experience significant increases in sales with incremental innovations but no reduction in sales with radical innovations. Obviously, the GDPR provides opportunities for start-ups to develop new markets (Martin et al. 2019). Consequently, entrepreneurship programmes could consider the GDPR as option and not necessarily as a barrier for start-ups. However, this group is much smaller than the group perceiving negative impacts. Finally, policies related to knowledge intensive sectors might exploit the potential of the GDPR as a cross-sectoral regulation.

Finally, the GDPR did so far not generate additional turnover with radical innovations, as one may have expected according to the Porter Hypothesis and the results found for rigorous environmental regulations (Ambec et al. 2013). In contrast, we observe so far a significant shift towards incremental innovation. Firms are focusing on assuring compliance with the GDPR, which might reduce resources available for innovation projects aiming for radically new solutions. Such a shift from radical to incremental innovation, in case it would persist over a longer time and is not just a short-term phenomenon, could negatively affect economic growth, as radical innovation tend to have significantly higher positive impacts on productivity and generating new demand.

Policymakers might relax this trade-off by facilitating compliance with the GDPR and setting up a funding scheme for small firms interested in developing radical solutions. It could compensate for their structural disadvantages related to large European firms and, more importantly, their competition with US-based BigTechs. A stronger legitimisation for such a public intervention is the spill-overs of the generated solutions for the level of data protection in the EU and beyond.

7. Limitations and future Research

Our study faces several limitations. First, our empirical study is based on of German firms, which challenges the transferability of our findings to other European countries. Second, due to the data protection sensitive culture within Germany (see Bygrave 2010), firms may have overrated the actual consequences of the GDPR on their innovation activities, which could lead to either overestimating or underestimating the impact of the GDPR, depending on which type of firms overrated the role of the GDPR. Third, it has to be pointed out that the survey data at hand only allow for the analysis of short-term impacts of the GDPR. Medium or even long-term impacts can be only measured in the coming years. Therefore, our results offer only a preliminary snapshot. This has important implications in particular for the distinction between incremental and radical innovation, which might be realised only in later years. Furthermore, firms might adjust further their innovation strategies specifically to the requirements and opportunities of the GDPR, which is not considered in the data we rely on. In summary, a replication of our analysis in a few years is required based on more GDPR-specific data.

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Appendix

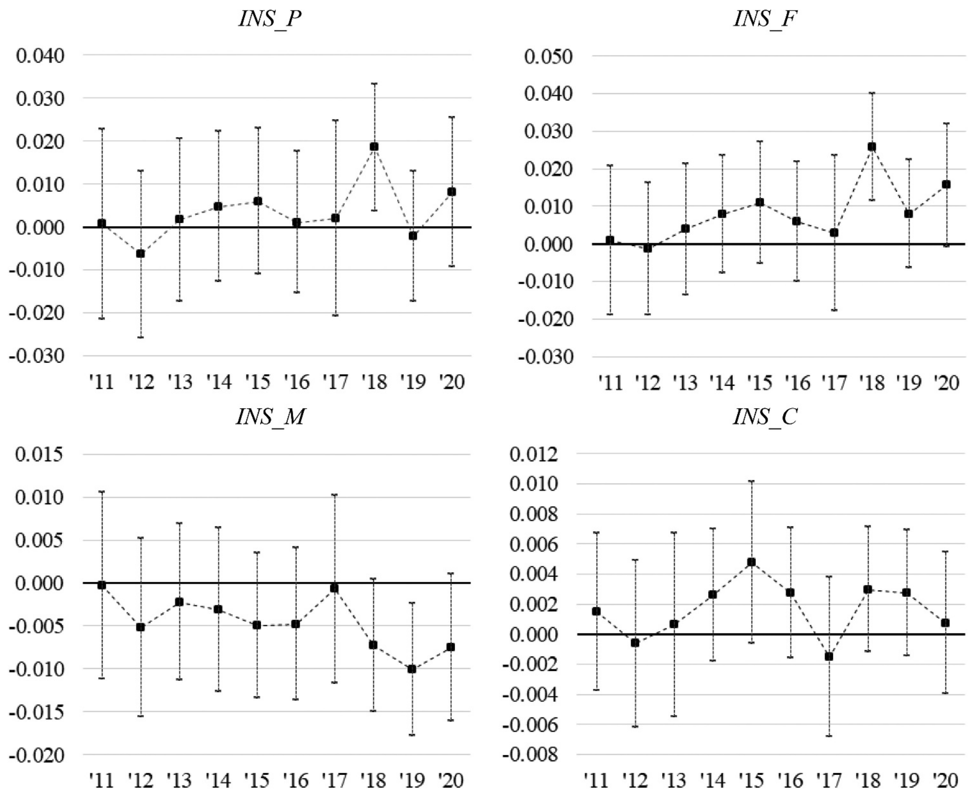

Figure A1. Test of common trend assumption for treated firms and for non-treated firms. INS_P: share of sales for product innovation; INS_F: share of sales from product innovation that were only new to the firm; INS_M: share of sales from product innovation that were new to the firm's market; INS_C: share of unit cost reduction owing to process innovation. Vertical lines indicate 95% confidence intervals. Source: MIP.

Table A1. Results of a panel probit estimation on the probability that a firm's innovation activities are affected by the GDPR.

	Marginal effect	Standard error	t Value	Significance
No. of employees (log)	−0.002	0.002	−0.73	
Age (no. of years, log)	0.068	0.005	13.34	***
Share of graduated employees	0.066	0.011	5.79	***
Innovation activity	0.107	0.005	22.08	**
Industry (NACE rev. 2)				
Food & beverages (10–12)	−0.064	0.023	−2.81	***
Textiles & clothing (13–15)	−0.096	0.026	−3.66	***
Wood & paper products (16–17)	−0.071	0.024	−2.97	***
Chemicals & pharmaceuticals (20–21	−0.050	0.025	−2.03	**
Rubber & plastic products (22)	−0.076	0.026	−2.92	***
Metals & building materials (23–24)	−0.086	0.026	−3.31	***
Metal products (25)	−0.080	0.021	−3.75	***
Electronics & electrical equipment (26–27)	−0.064	0.021	−3.10	***
Machinery & equipment (28)	−0.067	0.022	−3.01	***
Vehicles (29–30)	−0.089	0.029	−3.10	***
Other manufacturing (31–33)	−0.027	0.021	−1.33	
Energy supply & mining (5–9, 19, 35)	−0.080	0.025	−3.13	***
Water supply & waste management (36–39)	−0.102	0.023	−4.45	***
Wholesale trade (46)	−0.016	0.022	−0.76	
Transport & logistics (49–53)	−0.032	0.022	−1.50	
Media services (18, 58–60)	0.011	0.022	0.48	
ICT services (61–63)	0.021	0.021	0.98	
Financial services (64–66)	0.025	0.024	1.05	
Engineering & R&D services (71–72)	−0.047	0.020	−2.36	**
Consulting services (69–70, 73)	0.021	0.020	1.01	
Other business services (74, 78–82)	0.014	0.020	0.69	
All other industries	−0.072	0.027	−2.66	***
No. observations		27,071		
No. firms		6,255		
Log likelihood		−8,213.7		

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.
Source: MIP.

Table A2. Moments of model variables for treated firms and for non-treated firms before and after the matching.

	Treated			Non-treated before matching			Non-treated after matching		
	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
No. of employees (log)	3.162	2.243	0.673	3.121	2.246	0.584	3.162	2.243	0.673
Age (no. of years, log)	3.198	0.567	0.004	3.187	0.627	−0.232	3.198	0.567	0.004
Share of graduated employ.	0.283	0.087	1.060	0.227	0.075	1.414	0.283	0.087	1.060
Innovation activity	0.786	0.168	−1.394	0.488	0.250	0.049	0.786	0.168	−1.394
Food & beverages	0.035	0.034	5.079	0.042	0.040	4.592	0.035	0.034	5.079
Textiles & clothing	0.023	0.022	6.369	0.029	0.028	5.629	0.023	0.022	6.368
Wood & paper products	0.029	0.028	5.577	0.037	0.036	4.871	0.029	0.028	5.577
Chemicals & pharmaceut.	0.031	0.030	5.449	0.027	0.027	5.780	0.031	0.030	5.448
Rubber & plastic products	0.019	0.018	7.082	0.027	0.026	5.839	0.019	0.018	7.081
Metals & building materials	0.023	0.022	6.417	0.030	0.029	5.483	0.023	0.022	6.416
Metal products	0.042	0.041	4.540	0.066	0.062	3.485	0.042	0.041	4.540
Electronics & electrical equ.	0.064	0.060	3.570	0.063	0.059	3.614	0.064	0.060	3.569
Machinery & equipment	0.041	0.039	4.661	0.039	0.037	4.776	0.041	0.039	4.661
Vehicles	0.058	0.055	3.780	0.049	0.047	4.169	0.058	0.055	3.779
Other manufacturing	0.021	0.021	6.672	0.035	0.034	5.068	0.021	0.021	6.672
Energy supply & mining	0.029	0.028	5.645	0.066	0.061	3.503	0.029	0.028	5.644
Water supply & waste man.	0.041	0.039	4.641	0.037	0.036	4.874	0.041	0.039	4.640
Wholesale trade	0.049	0.046	4.188	0.061	0.057	3.663	0.049	0.046	4.188
Transport & logistics	0.045	0.043	4.409	0.037	0.036	4.871	0.045	0.043	4.409
Media services	0.081	0.074	3.079	0.040	0.039	4.677	0.081	0.074	3.079
IT services	0.043	0.041	4.521	0.022	0.022	6.483	0.043	0.041	4.521
Financial services	0.101	0.091	2.640	0.093	0.084	2.809	0.102	0.091	2.640
Engineering & R&D serv.	0.095	0.086	2.761	0.062	0.058	3.638	0.095	0.086	2.761
Consulting services	0.075	0.069	3.228	0.066	0.061	3.509	0.075	0.069	3.228
Other business services	0.014	0.014	8.166	0.026	0.026	5.932	0.014	0.014	8.165
All other industries	0.031	0.030	5.387	0.028	0.027	5.765	0.031	0.030	5.387

Source: MIP.

Table A3. Results of CDiD estimations on the effect of GDPR on innovation output: assumption that GDPR came into force in 2016.

	INS_P	*INS_F*	*INS_M*	*INS_C*
	(1)	(2)	(3)	(4)
GDPR(2016)	0.002	0.003	−0.001	−0.002
	(0.008)	(0.007)	(0.003)	(0.002)
GDPR(2016)_pre	−0.004	−0.007	0.003	−0.003
	(0.008)	(0.008)	(0.004)	(0.003)
RDINP in *t*-1	0.242	−0.396	0.637	−0.012
	(0.523)	(0.485)	(0.469)	(0.134)
NRDINP in *t*-1	1.019***	0.538**	0.481	0.211*
	(0.353)	(0.236)	(0.297)	(0.109)
DIG in *t*-1	−0.020	1.124	−1.145*	−0.112
	(1.625)	(1.520)	(0.608)	(0.457)
EXP in *t*-1	0.002	0.006	−0.004	−0.005
	(0.021)	(0.019)	(0.014)	(0.005)
MKT	0.946	1.014	−0.068	0.188
	(1.117)	(1.039)	(0.587)	(0.283)
EMP	0.003	0.004	−0.002	0.001
	(0.006)	(0.006)	(0.004)	(0.002)
HC	0.014	0.005	0.009	0.004
	(0.014)	(0.015)	(0.010)	(0.005)
Constant	0.078***	0.058***	0.020*	0.010
	(0.021)	(0.019)	(0.012)	(0.006)
No. observations	28,814	28,814	28,814	28,687
No. firms	6,190	6,190	6,190	6,172
R-squared	0.016	0.012	0.009	0.007
Year dummies	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table A4. Results of CDiD estimations on the effect of GDPR on innovation output: placebo test for GDPR introduced in 2014.

	INS_P	INS_F	INS_M	INS_C
	(1)	(2)	(3)	(4)
GDPR(2014)	0.002	0.005	−0.003	0.000
	(0.008)	(0.007)	(0.004)	(0.002)
GDPR(2014)_pre	−0.007	−0.007	0.000	−0.002
	(0.008)	(0.008)	(0.004)	(0.002)
RDINP in *t*-1	0.241	−0.396	0.637	−0.013
	(0.523)	(0.485)	(0.469)	(0.134)
NRDINP in *t*-1	1.018***	0.537**	0.481	0.212*
	(0.353)	(0.237)	(0.297)	(0.109)
DIG in *t*-1	−0.025	1.119	−1.144*	−0.112
	(1.624)	(1.519)	(0.608)	(0.457)
EXP in *t*-1	0.002	0.006	−0.004	−0.005
	(0.021)	(0.019)	(0.014)	(0.005)
MKT	0.948	1.017	−0.068	0.187
	(1.117)	(1.038)	(0.587)	(0.283)
EMP	0.003	0.004	−0.002	0.001
	(0.006)	(0.006)	(0.004)	(0.002)
HC	0.014	0.005	0.009	0.004
	(0.014)	(0.015)	(0.010)	(0.005)
Constant	0.079***	0.057***	0.022*	0.009
	(0.022)	(0.020)	(0.012)	(0.006)
No. observations	28,814	28,814	28,814	28,687
No. firms	6,190	6,190	6,190	6,172
R-squared	0.016	0.012	0.009	0.007
Year dummies	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Table A5. Results of CDiD estimations on the effect of GDPR on innovation output: split models by size.

	<20 employees				20 to 99 employees				100+ employees			
	INS_P	*INS_F*	*INS_M*	*INS_C*	*INS_P*	*INS_F*	*INS_M*	*INS_C*	*INS_P*	*INS_F*	*INS_M*	*INS_C*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GDPR_OB	0.001	0.018*	−0.016***	0.002	0.019*	0.022*	−0.003	0.005*	0.015	0.012	0.002	−0.000
	(0.010)	(0.009)	(0.006)	(0.003)	(0.011)	(0.011)	(0.005)	(0.003)	(0.013)	(0.012)	(0.005)	(0.004)
GDPR_pre	−0.004	0.003	−0.007	0.002	0.005	0.004	0.001	0.001	0.008	0.007	0.000	0.002
	(0.010)	(0.009)	(0.006)	(0.003)	(0.011)	(0.011)	(0.005)	(0.003)	(0.015)	(0.014)	(0.005)	(0.005)
RDINP	−0.061	−0.790	0.729	−0.227	0.550	−0.125	0.675	0.435**	1.378	1.414	−0.036	−0.015
	(0.662)	(0.714)	(0.534)	(0.192)	(1.039)	(0.605)	(1.112)	(0.189)	(0.934)	(0.935)	(0.408)	(0.222)
NRDINP	0.965**	0.560*	0.405	0.145	0.844	0.313	0.531	0.310**	1.869	1.260	0.609	0.237
	(0.430)	(0.336)	(0.355)	(0.170)	(0.643)	(0.321)	(0.606)	(0.148)	(1.204)	(0.892)	(0.471)	(0.207)
DIG	0.195	1.653	−1.458	−0.068	−2.167	−1.595	−0.572	0.031	2.603	3.717	−1.114	−0.505
	(2.547)	(2.330)	(1.048)	(0.821)	(2.528)	(2.489)	(0.737)	(0.418)	(2.951)	(2.841)	(0.899)	(0.673)
EXP	−0.001	−0.005	0.004	−0.012	0.001	0.019	−0.018	0.009	0.012	0.010	0.002	−0.009
	(0.038)	(0.033)	(0.027)	(0.010)	(0.032)	(0.028)	(0.019)	(0.006)	(0.027)	(0.023)	(0.017)	(0.008)
MKT	1.766	1.711	0.055	0.053	−0.309	0.374	−0.683	0.481	−0.470	−0.883	0.413	0.168
	(1.806)	(1.666)	(0.989)	(0.495)	(1.964)	(1.843)	(0.871)	(0.417)	(1.535)	(1.415)	(0.702)	(0.283)
EMP	0.006	0.006	−0.000	−0.000	0.001	0.011	−0.010	0.002	0.000	−0.002	0.003	0.003
	(0.010)	(0.009)	(0.006)	(0.003)	(0.013)	(0.011)	(0.008)	(0.002)	(0.009)	(0.009)	(0.002)	(0.003)
HC	0.005	−0.013	0.018	0.000	0.025	0.048*	−0.023	0.007	0.065	0.035	0.030	0.031*
	(0.017)	(0.019)	(0.013)	(0.008)	(0.030)	(0.027)	(0.017)	(0.005)	(0.052)	(0.050)	(0.025)	(0.016)
Constant	0.082***	0.059***	0.024*	0.013*	0.078	0.018	0.061*	−0.004	0.042	0.049	−0.007	0.001
	(0.023)	(0.020)	(0.013)	(0.007)	(0.051)	(0.045)	(0.033)	(0.009)	(0.053)	(0.053)	(0.014)	(0.016)
No. observ.	14,068	14,068	14,068	14,108	9,831	9,831	9,831	9,753	4,915	4,915	4,915	4,826
No. firms	3,100	3,100	3,100	3,085	2,029	2,029	2,029	2,028	1,061	1,061	1,061	1,059
R-squared	0.017	0.016	0.011	0.007	0.019	0.016	0.016	0.023	0.029	0.024	0.014	0.015
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: MIP.

Table A6. Results of CDiD estimations on the effect of GDPR on innovation output: split models by age.

	<16 years				16 to 35 years				>35 years			
	INS_P (1)	*INS_F* (2)	*INS_M* (3)	*INS_C* (4)	*INS_P* (5)	*INS_F* (6)	*INS_M* (7)	*INS_C* (8)	*INS_P* (9)	*INS_F* (10)	*INS_M* (11)	*INS_C* (12)
GDPR_OB	0.002	0.032**	−0.030***	0.002	0.006	0.010	−0.004	0.003	0.025***	0.021**	0.004	0.004
	(0.016)	(0.015)	(0.010)	(0.004)	(0.009)	(0.010)	(0.005)	(0.003)	(0.009)	(0.009)	(0.005)	(0.003)
GDPR_pre	−0.000	0.009	−0.010	0.007	0.003	0.007	−0.003	−0.002	−.001	−0.005	0.004	0.004
	(0.017)	(0.014)	(0.011)	(0.005)	(0.010)	(0.009)	(0.004)	(0.002)	(0.009)	(0.009)	(0.004)	(0.003)
RDINP	−0.482	−0.716	0.234	−0.029	1.008	0.195	0.813**	−0.051	.612	−0.589	1.201	0.119
	(0.853)	(0.775)	(0.796)	(0.237)	(0.648)	(0.764)	(0.357)	(0.173)	(1.066)	(0.642)	(1.315)	(0.190)
NRDINP	1.113	−0.150	1.262**	0.238	1.239***	1.188***	0.051	0.199	0.647	0.365	0.282	0.226
	(0.739)	(0.456)	(0.640)	(0.267)	(.420)	(0.417)	(0.167)	(0.122)	(.703)	(0.266)	(0.691)	(0.166)
DIG	−4.580*	−2.192	−2.388	−0.979	0.047	0.543	−0.496	0.957***	6.345	6.786	−0.440	−1.125*
	(2.657)	(2.310)	(1.494)	(1.192)	(1.673)	(1.653)	(0.692)	(0.364)	(4.403)	(4.268)	(0.810)	(0.669)
EXP	.007	0.018	−0.010	−0.017	−.027	−0.004	−0.023	−0.004	.025	0.003	0.022	0.007
	(0.050)	(0.042)	(0.041)	(0.014)	(.030)	(0.029)	(0.015)	(0.005)	(.030)	(0.025)	(0.016)	(0.006)
MKT	−0.361	0.937	−1.298	−0.290	2.231	1.455	0.776	0.376	0.556	−0.021	0.578	0.503
	(2.170)	(2.056)	(1.235)	(0.649)	(1.433)	(1.334)	(0.813)	(0.281)	(1.862)	(1.640)	(0.761)	(0.357)
EMP	−0.005	−0.004	−0.001	0.003	0.010	0.014	−0.004	−0.001	0.005	0.002	0.004	0.003
	(.010)	(0.010)	(0.008)	(0.003)	(0.011)	(0.010)	(0.005)	(0.003)	(0.009)	(0.007)	(0.005)	(0.003)
HC	−0.007	−0.016	0.008	0.011	.013	0.001	0.012	−0.006	0.058**	0.052**	0.007	0.018**
	(0.029)	(0.026)	(0.021)	(0.012)	(.019)	(0.024)	(0.012)	(0.006)	(0.024)	(0.022)	(0.010)	(0.008)
Constant	0.144***	0.092***	0.051*	0.008	.053	0.024	0.029*	0.013	0.015	0.027	−0.012	−0.005
	(0.037)	(0.034)	(0.027)	(0.011)	(0.036)	(0.032)	(0.015)	(0.010)	(0.035)	(0.030)	(0.019)	(0.012)
No. observ.	7,307	7,307	7,307	7,309	13,141	13,141	13,141	13,102	8,366	8,366	8,366	8,276
No. firms	1,779	1,779	1,779	1,776	2,786	2,786	2,786	2,772	1,625	1,625	1,625	1,624
R-squared	0.017	0.016	0.022	0.014	0.020	0.015	0.014	0.011	0.033	0.026	0.022	0.017
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
Source: MIP.

Table A7. Results of CDiD estimations on the effect of GDPR on innovation output: split models by B2B and B2C industry.

	B2B industries				B2C industries			
	INS_P (1)	*INS_F* (2)	*INS_M* (3)	*INS_C* (4)	*INS_P* (5)	*INS_F* (6)	*INS_M* (7)	*INS_C* (8)
GDPR	0.015	0.030***	−0.015***	0.002	0.002	0.003	−0.001	0.003
	(0.009)	(0.009)	(0.006)	(0.003)	(0.010)	(0.010)	(0.004)	(0.003)
GDPR_pre	0.004	0.012	−0.008	0.000	−0.002	−0.005	0.003	0.005*
	(0.009)	(0.009)	(0.006)	(0.003)	(0.009)	(0.009)	(0.004)	(0.003)
RDINP	0.502	−0.327	0.828	0.039	−0.875	−0.774	−0.102	−0.296
	(0.605)	(0.557)	(0.553)	(0.127)	(0.877)	(0.931)	(0.632)	(0.463)
NRDINP	0.935**	0.579*	0.356	0.167*	1.224**	0.478	0.746	0.303
	(0.422)	(0.323)	(0.324)	(0.089)	(0.615)	(0.292)	(0.579)	(0.267)
DIG	−0.284	1.049	−1.333	0.243	0.110	1.023	−0.913	−0.580
	(2.013)	(1.881)	(0.961)	(0.559)	(2.667)	(2.502)	(0.652)	(0.750)
EXP	0.007	0.015	−0.008	0.001	−0.006	−0.011	0.005	−0.019
	(0.028)	(0.022)	(0.019)	(0.004)	(0.030)	(0.032)	(0.020)	(0.014)
MKT	1.617	2.344	−0.727	0.503*	0.095	−0.620	0.715	−0.253
	(1.485)	(1.440)	(0.862)	(0.285)	(1.725)	(1.489)	(0.752)	(0.547)
EMP	0.014	0.014*	−0.000	−0.002	−0.012	−0.009	−0.004	0.005
	(0.009)	(0.008)	(0.005)	(0.002)	(0.009)	(0.007)	(0.005)	(0.003)
HC	0.011	0.005	0.006	−0.003	0.019	0.006	0.013	0.016
	(0.017)	(0.021)	(0.014)	(0.006)	(0.026)	(0.021)	(0.012)	(0.011)
Constant	0.044	0.010	0.034*	0.018**	0.112***	0.096***	0.016	−0.006
	(0.031)	(0.029)	(0.017)	(0.007)	(0.029)	(0.023)	(0.016)	(0.011)
No. observ.	16,671	16,671	16,671	16,648	12,143	12,143	12,143	12,039
No. firms	3,639	3,639	3,639	3,623	2,551	2,551	2,551	2,549
R-squared	0.019	0.017	0.011	0.007	0.018	0.013	0.015	0.016
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.
Source: MIP.

Table A8. Definition of model variables and descriptive statistics for additional model variants.

Variable	Definition	# obs.	Mean	SD	Min	Max
IN_P	1 if firm has introduced a product innovation, 0 otherwise	28,814	0.2656	0.4417	0	1
IN_F	1 if firm has introduced a product innovation only new to the firm, 0 otherwise	28,814	0.2352	0.4241	0	1
IN_M	1 if firm has introduced a product innovation new to the firm's market, 0 otherwise	28,814	0.1004	0.3005	0	1
IN_C	1 if firm has introduced a cost-reducing process innovation, 0 otherwise	28,687	0.1034	0.3045	0	1
INS_P	for IN_P > 0	7,654	0.2527	0.2367	0.0	1.0
INS_F	for IN_F > 0	6,777	0.2224	0.2160	0.0	1.0
INS_M	for IN_M > 0	2,893	0.1475	0.1835	0.0	1.0
INS_C	for IN_C > 0	2,966	0.0854	0.0880	0.0	1.0
GDPR_OB	1 if firm reported that data protection regulation has complicated innovation activities, 0 otherwise	28,814	0.1236	0.3292	0	1
GDPR_SU	1 if firm reported that data protection regulation has facilitated innovation activities, 0 otherwise	28,814	0.0162	0.1262	0	1

Source: MIP.

Table A9. Results of conditional fixed-effect DiD panel estimations on the effect of GDPR on innovation output: split models by manufacturing and services.

	Manufacturing				Services			
	INS_P (1)	*INS_F* (2)	*INS_M* (3)	*INS_C* (4)	*INS_P* (5)	*INS_F* (6)	*INS_M* (7)	*INS_C* (8)
GDPR	0.010	0.014	−0.003	0.000	0.009	0.021**	−0.012**	0.004
	(0.010)	(0.009)	(0.005)	(0.003)	(0.009)	(0.009)	(0.005)	(0.003)
GDPR_pre	0.003	0.000	0.002	0.000	0.001	0.007	−0.007	0.003
	(0.010)	(0.009)	(0.005)	(0.003)	(0.009)	(0.008)	(0.005)	(0.002)
RDINP	0.204	−0.659	0.864*	0.113	0.235	−0.256	0.491	−0.099
	(0.586)	(0.628)	(0.461)	(0.248)	(0.757)	(0.678)	(0.693)	(0.154)
NRDINP	1.066***	0.679*	0.387*	0.195	0.958*	0.408	0.549	0.235
	(0.397)	(0.351)	(0.206)	(0.124)	(0.540)	(0.322)	(0.496)	(0.167)
DIG	1.306	2.512	−1.205	1.527***	−0.716	0.469	−1.185**	−0.649
	(2.169)	(1.880)	(1.724)	(0.514)	(2.027)	(1.911)	(0.580)	(0.579)
EXP	−0.024	−0.015	−0.009	−0.005	0.038	0.036	0.002	−0.004
	(0.030)	(0.027)	(0.020)	(0.006)	(0.029)	(0.024)	(0.021)	(0.009)
MKT	−0.103	−0.359	0.256	0.075	1.690	1.960	−0.270	0.188
	(1.796)	(1.658)	(0.893)	(0.488)	(1.407)	(1.316)	(0.760)	(0.343)
EMP	0.005	0.008	−0.003	0.001	0.001	0.002	−0.001	0.001
	(0.012)	(0.009)	(0.008)	(0.004)	(0.007)	(0.007)	(0.004)	(0.002)
HC	0.051*	0.038	0.013	0.009	−0.001	−0.008	0.007	0.002
	(0.027)	(0.026)	(0.012)	(0.008)	(0.017)	(0.018)	(0.013)	(0.007)
Constant	0.064	0.032	0.032	0.009	0.082***	0.059**	0.024*	0.005
	(0.044)	(0.034)	(0.027)	(0.015)	(0.025)	(0.023)	(0.013)	(0.006)
No. observ.	13,133	13,133	13,133	13,180	15,681	15,681	15,681	15,507
No. firms	2,812	2,812	2,812	2,805	3,378	3,378	3,378	3,367
R-squared	0.022	0.014	0.016	0.012	0.018	0.017	0.009	0.010
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, *$p < 0.1$, **$p < 0.05$, *** $p < 0.01$.
Source: MIP.

Table A10. Results of conditional fixed-effect DiD panel estimations on the effect of GDPR on innovation output: split models by knowledge intensity of industries.

	Knowledge-intensive industries				Not knowledge-intensive industries			
	INS_P (1)	*INS_F* (2)	*INS_M* (3)	*INS_C* (4)	*INS_P* (5)	*INS_F* (6)	*INS_M* (7)	*INS_C* (8)
GDPR	0.016	0.036***	−0.020***	0.002	0.005	0.003	0.002	0.004*
	(0.012)	(0.011)	(0.007)	(0.003)	(0.007)	(0.007)	(0.003)	(0.002)
GDPR_pre	0.007	0.016	−0.009	0.001	−0.003	−0.005	0.002	0.003
	(0.012)	(0.011)	(0.007)	(0.003)	(0.007)	(0.006)	(0.003)	(0.002)
RDINP	0.087	−0.655	0.742	−0.034	2.169**	1.807**	0.362	0.128
	(0.571)	(0.535)	(0.520)	(0.143)	(0.984)	(0.841)	(0.679)	(0.356)
NRDINP	1.135*	0.657	0.478	0.232	0.863**	0.383*	0.481	0.190
	(0.586)	(0.432)	(0.477)	(0.174)	(0.387)	(0.197)	(0.357)	(0.131)
DIG	−1.472	−0.301	−1.171	−0.427	4.254	5.003	−0.749	0.833*
	(1.763)	(1.619)	(0.784)	(0.590)	(3.507)	(3.423)	(0.845)	(0.501)
EXP	0.011	0.008	0.003	−0.004	−0.007	0.007	−0.013	−0.006
	(0.031)	(0.026)	(0.022)	(0.007)	(0.025)	(0.023)	(0.012)	(0.007)
MKT	0.484	0.449	0.035	0.124	1.017	1.171	−0.154	0.222
	(1.693)	(1.674)	(0.870)	(0.450)	(1.303)	(0.994)	(0.704)	(0.259)
EMP	0.003	0.003	0.000	0.002	0.004	0.006	−0.002	0.001
	(0.009)	(0.009)	(0.006)	(0.003)	(0.009)	(0.007)	(0.004)	(0.002)
HC	0.027	0.017	0.010	0.006	−0.009	−0.018	0.009	0.000
	(0.019)	(0.020)	(0.014)	(0.008)	(0.019)	(0.020)	(0.009)	(0.006)
Constant	0.101***	0.069**	0.033	0.006	0.038	0.022	0.016	0.005
	(0.032)	(0.030)	(0.021)	(0.009)	(0.029)	(0.026)	(0.013)	(0.008)
No. observ.	11,835	11,835	11,835	11,951	16,979	16,979	16,979	16,736
No. firms	2,614	2,614	2,614	2,609	3,576	3,576	3,576	3,563
R-squared	0.022	0.019	0.013	0.007	0.018	0.014	0.011	0.012
Year dum.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses, $*p < 0.1$, $**p < 0.05$, $***p < 0.01$.
Source: MIP.

Table A11. Results of conditional fixed-effect DiD panel estimations on the effect of GDPR on innovation output for split models: GDPR as obstacle vs. As support for innovation.

	GDPR_OB				*GDPR_SU*				
Split	*INS_P*	*INS_F*	*INS_M*	*INS_C*	*INS_P*	*INS_F*	*INS_M*	*INS_C*	No. ob-serv./
Model	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	firms[a]
<20	−0.005	0.017*	−0.022**	0.004	0.014	0.049**	−0.034	0.002	14,068
employees	(0.012)	(0.010)	(0.009)	(0.003)	(0.023)	(0.020)	(0.026)	(0.011)	[3,100]
20–99	0.014	0.017	−0.003	0.005**	0.061**	0.065**	−0.004	−0.001	9,831
employees	(0.012)	(0.012)	(0.005)	(0.003)	(0.030)	(0.030)	(0.007)	(0.004)	[2,029]
100+	0.006	0.005	0.001	−0.003	0.064*	0.055	0.009	0.016*	4,915
employees	(0.013)	(0.012)	(0.006)	(0.004)	(0.036)	(0.036)	(0.007)	(0.009)	[1,061]
<16	−0.014	0.026*	−0.041**	0.003	0.037	0.100***	−0.063	−0.002	7,307
years	(0.020)	(0.016)	(0.017)	(0.005)	(0.037)	(0.032)	(0.038)	(0.014)	[1,779]
16–30	0.003	0.008	−0.004	0.004	0.028	0.030	−0.002	0.007	13,141
years	(0.010)	(0.010)	(0.005)	(0.003)	(0.025)	(0.025)	(0.007)	(0.008)	[2,786]
>30	0.023**	0.020**	0.003	0.003	0.054***	0.041**	0.013	0.004	8,366
years	(0.010)	(0.009)	(0.005)	(0.003)	(0.019)	(0.019)	(0.009)	(0.006)	[1,625]
B2B	0.006	0.025***	−0.019**	0.002	0.049*	0.084***	−0.035	0.003	16,671
industries	(0.011)	(0.009)	(0.008)	(0.003)	(0.026)	(0.023)	(0.022)	(0.007)	[3,639]
B2C	0.000	0.002	−0.002	0.005*	0.027	0.025	0.003	0.004	12,143
industries	(0.010)	(0.010)	(0.004)	(0.003)	(0.020)	(0.020)	(0.010)	(0.010)	[2,551]
Manufac-	0.007	0.011	−0.003	0.000	0.034*	0.038**	−0.004	0.001	13,133
turing	(0.011)	(0.010)	(0.005)	(0.003)	(0.020)	(0.019)	(0.008)	(0.006)	[2,812]
Services	0.000	0.018*	−0.018**	0.005*	0.041*	0.065***	−0.025	0.004	15,681
	(0.010)	(0.009)	(0.008)	(0.003)	(0.023)	(0.021)	(0.020)	(0.008)	[3,378]
Knowl.-int.	0.005	0.032***	−0.027***	0.004	0.047*	0.076***	−0.029	−0.001	11,835
industries	(0.013)	(0.011)	(0.010)	(0.003)	(0.028)	(0.025)	(0.022)	(0.010)	[2,614]
Not knowl.-	0.003	0.001	0.002	0.003	0.031**	0.034**	−0.003	0.009**	16,979
int. ind.	(0.008)	(0.007)	(0.003)	(0.002)	(0.016)	(0.017)	(0.010)	(0.004)	[3,576]

Robust standard errors in parentheses, $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.
a: Number of observations for *INS_F* and *INS_M* (number of observations for *INS_C* differ slightly), number of firms in squared brackets.
Source: MIP.

Table A12. Structural characteristics of firms negatively, positively and not affected by the GDPR in their innovation activities.

	Negatively	Positively	Not	Sig.
Size (no. employees, FTE)	331	1,865	278	**
Size class (share in %)				
<20 employees	48.0	43.0	49.5	**
20–99 employees	31.0	32.1	31.7	**
100–499 employees	14.7	14.9	13.8	**
500+ employees	6.3	1.0	5.0	**
Age (years)	31.2	31.1	32.2	
Industry (share in %)				
- Food, beverages, tobacco	3.3	1.9	4.5	**
- Textiles, clothing	1.9	1.9	2.7	
- Wood & paper products	2.9	3.2	4.0	
- Chemicals, pharmaceuticals	2.8	1.6	3.0	
- Rubber and plastics products	1.8	3.2	3.2	**
- Metals and non-metallic materials	2.3	2.3	3.5	*
- Metal products	5.0	3.6	7.4	**
- Electronic and electrical products	6.0	6.5	6.1	
- Machinery and equipment	4.4	2.3	4.5	
- Vehicles	1.6	1.0	1.9	
- Other manufacturing	5.6	3.9	5.4	
- Energy supply, mining, petroleum products	2.4	1.6	3.5	*
- Water supply, waste disposal	2.7	2.9	5.6	**
- Wholesale trade	4.7	3.9	3.6	
- Transport services	5.7	4.9	6.7	
- Media services, printing	5.1	5.2	3.2	**
- ICT services	6.8	16.2	3.7	**
- Financial services	5.7	4.9	1.3	**
- Engineering and R&D services	8.7	4.9	8.7	
- Consulting services	7.8	11.7	4.7	**
- Business services	8.6	8.4	7.5	
- Construction	1.5	.6	2.7	**
- All other industries	2.8	3.6	2.5	

Sig: $*p < 0.05$, $**p < 0.01$.
Source: MIP, survey year 2019.