How Do Data Affect Firms' Innovation Strategy: Evidence From the General Data Protection Regulation *

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Abstract

I examine how firms' customer data availability influences their managers' innovation resource allocation between exploitative (incremental) and exploratory (radical) innovation. I use the European Union (EU) General Data Protection Regulation (GDPR) as a plausibly exogenous shock to customer data availability in estimating a difference-in-differences specification. I employ a patent-based innovation output measure and develop and test a novel innovation input workforce-based measure. I find that, upon a negative shock to customer personal data availability, firms allocate more innovation resources to exploration relative to exploitation. The results are stronger for firms in B2C versus B2B industries and firms with more volatile customer demand. My results suggest that higher customer data availability leads firms to focus more on exploitative innovation, deterring the exploratory innovation crucial to economic growth.

Keywords: digital economy, data, innovation, exploitation, exploration, GDPR
JEL Codes: D83, K20, L86, O00, O14, O30, O31, O33

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1 Introduction

In the past 15 years, the digital economy has grown two and a half times faster than global GDP (*Bloomberg Tax*, 2024). In this rising digital economy, data has provided understanding both through insights, such as in e-commerce and advertising, and as inputs to artificial intelligence (i.e., big data) models. The advent, improvement, and widespread use of digital technologies has facilitated the otherwise traditionally difficult mass collection and analysis of data. Commentators have even proclaimed that "data is the new oil" (*The Economist*, 2017; see Appendix C). In particular, data is thought to benefit corporate performance, such as to help firms improve their investments and operations and increase revenue (e.g., Zhu, 2019; Ferracuti et al., 2024; Goldberg et al., 2024). Some commentators also say that data can contribute to innovation (e.g., Deming, 2021; Veldkamp, 2023b). Yet, despite the many purported commercial benefits, one could argue that data might deter the more radical type of innovation crucial to economic growth (Schumpeter, 1942; Romer, 1990).

I examine how firms' customer data availability influences their managers' resource allocation between exploitative (incremental and certain) and exploratory (radical and uncertain) innovation. Customer data is a type of data that yields information about customer preferences that firms can use to tailor future offerings to increase sales and improve customer satisfaction and retention (Hagel and Rayport, 1997). The innovation literature distinguishes between two types of innovation by firms: exploitation or exploration. The former refers to the incremental improvement of existing products, services, or processes; the latter to the radical, riskier search for novel ideas and development of potentially groundbreaking products, services, or processes (March, 1991; Manso, 2011). Taking Apple Inc. as an example, its frequent upgrading of its iPhone is exploitative. In contrast, its development of the Vision Pro—which was unlike any other technology at the time—is exploratory. Firms' implemented innovation strategies can be arranged on a spectrum, from pure exploitation on one end to pure exploration on the other (March, 1991).

I argue that firms' customer data availability leads them to allocate more of their finite innovation resources toward exploitative innovation, relative to exploratory innovation. Innovation resource allocation decisions can be crucial for firms' profitability and long-term survival. A firm's investment in innovation is restricted by factors including, but not limited to, information constraints and management control (Romer, 1993; Jones, 2023; Glaeser and Lang, 2024). Firms thus cannot fund all positive net present value innovation projects and will consider investments to fund relative to each other. However, firms also have limited foresight about the expected risk-adjusted payoffs of innovation (March, 1991; Manso, 2011; Bubeck and Cesa-Bianchi, 2012; Balsmeier et al., 2017).

Customer data can help reduce risk and uncertainty around and improve those payoffs through the customer demand insights they generate to increase sales and improve customer satisfaction and retention (Hagel and Rayport, 1997; Veldkamp, 2023b). Customer data, a byproduct of customer interactions with a firm's offerings, will do so for exploitation more than for exploration, as data on existing offerings cannot reveal as much about the prospects of radically new ones. In other words, exploitation is more sensitive to changes in customer data than exploration. However, strong priors about exploitation, managers' risk-taking incentives, and the ability to implement a "spray and pray" approach for collecting customer insights may temper the strength of this asymmetric influence of customer data on exploitation versus exploration (Holmström, 1979; Ewens et al., 2018).

To test the causality of my hypothesis, I use a difference-in-differences identification design that exploits the passage of the European Union (EU) General Data Protection Regulation (GDPR) in 2016. I use GDPR as a negative and arguably exogenous change to affected firms' customer data availability. GDPR regulates and restricts the collection, processing, and storage of European residents' personal data to protect their privacy. I choose this regulation as my shock because it is the world's most significant regulation for personal data protection. The European Commission described it as the "toughest privacy and security law in the world" and the "global north star for privacy law" (European Data Protection

Supervisor; Wolford). GDPR requires that any entity (e.g., company) in the world handling the personal data of EU residents acquire their consent to do so. GDPR thus decreased affected firms' customer data availability by decreasing its volume and the degree to which it accurately represented their customer base (e.g., if certain demographics are more or less likely to grant consent for personal data collection) (Dubé et al., 2024). My treatment group consists of firms that are affected by GDPR because they handled EU residents' personal data at the time of the shock, while my control group consists of unaffected firms that did not handle EU residents' personal at the time of the shock. I identify affected firms by observing whether they generated significant revenues from the European Union.

I run two separate main tests, the results of which confirm my hypothesis. First, I use a patent-based measure to study the output of firms' innovation resource allocation choices. I construct my patent-based measure based on the measure first proposed and studied by Balsmeier et al. (2017), which represents the similarity between the technological patent portfolio profiles of a firm in the current year and the prior year. The profile is the distribution of the number of patents filed in "new to the firm" technology classes versus "known to the firm" technology classes, in a given year. The technological profiles of firms that exploit will more resemble their past profiles; those that explore will look more different year to year. The innovation output main test sample consists of firm-year observations in 2010–2021 for U.S. firms that operate on e-commerce platforms or have analytics technologies on their websites.

Second, I develop and test a novel workforce-based measure to study firms' inputs to innovation by studying their human capital decisions. I do so because investing in innovation capabilities does not guarantee successful outcomes (Menguc and Auh, 2008; Grabner et al., 2018). However, the literature does not propose proxies for firms' allocation of innovation resources toward inputs to innovation. Therefore, I develop and test a novel measure that does so. I examine human capital characteristics because firms increasingly rely on knowledge workers to create value via innovation (Rubera and Kirca, 2012; Zumbrun, 2016; Glaeser et al., 2023). My measure divides total salaries paid to exploratory innovation job positions by total salaries paid to exploitative innovation job positions in a firm and year. The innovation input main test sample is over a shorter period of 2013–2021, due to greater sensitivity of firms' human capital to confounding noise and external factors with a longer pre-period.

In line with my hypothesis, I find that lower customer personal data availability increases firms' innovation resource allocation to exploration relative to exploitation, for both the innovation output and input tests. Specifically, the technological patent portfolio profiles of affected firms look less similar to their past profiles for firms in the output test, and total salaries paid to exploratory innovation job positions divided by total salaries paid to exploitative innovation job positions in a firm within a year increases for affected firms for the input test. Thus, my study shows that firms that experience lower customer data availability allocate more of their innovation resources to exploration, a key driver of economic growth, relative to exploitation.

I further run tests that support my argument that firms' customer data availability drives my results. These cross-sectional tests are along the dimensions of industry and customers. Firms in B2C industries react more strongly to GDPR than firms in B2B industries, consistent with their greater reliance on individual customers and their personal data. Firms operating in industries with more volatile customer demand react more strongly to GDPR, consistent with customer data insights amortizing or losing relevance more quickly.

This paper contributes to the literature in several ways. First, it contributes to the nascent literature on digital data. Despite the significance of digital data in the modern economy, very little empirical evidence is available on the topic. A few recent papers in accounting have begun to study the consequences of operating in the digital space (e.g., Armstrong et al., 2023; Chen and Srinivasan, 2024; Ferracuti et al., 2024). Notable advances at the frontier of studying digital data also include finance and economics papers valuing data as an asset or studying the economics of data and consequences of its nonrival nature (e.g., Jones and Tonetti, 2020; Veldkamp, 2023b). My paper fills a void by contributing to evidence on customer data, a significant type of data for firms with a digital presence.

Second, this paper extends the growing accounting literature on innovation. (See Glaeser and Lang, 2024, for a review.). Studies have investigated how innovation decisions can be influenced by contracting, delegation, or disclosure policy (e.g., Manso, 2011; Dutta and Fan, 2012; Laux and Stocken, 2018; Laux and Ray, 2020; Baldenius and Azinovic-Yang, 2023; Chen et al., 2024). However, my research is the first to show that customer data's asymmetric influence on exploitative versus exploratory innovation can influence firms' innovation strategies that, on a societal level, may affect economic growth.

Third, I contribute to the literature on the implications of firms' internal information environment for managerial decision-making. Research has shown that internal information facilitates various managerial decisions, such as tax planning, hiring, firm transparency, and investment (e.g., Gallemore and Labro, 2015; Heitzman and Huang, 2019; Samuels, 2021; Ferracuti, 2022; Binz et al., 2023; Baldenius and Azinovic-Yang, 2023).

The paper is organized as follows. Section 2 provides background and hypotheses development. Section 3 delves into the sample and research design. Section 4 provides empirical results, robustness checks, and discussion. Section 5 concludes.

2 Background and hypothesis development

2.1 The role of customer data in improving payoffs and reducing risk and uncertainty

Customer data provides information about innovation payoffs. Data, a type of information, can broadly be described as "observations... [in] digital form... from which knowledge can be drawn" (Jones and Tonetti, 2020; Veldkamp, 2023b). The knowledge constitutes the data's value, which can take the form of strategic insights or marginal improvements in the probabilities of commercial success or payoffs (Veldkamp, 2023b; International Valuation Standards Council, 2024). These payoffs can come from firms' investments in innovation, where innovation "requires a deep understanding of whether customers need or desire that invention" (Keeley et al., 2013). Customer data provides this understanding by yielding information that firms can use to tailor future offerings to increase sales and improve customer satisfaction and retention (Hagel and Rayport, 1997).

The traditionally difficult mass collection and analysis of customer data is facilitated by the widespread use of digital technologies. Analytic technologies on websites track visitors through code. This code sends data, such as a unique user ID, time stamp, and other user personal information, to the website's servers whenever someone views the website. This kind of information from the tracking of potential customers' behavior and their demographic information can be aggregated to yield customer demand insights (Farboodi and Veldkamp, 2022). Google Analytics is one example of a digital analytic technology provider.

Customer data can include multiple types of personal information, including page views, time spent on a page, clicks, user flow (i.e., individuals' paths among different pages in a session), demographics, whether users are new versus returning, and even the types of devices or browsers through which users visit (Goldberg et al., 2024). In aggregate, these individual statistics can produce insights. For instance, through data on the number of repeat viewings or the time spent on a page, firms can identify product features that grab customer attention. Through analyzing a user's pages visited per session, one can gauge interest in a business's products in general. Comparing the exit pages of sessions that end in a purchase versus those that do not can help companies identify disliked products and product features. Likewise, a user's flow through product pages can help companies figure out which products customers find complementary or related to each other. These insights about customer preferences as well as their potential variation among different demographics can help firms tailor future offerings.[1] (See Appendix D for a discussion by Fossil Group, a company in my sample.)

[1]The combination of digital customer personal data can yield even more insights. For example, in combination with transaction data, which firms already traditionally had in the offline world, such as the ratio of transactions for a specific product from a returning versus new user, firms can infer customer loyalty. As another example, if a company buys or has access to comparable data on rivals, it could also infer insights about how customers' preferences compare with those of its rivals.

Customer data can improve expected firm payoffs and reduce their riskiness through its strategic insights (Farboodi and Veldkamp, 2022; Veldkamp, 2023b).[2] Data-derived insights can give managers clues for ways to better satisfy customer preferences for future offerings. Even if customer data foretells negative payoffs, companies can use the derived insights to determine disliked features to avoid in future offerings, thus then increasing the magnitude and likelihood of their payoffs. Customer data insights also help managers discriminate among potential avenues for exploitation or exploration, winnowing investment opportunities to only the most attractive risk-return trade-offs.

In addition, customer data can reduce uncertainty (Farboodi and Veldkamp, 2022; Veldkamp, 2023b). One definition of uncertainty is the "difference between the amount of information required to perform the task and the amount of information already possessed by the organization" (Galbraith, 1973). In reducing uncertainty, customer data improves payoff forecast precision (Dichev and Qian, 2022; Farboodi and Veldkamp, 2022; Veldkamp, 2023b). First, managers are receiving more new information in general about expected payoff and risk. Second, the data-derived insights managers implement in seeking to improve expected payoffs are based on this increase in hard data, rather than on a random gamble.

Digital customer data is also unique in that it can yield valuable insights about unmet needs and preferences, even if potential customers do not purchase or transact with a firm, a phenomenon less likely without digital technologies (Thomas, 2024). For instance, without digital customer data, a firm may infer the lack of revenue from a product as a lack of customer demand for the product. However, customers may actually be clicking and spending a lot of time on the product webpage, reflecting interest. Thus, customer data can help firms discover otherwise hidden insights that provide them clues to dig deeper into why interested customers do not make purchases to then potentially improve payoffs.

[2]Expected payoffs are expected net payoffs, where these values already consider firms' data collection and processing costs. I assume that firms find net positive value from information or insights generated from digital customer data, or else firms would avoid collecting and processing it in the first place.

2.2 General Data Protection Regulation (GDPR)

The European Union General Data Protection Regulation (GDPR), passed into law on April 27, 2016 and was implemented on May 25, 2018. It regulates the collection, processing, and storage of European residents' personal data and thus seeks to protect their privacy. GDPR applies to any entity (e.g., company) that handles personal data of EU residents, even if the entity resides outside of the EU. A guiding principle of GDPR is data minimization, which manifests through requirements such as firms needing to have a legal basis for handling personal data, primarily through data subjects' consent, that limit firms' ability to collect and analyze their customers' personal data (Goldberg et al., 2024).[3]

GDPR thus decreased the volume and representativeness of customer personal data available to affected firms, which lowered the depth and accuracy of the strategic insights firms could derive from this data. The value of strategic insights from data, where value refers to the marginal improvement in the probability of commercial success, decreases with a lower volume of available data (International Valuation Standards Council, 2024). The accuracy and thus value of strategic insights drawn from data also decreases as the collected data becomes less representative of a firm's customer base (e.g., if certain demographics are more or less likely to grant consent for personal data collection) (Dubé et al., 2024).[4]

GDPR is described by the European Commission as the "toughest privacy and security law in the world" and has become the "global north star for privacy law" (Wolford). It

[3] GDPR declares that "personal data [should] be: processed lawfully, fairly and in a transparent manner in relation to the data subject" under its principle of "lawfulness, fairness and transparency" (Regulation (EU) 2016/679). According to GDPR, personal data is "any information relating to an identified or identifiable natural person," where such a person is also called a "data subject" (Regulation (EU) 2016/679). "The data subjects are identifiable if they can be directly or indirectly identified, especially by reference to an identifier such as a name, an identification number, location data, an online identifier or one of several special characteristics, which expresses the physical, physiological, genetic, mental, commercial, cultural or social identity of these natural persons. In practice, these also include all data which are or can be assigned to a person in any kind of way" (Regulation (EU) 2016/679). I asked and clarified with Anu Talus, current chair of the European Data Protection Board, that to "process" data includes any form of handling data, such as collecting, cleaning, analyzing, and selling data.

[4] If a firm's data sample does not accurately capture the distribution of the individual characteristics of its customer base, it could draw erroneous insights from the data. Erroneous insights, such as inferring incorrectly that the customer base consists primarily of a certain age range, as an example, could lead firms to inefficiently target certain demographic groups and thus could hurt their performance.

replaced the 1995 EU Data Protection Directive, which had been established two decades earlier in the Internet's infancy. The GDPR answered calls for a single EU-wide comprehensive personal data protection regulation with global application. Hence, the GDPR's effect on firms' decisions to focus on particular innovation strategies as influenced by data availability was significant.

Evidence validating the significance of GDPR in decreasing firms' data availability lies in the literature as well as in annual reports of firms that rely heavily upon personal data in their businesses. The literature demonstrates that non-consent rates after GDPR have ranged between 4 percent and 13 percent (Goldberg et al., 2024). In addition, in response to the GDPR, firms decreased data storage and processing, becoming less "data-intensive" (Demirer et al., 2024; Goldberg et al., 2024).

In terms of annual reports, excerpts from Item 1A validate GDPR's effect on firms' practices around the collection and analysis of EU residents' personal data. For example, Activision Blizzard states awareness and anticipation of GDPR's implementation in 2018 as early as its 2016 10-K, the year the GDPR passed. Excerpts also validate that companies expected and feared penalties from enforcement if they did not abide by the regulation. I thus expect the firms in my sample to begin altering their innovation strategies upon the passage of the GDPR in 2016. (See Appendix E, Exhibits 1 to 3.)

Anecdotal evidence also validates GDPR as a significant negative shock to firms' customer data availability. As an example, Meta, which is focused on social networking and relies heavily on the personal data it collects to earn advertising revenues, predicted and observed a negative trend in monthly active users in Europe around the implementation of GDPR in May 2018. Mark Zuckerberg, CEO, stated in his company's second quarter of 2018 earnings call that Meta saw monthly active users go "down by about 1 million people" after GDPR implementation (see Appendix E, Exhibit 4). The regulation required firms like Meta to obtain users' consent to collect their data.

2.3 Hypothesis development

Customer data availability could influence the innovation strategies of firms. Firms allocate their finite innovation resources between exploitative and exploratory innovation, the outcomes of which can be crucial for their profitability and long-term survival. A firm's investment toward innovation is restricted by factors including, but not limited to, information constraints and management control (Romer, 1993; Jones, 2023; Glaeser and Lang, 2024). Firms thus cannot fund all positive net present value innovation projects and will consider investments relative to each other. However, firms also have limited certainty about the expected risk-adjusted payoffs of innovation (March, 1991; Manso, 2011; Bubeck and Cesa-Bianchi, 2012; Balsmeier et al., 2017).

As described in Section 2.1, customer data availability can improve firms' payoffs through their decisions in tailoring offerings and can reduce their riskiness and uncertainty (Hagel and Rayport, 1997; Jones and Tonetti, 2020; Veldkamp, 2023b).

An asymmetry exists, in that customer data availability improves firms' payoffs from and reduces risk and uncertainty of exploitation more than for exploration. Customer data, a byproduct of customer interactions with a firm's current offerings, relates more directly to the improvement of existing offerings (i.e., exploitation) than to new ideas for projects that do not yet have outcomes (i.e., exploration). As March (1991) speculated: "The certainty, speed, proximity, and clarity of feedback ties exploitation to its consequences more quickly and more precisely than is the case with exploration." In other words, exploitation is more sensitive to customer data changes than exploration. In addition, as is the standard assumption in the literature, risk-averse managers maximize their utility by investing in strategies with the highest certainty equivalence values (i.e., highest expected payoff with lowest risk) (Holmström, 1979). This leads to my hypothesis:

> ***H****: Firms shift their allocation of finite innovation resources toward exploitation relative to exploration with higher customer data availability.*

On the other side of the same coin, firms shift their allocation of finite innovation resources toward exploration relative to exploitation with lower customer data availability.

Some may argue that the magnitude of this hypothesized effect could be attenuated by several factors. First, one may claim that customer data could be marginally more informative for exploration rather than for exploitation, because less is known about exploration. However, although customer data is a type of information, what distinguishes it from information more broadly is that the insights from customer data informs directly and is specifically relevant to existing offerings rather than to a larger, amorphous set of less related ideas that do not yet have outcomes. Even if customer data did not have this distinguishing property, the knowledge about exploitation amortizes quickly in relevance and certainty without availability of timely information.

Some may also push against my argument that firms would prefer the type of innovation that becomes less risky and more certain with data availability. Such an argument may arise from the real options literature, where the option to invest in a project is analogous to a financial call option (Dixit and Pindyck, 1994). Under uncertainty, the possessor of the option will irreversibly invest in the project should the value of the future project rise sufficiently to justify both the cost of the project plus the extinguishing of the option value. It is a well-known property of real options that they are more valuable the greater the underlying uncertainty of the project's payoff. However, again, managerial decision-makers are assumed to be risk-averse, as is standard in the literature. Thus, risk aversion will temper managers' utility from real option value due to greater uncertainty.

Some may also raise the possibility that firms may seek to gather more information about less certain innovation types through implementing a "spray and pray" approach (Ewens et al., 2018). In this approach, firms invest a little in each of a wider selection of offerings to gather clues about customer insights, assuming they will abandon many of these. One way of doing this could be through putting out product prototypes, beta offerings, or "interest screeners" for concepts of future products (e.g., concept cars, some of which are never mass produced). However, the customer demand insights gained from this smaller-scale approach will be noisier than insights gained from customer data derived from customer interactions with established existing offerings available on a larger scale.

I test my hypothesis using GDPR as a negative shock to firms' customer data availability. The next section, Section 3, dives into the research design behind my tests.

3 Sample and research design

3.1 Sample selection

The sample includes U.S. companies that have e-commerce platforms or analytics technologies on their websites. E-commerce platforms and analytics technologies enable the collection of quantifiable personal data. I use BuiltWith to identify firms that implement these technologies at least as early as three years prior to GDPR passage in 2016. I study U.S. firms and do not include EU companies, because studying firms within one country allows more comparable samples and avoids concerns commonly raised about cross-country studies.

The sample varies based on which of two main tests I execute, where the main tests compare a firm's allocation of innovation resources to exploitative versus exploratory innovation before and after GDPR. For the first main test examining innovation output, I construct a patent-based measure based on the work of Balsmeier et al. (2017) with patent data obtained from PatentsView and Kogan et al. (2017). The sample consists of firm-years in 2010–2021.

For the second main test that examines firms' innovation input, I develop and test a measure using workforce data from Revelio Labs, which collects and standardizes hundreds of millions of online public profiles and résumés to construct aggregate measures of historical workforce composition (Revelio Labs). The sample of firms for this input test consists of the firm-years in 2013-2021. The shorter pre-period minimizes the influence of the greater sensitivity of firms' human capital to confounding noise and external factors. I also exclude less specialized firms, because these firms' focuses on different types of innovation are less likely to manifest through clearly delineated roles, and employees are more likely to balance responsibility for both types.

I retain observations that have non-missing values of my variables and controls of interest. This yields a final sample of 4,662 and 2,838 firm-year observations for my innovation output and input tests, respectively. For the samples, I exclude firms that generate significant revenues from advertising. I do so to allay the concern that the results could be due to GDPR's negative shock to personal data which forced firms with significant advertising revenues to innovate in a more exploratory way to survive. I also exclude early-stage startups; I do so by not including private firms in my sample. The only innovation option early-stage startups have is exploration at the earliest development stages, due to likely having no or very underdeveloped products and services to exploit. The sample selection procedures are outlined in Appendix A.

3.2 Variable measurement

3.2.1 Key dependent variable

The key dependent variable for my analysis captures firms' allocation of their innovation resources between exploration and exploitation.

For the innovation output test, I use a patent-based measure as my proxy. Characteristics of patents can proxy for multiple elements of a firm's innovative activities (Hall et al., 2001; Lerner and Seru, 2022). Balsmeier et al. (2017) introduced a patent-based proxy to measure a firm's resource allocation to exploitation versus exploration. This proxy differentiates between patents filed in "new to the firm" technology classes and those filed in "known to the firm" technology classes. Balsmeier et al. (2017) observe the distribution of the number of patents (in year of filing) per technology class and firm. Following Jaffe (1989), they then calculate the similarity between the distribution of patents across technology classes filed by a firm in a given year and the same firm's prior distribution of patents across technology classes. The technological profiles of firms that exploit will more resemble their prior profiles;

those that explore will look more different from year to year. I follow Balsmeier et al. (2017), but I use one minus their proxy and then scale it up by 100 as my measure, *Exploratory Patent Portfolio*. My proxy ranges from 0 to 100, where values closer to 100 represent a more exploratory, rather than exploitative, patent portfolio.

Results for the innovation output measure may manifest only after a delay, consistent with the slow-moving nature of innovation noted in the literature (Galasso and Schankerman, 2015; Glaeser et al., 2020). However, since my sample period extends three years after GDPR and thus spans the two to three year lag in patent outcomes noted in the literature, this lag should not significantly affect the results.

I also test for firms' innovation input using with a novel measure I develop that considers human capital investment decisions. I study firms' innovation input because investing in innovation capabilities does not guarantee successful innovation outcomes (Menguc and Auh, 2008; Grabner et al., 2018). I also develop this novel measure due to the absence of a comparable measure in the literature.[5] I examine human capital characteristics because firms increasingly rely on knowledge workers to create value via innovation (Rubera and Kirca, 2012; Zumbrun, 2016; Glaeser et al., 2023).

The input proxy *Explore-to-Exploit Salary Ratio*, divides the total salaries paid to exploratory innovation role employees by the total salaries paid to exploitative innovation role employees in a firm within a year. More money spent on salaries of innovation job roles represent a firm's intent to grow and invest more resources in specific innovation strategies. I manually identify job roles, broken down into 150 types by Revelio Labs, as exploratory, exploitative, or neither. I mark jobs as "exploratory" if they value experimentation, give room for failure in exploring new ideas, involve potentially nonlinear processes, and are char-

[5] I do not use R&D expenses as a variable proxy for studying firms' resource allocation between exploitation and exploration. Mezzanotti and Simcoe (2023) find that R&D itself consists of both exploratory and exploitative activities. They describe the 'research' of R&D as having a more exploratory nature, while the 'development' has a more exploitative nature. However, no firm data with this granular breakdown of R&D expenditures exists. The closest datasets available with this sort of breakdown of R&D expenditures are the ABS and BERD datasets collected by the US Census, but they are only available on a national level, not at an identifiable firm level.

acterized by more uncertainty around their deliverables or results. These types might focus more on developing differentiating products in new markets. I mark jobs as "exploitative" if they involve more predictable and normalized processes and value reliable execution for improving production efficiency and financial performance of existing products in current markets. I mark jobs as neither if they could encourage both exploration and exploitation or if neither exploratory nor exploitative innovation appears integral to them (see Appendix F for my categorization) (Keeley et al., 2013). See Appendix G for examples of job postings for an exploratory and exploitative innovation job for a firm in my sample, Coca-Cola.

3.2.2 Key independent variable

The key independent variable for my analysis is firms' customer data availability. The analysis uses a difference-in-differences research design that uses GDPR as a shock to customer data collection. My treatment group consists of U.S. firms in my sample that experienced a negative shock to customer data value from GDPR, due to their significant presence and revenue generation from the European Union, while my control group consists of firms that did not. I determine whether a firm is treated (i.e., the variable *EU Rev Exposure* takes on the value 1) based on segment disclosures in 10-Ks, as collected from WRDS Compustat Segments. I determine treatment based on whether the firm has a significant EU presence in 2015, the year leading up to GDPR passage. Firms likely anticipated GDPR in 2015, leading up to passage in 2016, because the European Council agreed to a general approach in 2015, implying a high likelihood of passage soon after. *Post-GDPR* is a dummy variable that indicates whether a firm-year observation in my sample is in the year of or after the GDPR passage of 2016 and 0 if the observation is before 2016. *Affected by GDPR* is the interaction term of *EU Rev Exposure* with *Post-GDPR*, the coefficient of which represents my main result of interest.

GDPR satisfies the conditions necessary for the feasibility and validity of my difference-in-differences identification design. The innovation outcomes I study are not confounded or influenced by other shocks at the time or by factors other than customer data value changes. The shock is plausibly exogenous because the stated mission of GDPR was to protect EU individuals' privacy, not to influence innovation.

3.2.3 Discussion about using GDPR shock for analyses

In this section, I address concerns one may harbor about whether other relevant shocks coincided with GDPR. The sample period does not coincide with the passing of GDPR-like laws in other countries, as these countries followed in the footsteps of the European Union's GDPR later on as their "north star" (European Data Protection Supervisor; Wolford).

U.S. state-level privacy laws are also not a concern and would not significantly disrupt my results. First, within my sample period, only a few U.S. states had a GDPR-like data privacy law that would have lowered data value (e.g., CCPA in California).[6] Second, unless a business only serves customers within one of these states with its online platform (which is very unlikely), firms can collect data on other states' customers too. Therefore, even data privacy laws for affected states prohibited 100 percent of the collection of customers' personal data in the extreme, overall concerns about U.S. state laws for identification are not significant.

The Privacy Shield also is not a concern for results during the sample period, because it coincides with GDPR passage but has the same effect as GDPR on the value of data available to firms. The Privacy Shield was an EU regulation that regulated data transfers out of the European Union starting in 2016. Because this regulation discourages the aggregation of separate cross-border datasets for analysis on bigger datasets that would generate larger amounts of and deeper insights, the Privacy Shield has the same effect as GDPR on data value in that it decreases the value of insights that firms can generate from their data due to data fragmentation across international borders. Therefore, it would increase the potency of

[6] CCPA, or the California Consumer Privacy Act, was the first significant state data privacy law passed in the United States. It was passed in 2018 and took effect in 2020. This regulation and any similar regulations in other states that followed, should not affect the U.S.-only sample of treatment and control firms differentially.

my independent variable of lowered value of available data. The Privacy Shield regulation implemented to allow for cross-border transfers was stricter than the previous version, and thus it lowered the value of available data by restricting cross-border data flows.

3.2.4 Control variables

I control for factors that may relate to a firm's allocation of exploitation versus exploration innovation or to its data value to increase the precision and accuracy of my estimates. For both my innovation output and input tests, I control for financing frictions and investment opportunities through the variables *Firm Size*, *Book-to-Market*, and *Leverage*, as the literature has done (e.g., Balsmeier et al., 2017; Glaeser and Landsman, 2021; Kim and Valentine, 2021). For my patent-based innovation output test, I additionally control for *R&D*, *Sales*, *PPE*, and *Employees*, following Balsmeier et al. (2021). I construct the variables using data from CRSP/Compustat. See Appendix B for variable definitions and constructions. Firm fixed effects control for time-invariant firm characteristics that might affect outcomes, including industry characteristics. Year fixed effects account for macro factors within each annual cross-section, e.g., economic indicators or consumer sentiment and propensity to spend.

3.3 Research design

The primary empirical analyses employ a difference-in-differences design around the passage of and implementation of GDPR. The model used is as follows:

$$\textit{INNOVATION TYPE FOCUS}_{i,t} = \beta_0 + \beta_1 \cdot \textit{Affected by GDPR}_{i,t} + \gamma \cdot X_{i,t} + \delta_i + \lambda_t + u_{i,t} \quad (1)$$

The unit of observation is at the firm i and year t level. $\textit{INNOVATION TYPE FOCUS}_{i,t}$ is one of two main proxies I test for a firm's focus on an exploitative versus exploratory innovation strategy. One proxy is the Balsmeier et al. (2017) patent-based measure *Exploratory Patent Portfolio* for the output test. The second is the *Explore-to-Exploit Salary*

Ratio measure for the input test based on workforce data. The coefficient on the interaction term, *Affected by GDPR* (i.e., β_1), captures the impact of the GDPR. Thus, I predict β_1 to be positive for all the $INNOVATION\ TYPE\ FOCUS_{i,t}$ measures, because I expect lower data availability to induce firms to allocate more innovation resources to exploratory relative to exploitative innovation. $X_{i,t}$ represents a vector of time-varying firm controls, where the set of controls for the output and input tests differ slightly, as mentioned in Section 3.2.4. δ represents firm fixed effects, and λ represents year fixed effects. I cluster standard errors at the firm level.

4 Empirical Results

4.1 Descriptive Statistics

I present descriptive statistics for the main variables, control variables, cross-sectional and heterogeneity test variables for the patent-based innovation output test, as well as GDPR validation test variables in Table 1 Panel A. Due to the novelty of the workforce-based innovation input measure as well as the use of Revelio Labs data for the variable's construction, I feature descriptive statistics separately for the innovation input test measure in Table 6 Panel A. All unbounded continuous variables are winsorized at the first and 99th percentile.

Descriptive statistics in Table 1 Panel A show that the main patent-based dependent variable of *Exploratory Patent Portfolio* in my sample has a heavy skew toward having more exploitative patent activity, as the mean in my sample is 0.316, whereas the mean of the sample of Balsmeier et al. (2017), who proposed and first tested this variable, is closer to the middle of the 0 to 1 range, at 0.54. The lower mean in my sample implies the digital firms in my sample are on average more exploitative than exploratory in their innovation activities than a sample (e.g., the sample of Balsmeier et al., (2017)) that also includes non-digital firms. This statistic difference already implies an empirical relation between higher data availability in digital firms and higher exploitative activity, consistent with my economic story. Table 1 Panel A also shows that on average, firms file more exploitative patents than exploratory patents in any given year, consistent with the notion that any non-early firm that provides offerings to customers primarily exploits by default.

Descriptive statistics in Table 6 Panel A show that total salaries paid to exploratory-role employees is on average 41.8% (mean = 0.418) of total salaries paid to exploitative-role employees in a given firm in a given year. The total salaries paid to exploratory-role employees, scaled by the total salaries paid to all employees at a firm in a given year, is less than the total salaries paid to exploitative-role employees scaled by the total salaries paid to all employees at a firm in a given year.

Table 1 Panel B and Table 6 Panel B present the industry distribution across firm-years in my patent-based innovation output and input sample, respectively, based on 2-digit SIC code. In the output test sample, the most heavily represented industry is manufacturing, with 2,903 firm-years. The second most heavily represented industry is services with 794 firm-years. In the workforce-based innovation input test sample, the most heavily represented industry for this sample is also manufacturing, with 1,275 firm-years. However, the second most heavily represented industry for the innovation input sample is finance, insurance, and real estate with 643 firm-years, and services comes in at a close third with 442 firm-years.

Table 1 Panel C and Table 6 Panel C present the year distribution across my innovation output and input samples. The sample is balanced and well-distributed across each year with around 200-400 firm-year observations each year. Earlier years have lower numbers of observations due to fewer firms having adopted any analytics technologies at the time.

Table 1 Panel D presents the distribution of patent subclasses across the patents in my sample. The highest percentage of patents filed in my sample are the subclasses of electricity (subclass H) and physics (subclass G).

4.2 Stock Market Reaction to GDPR

I validate GDPR as a plausibly exogenous and significant negative shock to affected firms' data availability by examining the presence and direction of a stock market reaction. I study an event leading up to the passage of GDPR in 2016, as well as first day of GDPR implementation, to study the market returns with event studies. *Market Reaction to GDPR Approach Plan* captures the reaction to European Council's first agreeing to a general approach on GDPR on June 15, 2015, while *Market Reaction to GDPR Implementation* captures the reaction to GDPR's first day of implementation on May 25, 2018. These two return variables are defined as the price on the event date minus the price the day before, divided by the price the day before. Table 2 showcases weakly and strongly negative significant coefficients (coef = -0.003, t-stat = -1.87; coef = -0.006, t-stat = -3.02) on *EU Rev Exposure* in Columns (1) and (2), respectively. The interpretation of the Table 2 results is that firms in 2015 already started to anticipate GDPR's passage in 2016, validating my choice of 2015 as the basis for determining treatment. In addition, treatment firms' strong negative reaction to GDPR implementation validates GDPR as a plausibly exogenous and significant negative shock to affected firms' data availability and thus value.

4.3 Evidence from innovation output tests

My hypothesis predicts that lower customer data availability induces firms to allocate more of their innovation resources to exploratory relative to exploitative innovation. The results of the innovation output test align with this hypothesis.

I present results of estimating Eq. (1), the difference-in-differences test that models innovation output resource allocation *Exploratory Patent Portfolio*, in Table 3. Column (1) estimates results without control variables. Column (4) estimates the model with controls. The positive significant coefficients on *Affected by GDPR* indicate that GDPR did induce firms to allocate more resources to exploratory innovation. The coefficient in Column (4) indicates that a significant negative shock to a firm's customer data availability is associated with 29.9% greater patent-based exploratory activity, compared to unaffected firms (coef = 0.299; t-stat = 2.23). This shift toward exploratory patenting activity is economically significant, representing 13.5% of the sample standard deviation of *Exploratory Patent Portfolio*.[7]

The results also examine the changes in exploratory and exploitative activity separately in explaining the orientation toward exploratory innovation. The positive shift is driven by a greater decrease in exploitative patenting than for exploratory patenting. Columns (2) and (3) provide results from my difference-in-differences tests by regressing *Exploratory Patenting* and *Exploitative Patenting* on *Affected by GDPR* without controls, respectively. Columns (5) and (6) run the model in Columns (2) and (3) with controls. Columns (2) and (5) show that *Exploratory Patenting* decreases for firms affected by GDPR (coef = -0.006 for Column (2); coef = -0.012 for Column (5)), and Columns (3) and (6) show that *Exploitative Patenting* decreases as well—but more—for affected firms (coef = -0.168 for Column (3); coef = -0.170 for Column (6)). Consistent with my hypothesis, exploitation is more sensitive to a negative change in data availability than exploration, thus decreasing more than exploration.[8]

A key identifying assumption for my main tests is pre-shock parallel trends. Though there may be differences between the treatment and control firms, the parallel trends assumption requires that those differences be constant in the pre-event period and likely would have continued to be constant, absent the treatment. To test this assumption, Figure 1 plots the year-by-year coefficient estimates for my main difference-in-differences regression model with controls, fixed effects, and clustering by year. The omitted year is 2015. Figure 1 visually confirms that the parallel trends assumption holds.

[7]The innovation outcome results also cannot be explained by an alternative story driven by a negative impact to cash flow. I estimate Eq. (1), but with operating cash flow scaled by assets as the dependent variable, and I find no significant change upon the GDPR shock (t-stat = -1.05).

[8]The results are also consistent with the notion that data benefits innovation in general, though this is not the question I study in this paper. The level of innovation in the form of patenting, as proxied by the natural log of one plus the total number of patents filed, decreases upon lower data availability from GDPR (t-stat = -2.29).

4.4 Robustness tests

Due to potential concern about the skewness of the *Exploratory Patent Portfolio* variable, I examine high dimensional fixed quantile regressions with controls and firm and year fixed effects at the percentiles of 10, 25, 50, 75, and 90 in Table 4 Panel A. At almost every quantile tested (i.e., 25, 50, 75, 90), results are positive and statistically significant, consistent with my hypothesis.

In Table 4 Panel B, I also address potential concern about observations in the GDPR transition period years influencing results. I run Eq. (1) after dropping observations in the transition years of 2016 to 2018 for output test variable *Exploratory Patent Portfolio*. Columns (1) and (2) present results without and with controls, respectively. Columns (1) and (2) show that the positive significant relation between *Exploratory Patent Portfolio* and *Affected by GDPR* is still strong and significant among firms affected by GDPR (coef = 0.382; t-stat = 2.53; for Column (2)), in line with my hypothesis.

4.5 Cross-sectional tests

I conduct tests that support the hypothesis that data availability drives the results of my main tests. I report cross-sectional analyses of innovation output resource allocation around GDPR along the dimensions of industry and customers in Table 5. The analyses present results from the regression of *Exploratory Patent Portfolio* on *Affected by GDPR* estimated using Eq. (1). All columns include the baseline regression with a full set of control variables, firm and year fixed effects, and clustering standard errors by firm.

4.5.1 B2C vs. B2B

I provide evidence consistent with firms in B2C industries versus B2B industries reacting more strongly to GDPR. Between Columns (1) and (2), the sample is split based on *B2C Dummy*, or whether firms are in a B2C or B2B industry. I follow Tacheva et al. (2020) in categorizing firms as B2B versus B2C. Columns (1) and (2) show that the positive relation between *Exploratory Patent Portfolio* and *Affected by GDPR* is on average stronger among B2C firms (coef = 0.769) in the sample compared to B2B firms (coef = 0.055). The results are consistent with the notion that firms that sell primarily to individuals rather than to other businesses react more strongly to changes in the availability of customer data due to GDPR. This difference between subsamples is significant at the 5% level (p-value = 0.026; F-stat = 4.973).

4.5.2 Firm exposure to customer demand volatility

I provide evidence consistent with firms operating in industries where customer demand is more volatile and where insights from data thus amortize more quickly, reacting more strongly to GDPR. Between Columns (3) and (4), the sample is split based on whether the value of *Customer Demand Volatility* is in the top three deciles versus the bottom three deciles of the sample in a given year. *Customer Demand Volatility* is the standard deviation of revenues of firms within an SIC 2-digit industry in a given year. Columns (3) and (4) show that the positive relation between *Exploratory Patent Portfolio* and *Affected by GDPR* is on average stronger among firms in the top three deciles of *Customer Demand Volatility* in the sample (coef = 0.656),than in the bottom three deciles (coef = 0.014). The results are consistent with firms in industries with more volatile customer demand relying on more timely insights gained from customer data. This difference between subsamples is significant at the 5% level (p-value = 0.033; F-stat = 4.580).

4.6 Evidence from innovation input tests

My hypothesis predicts that lower customer data availability induces firms to allocate more of their innovation resources to exploratory relative to exploitative innovation. The results of the innovation input test align with this hypothesis as well.

I present the results of estimating Eq. (1), the difference-in-differences test that models innovation input resource allocation *Explore-to-Exploit Salary Ratio*, in Table 6 Panel D.

Column (1) and Column (4) presents results without and with control variables, respectively. The positive significant coefficients on *Affected by GDPR* in Columns (1) and (4) indicate that GDPR did induce firms to allocate more to exploratory relative to exploitative innovation, as captured by *Explore-to-Exploit Salary Ratio*. The coefficient in Column (4) indicates that a significant negative shock to a firm's customer data availability is associated with a 9.8% greater ratio of total salaries paid to exploratory-role employees to total salaries paid to exploitative-role employees for firms affected by GDPR, compared to unaffected firms (coef = 0.098; t-stat = 2.20). This shift in salaries paid toward exploratory-role employees is economically significant, as it represents 15.0% of the sample standard deviation of *Explore-to-Exploit Salary Ratio*.

The results also examine the changes in exploratory and exploitative activity separately in explaining the orientation toward exploratory innovation. Columns (2) and (3) provide results from my difference-in-differences tests by regressing *Exploratory Employee Salary Ratio* and *Exploitative Employee Salary Ratio* on *Affected by GDPR* without controls, respectively. Columns (5) and (6) run the model in Columns (2) and (3) with controls. Columns (2) and (5) show that exploratory activity increases for firms affected by GDPR (coef = 0.004; coef = 0.006), and Columns (3) and (6) show that exploitative activity decreases for those firms (coef = -0.012; coef = -0.013). Consistent with my hypothesis, upon a decrease in customer data availability, firms shift toward exploration and away from exploitation.[9]

4.7 Data expansion using machine learning technique SMOTE

I present results after balancing my innovation output test dataset through data expansion using the synthetic minority over-sampling technique (SMOTE) in Table 7. SMOTE is a machine learning algorithm that helps balance datasets. My treatment group for my

[9] The results are also consistent with the notion that data benefits innovation in general, though this is not the question I study in this paper. The level of innovation in the form of human capital, as proxied by the salaries paid to all innovation-related employees scaled by salaries paid to all employees at the firm, exhibits a negative trend with lower data availability, though it does not change significantly upon GDPR (t-stat = -0.71).

innovation output test is only 26.6% of my sample, and having an imbalanced sample can lead to less precise estimates and lower statistical power. Therefore, I implement SMOTE to expand my dataset by generating synthetic observations for my treatment group, so that the number of observations in my treatment group matches the number of observations in my control group. I present the descriptive statistics after applying this technique in Table 7 Panel A. The distribution for *EU Rev Exposure* shows that, of the 5,992 observations, there are now equal numbers of treatment and control observations (2,996 observations) for the new expanded sample for the patent-based sample.

I present the results from estimating a difference-in-differences specification with this expanded sample in Table 7 Panel B. This model does not include firm or year fixed effects, because I cannot form those fixed effects due to the output of SMOTE not allowing for maintaining a firm-year panel structure. I thus also cannot cluster standard errors by firm. The specification I run is as follows, where *ITF* stands for *INNOVATION TYPE FOCUS*:

$$ITF_{i,t} = \beta_0 + \beta_1 \cdot \mathit{Affected\ by\ GDPR}_{i,t} + \delta \cdot \mathit{EU\ Rev\ Exposure}_i + \lambda \cdot \mathit{Post\text{-}GDPR}_t + \gamma \cdot X_{i,t} + u_{i,t} \tag{2}$$

Columns (1) and (2) present results for *Exploratory Patent Portfolio* without and with controls, respectively. The positive and significant coefficients align with my hypothesis (coef = 0.184, t-stat = 2.03, for Column (2)).

The coefficient in Column (2) indicates that a significant negative shock to a firm's value of customer data is associated with 18.4% greater patent-based exploratory activity, compared to unaffected firms. This magnitude is slightly lower than that in my main tests. This shift toward exploratory patenting activity is economically significant, as it represents 10.4% of the sample standard deviation of *Exploratory Patent Portfolio*.

5 Conclusion

In this study, I examine how firms' customer data availability influences their managers' resource allocation between exploitative and exploratory innovation. I find that, upon a negative shock to customer personal data availability, firms allocate more of their finite innovation resources to exploration relative to exploitation. I use the European Union (EU) General Data Protection Regulation (GDPR) as a plausibly exogenous shock to customer data value in estimating a difference-in-differences specification. My findings hold for both a patent-based innovation output measure and a novel innovation input workforce-based measure I develop and test. My results are stronger for firms in B2C versus B2B industries and firms with more volatile customer demand. The evidence suggests that higher customer data availability can lead firms to focus more on exploitative innovation, deterring the exploratory innovation crucial to economic growth.

I contribute to the nascent literature on digital personal data, the growing accounting literature on innovation, and the literature on the implications of firms' internal information environment for managerial decision-making. The innovation input workforce-based measure that I develop and test may also be useful for future research on firms' innovation strategies.

The results of my study may suggest that, contrary to common positive sentiment, more data is not always better. However, further research is needed to examine the implications of customer data for welfare outcomes.

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Table 1

Panel A: Descriptive Statistics for Innovation Output Sample

	N	*Mean*	*Std. Dev.*	*25%*	*Median*	*75%*
Main Test						
Exploratory Patent Portfolio	4,662	0.316	2.210	0	0.0004	0.035
Exploratory Patenting	4,662	0.126	0.323	0	0	0
Exploitative Patenting	4,662	1.399	1.757	0	0.693	2.398
Affected by GDPR	4,662	0.143	0.350	0	0	0
EU Rev Exposure	4,662	0.266	0.442	0	0	1
Post-GDPR	4,662	0.522	0.500	0	1	1
Assets	4,662	7.618	2.281	5.973	7.590	9.273
Leverage	4,636	0.239	0.201	0.054	0.222	0.360
Book-to-Market	4,367	0.459	0.386	0.200	0.368	0.621
Employees	4,585	1.278	2.183	-0.212	1.387	2.890
R&D	4,662	2.751	2.516	0	2.958	4.533
Sales	4,549	7.135	2.313	5.784	7.291	8.729
PPE	4,484	6.228	2.578	4.445	6.270	8.013
Cross-Sectional and Heterogeneity Test						
B2C Dummy	4,582	0.294	0.456	0	0	1
Customer Demand Volatility	4,662	1,781	5,811	184.2	389.9	1,058
Validation Test						
Market Reaction to GDPR Approach Plan	402	-0.006	0.018	-0.014	-0.007	0.0007
Market Reaction to GDPR Implementation	358	0.002	0.018	-0.007	0.001	0.009

Notes: This table presents descriptive statistics for the main dependent, independent, control, cross-sectional, and other variables used in innovation output regressions as well as control variables. Detailed definitions of all variables are provided in Appendix B.

Table 1

Panel B: Industry Distribution for Innovation Output Sample

2-Digit SIC Code	*Industry Title*	*Frequency*	*Percent*
10-14	Mining	148	3.17
15-17	Construction	43	0.92
20-39	Manufacturing	2,903	62.27
40-49	Transportation, Communications, Electric, Gas, And Sanitary Services	309	6.63
50-51	Wholesale Trade	71	1.52
52-59	Retail Trade	122	2.62
60-67	Finance, Insurance, And Real Estate	252	5.41
70-89	Services	794	17.03
99	Non-classifiable Establishments	20	0.43
Total		**4,662**	**100**

Notes: This table presents descriptive statistics for the industry of firm-year observations, by 2-digit SIC code, in the innovation output sample.

Table 1

Panel C: Year Distribution for Innovation Output Sample

Year	*Frequency*	*Percent*
2010	184	3.95
2011	321	6.89
2012	404	8.67
2013	432	9.27
2014	443	9.5
2015	446	9.57
2016	436	9.35
2017	425	9.12
2018	414	8.88
2019	392	8.41
2020	388	8.32
2021	377	8.09
Total	**4,662**	**100**

Notes: This table presents descriptive statistics for firm-year observations in the innovation output sample.

Table 1

Panel D: CPC Patent Subclass Distribution

CPC 1-digit Subclass	*Frequency*	*Percent*
A: Human Necessities	68,842	7.7
B: Performing Operations; Transporting	76,233	8.53
C: Chemistry, Metallourgy	40,065	4.48
D: Textiles; Paper	3,206	0.36
E: Fixed Constructions	13,463	1.51
F: Mechanical Engineering	45,074	5.04
G: Physics	317,392	35.5
H: Electricity	329,773	36.89
Total	**894,048**	**100**

Notes: This table presents descriptive statistics for the CPC 1-digit patent subclasses of patents in the innovation output sample.

Table 2

Market Reaction to GDPR

	(1) *Market Reaction to GDPR Approach Plan*	(2) *Market Reaction to GDPR Implementation*
EU Rev Exposure	-0.003*	-0.006***
	(-1.87)	(-3.02)
Constant	-0.005***	0.003***
	(-4.39)	(2.96)
Observations	402	358
R-squared	0.005	0.020

Notes: This table presents event study results. Column (1) features the results of estimating the regression of *Market Reaction to GDPR Approach Plan* on *EU Rev Exposure*. Column (1) executes an event study around the June 15, 2015 event that the European Council reached a general approach on the GDPR. Column (2) features the regression of *Market Reaction to GDPR Implementation* on *EU Rev Exposure*. Column (2) executes an event study around the first day GDPR is implemented or enforced on May 25, 2018. The unit of observation is at the firm level. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Table 3

The Effect of GDPR on Innovation Strategy Focus: Results for Output Tests

	(1) *Exploratory Patent Portfolio*	(2) *Exploratory Patenting*	(3) *Exploitative Patenting*	(4) *Exploratory Patent Portfolio*	(5) *Exploratory Patenting*	(6) *Exploitative Patenting*
Affected by GDPR	0.322**	-0.006	-0.168**	0.299**	-0.012	-0.170**
	(2.57)	(-0.23)	(-2.41)	(2.23)	(-0.44)	(-2.40)
Assets				0.041	0.023	0.141***
				(0.37)	(1.47)	(3.05)
Leverage				0.141	0.059	-0.109
				(0.86)	(1.26)	(-0.81)
Book-to-Market				-0.238	-0.004	-0.075
				(-1.49)	(-0.19)	(-1.41)
Employees				0.161	0.022	0.148**
				(1.12)	(1.06)	(2.16)
R&D				0.100	0.016	0.047
				(1.24)	(1.33)	(1.17)
Sales				0.094*	0.008	-0.093***
				(1.80)	(0.83)	(-2.64)
PPE				-0.378***	-0.041**	-0.043
				(-2.77)	(-2.32)	(-0.73)
Observations	4,662	4,662	4,662	4,100	4,100	4,100
R-squared	0.207	0.320	0.907	0.202	0.329	0.913
Firm FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES

Notes: This table presents difference-in-differences regression results from the Eq. (1) regression with either *Exploratory Patent Portfolio*, *Exploratory Patenting*, or *Exploitative Patenting* as the dependent variables. Column (1) includes the baseline regression with *Exploratory Patent Portfolio* and firm and year fixed effects. Column (2) is the baseline regression with firm and year fixed effects except with *Exploratory Patenting*, and Column (3) is the baseline regression with firm and year fixed effects except with *Exploitative Patenting*. Column (4-6) adds the vector of appropriate control variables to the regressions run in Columns (1-3). The unit of observation is at the firm-year level. The standard errors are clustered by firm. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Table 4

Panel A: The Effect of GDPR on Innovation Strategy Focus: Quantile Tests

Quantile:	(1) 10th	(2) 25th	(3) 50th	(4) 75th	(5) 90th
Affected by GDPR	-0.265**	0.115**	0.196***	0.509**	1.144**
	(-2.059)	(2.146)	(2.694)	(2.286)	(1.990)
Assets	0.0808	0.0539	0.0481	0.0260	-0.0190
	(0.532)	(1.301)	(0.704)	(0.128)	(-0.0392)
Leverage	-0.134	0.0514	0.0909	0.243	0.553
	(-0.563)	(0.525)	(0.773)	(0.895)	(0.861)
Book-To-Market	0.165	-0.107**	-0.165**	-0.388	-0.842
	(0.544)	(-2.177)	(-2.111)	(-1.229)	(-1.001)
Employees	-0.125	0.0680	0.109	0.268	0.591
	(-0.816)	(1.060)	(1.221)	(1.105)	(1.030)
R&D	-0.155	0.0172	0.0539	0.195	0.483
	(-1.480)	(0.487)	(1.105)	(1.399)	(1.402)
Sales	-0.0536	0.0462*	0.0675**	0.150*	0.316
	(-0.827)	(1.860)	(2.074)	(1.744)	(1.503)
PPE	0.133	-0.212***	-0.285***	-0.569**	-1.144*
	(0.726)	(-3.827)	(-3.813)	(-2.358)	(-1.914)
Observations	4,113	4,113	4,113	4,113	4,113
Firm FEs	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES

Notes: This table presents quantile regression results from the Eq. (1) regression with *Exploratory Patent Portfolio* as the dependent variable. Columns (1)-(5) are the baseline regressions with the vector of appropriate control variables along with firm and year fixed effects for the quantiles of 10, 25, 50, 75, and 90, respectively. The unit of observation is at the firm-year level. The standard errors are clustered by firm. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Table 4

Panel B: Results with Dropped Transition Period

	(1) *Exploratory Patent Portfolio*	(2) *Exploratory Patent Portfolio*
Affected by GDPR	0.378***	0.382**
	(2.70)	(2.53)
Assets		0.046
		(0.28)
Leverage		-0.009
		(-0.04)
Book-to-Market		-0.397
		(-1.43)
Employees		0.067
		(0.40)
R&D		0.087
		(0.97)
Sales		0.141**
		(2.35)
PPE		-0.268*
		(-1.81)
Observations	3,379	2,959
R-squared	0.248	0.228
Firm FEs	YES	YES
Year FEs	YES	YES

Notes: This table presents difference-in-differences regression results from the Eq. (1) regression with *Exploratory Patent Portfolio* as the dependent variable, but with observations for the years 2016 to 2018 dropped. Column (1) includes the baseline regression with firm and year fixed effects. Column (2) adds the vector of appropriate control variables. The unit of observation is at the firm-year level. The standard errors are clustered by firm. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Table 5

Cross-sectional analyses

	B2C vs. B2B		Customer Demand Volatility	
	(1) B2C	(2) B2B	(3) High	(4) Low
Affected by GDPR	0.769**	0.055	0.656**	0.014
	(2.56)	(0.48)	(2.25)	(0.18)
p-value	*0.026*		*0.033*	
F-stat	*4.973*		*4.580*	
Observations	1,188	2,912	1,204	1,528
R-squared	0.201	0.216	0.190	0.294
Controls	YES	YES	YES	YES
Firm FEs	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES

Notes: This table reports cross-sectional analyses of innovation output strategy focus around GDPR. The analyses present difference-in-differences regression results from the Eq. (1) regression with *Exploratory Patent Portfolio*. Between Columns (1) and (2), the sample is split based on *B2C Dummy*, or whether firms are in a B2C or B2B industry. Columns (3) and (4) mirror the presentation in Columns (1) and (2), but the sample is split based on whether the customer demand volatility level *Customer Demand Volatility* is in the top three deciles versus the bottom three deciles in the sample in a given year. All columns include the baseline regression with the full set of appropriate control variables, as well as firm and year fixed effects. The unit of observation is at the firm-year level. The standard errors are clustered by firm. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). t-statistics are in the parentheses. Detailed definitions of all variables are provided in Appendix B.

Table 6

Panel A: Descriptive Statistics for Innovation Input Sample

	N	*Mean*	*Std. Dev.*	*25%*	*Median*	*75%*
Explore-to-Exploit Salary Ratio	2,838	0.418	0.655	0.075	0.197	0.449
Exploratory Employee Salary Ratio	2,838	0.114	0.137	0.016	0.062	0.157
Exploitative Employee Salary Ratio	2,838	0.392	0.270	0.133	0.368	0.637
Affected by GDPR	2,838	0.125	0.331	0	0	0
EU Rev Exposure	2,838	0.186	0.389	0	0	0
Post-GDPR	2,838	0.704	0.457	0	1	1
Assets	2,838	6.676	1.726	5.637	6.725	7.848
Leverage	2,819	0.241	0.233	0.034	0.187	0.389
Book-to-Market	2,652	0.517	0.450	0.227	0.431	0.704

Notes: This table presents descriptive statistics for the main dependent and control variables used in regressions for the innovation input test. Detailed definitions of all variables are provided in Appendix B.

Table 6

Panel B: Industry Distribution for Innovation Input Sample

2-Digit SIC Code	*Industry Title*	*Frequency*	*Percent*
10-14	Mining	117	4.12
15-17	Construction	43	1.52
20-39	Manufacturing	1,275	44.93
40-49	Transportation, Communications, Electric, Gas, And Sanitary Services	213	7.51
50-51	Wholesale Trade	70	2.47
52-59	Retail Trade	35	1.23
60-67	Finance, Insurance, And Real Estate	643	22.66
70-89	Services	442	15.57
Total		**2,838**	**100**

Notes: This table presents descriptive statistics for the industry of firm-year observations, by 2-digit SIC code, in the innovation input test sample.

Table 6

Panel C: Year Distribution for Innovation Input Sample

Year	*Frequency*	*Percent*
2013	258	9.09
2014	283	9.97
2015	299	10.54
2016	316	11.10
2017	329	11.56
2018	343	12.12
2019	337	11.91
2020	345	12.16
2021	328	11.56
Total	**2,838**	**100**

Notes: This table presents descriptive statistics for firm-year observations in the innovation input sample.

Table 6

Panel D: The Effect of GDPR on Innovation Strategy Focus: Results for Input Tests

	(1)	(2)	(3)	(4)	(5)	(6)
	Explore-to-Exploit Salary Ratio	*Exploratory Employee Salary Ratio*	*Exploitative Employee Salary Ratio*	*Explore-to-Exploit Salary Ratio*	*Exploratory Employee Salary Ratio*	*Exploitative Employee Salary Ratio*
Affected by GDPR	0.086*	0.004	-0.012	0.098**	0.006	-0.013
	(1.75)	(0.65)	(-1.52)	(2.20)	(1.26)	(-1.59)
Assets				0.020	0.001	-0.005
				(1.26)	(0.31)	(-0.91)
Leverage				-0.089*	-0.010	0.003
				(-1.95)	(-1.55)	(0.22)
Book-to-Market				0.048**	0.006	-0.003
				(2.33)	(1.63)	(-0.65)
Observations	2,838	2,838	2,838	2,629	2,629	2,629
R-Squared	0.928	0.964	0.976	0.932	0.965	0.975
Firm FEs	YES	YES	YES	YES	YES	YES
Year FEs	YES	YES	YES	YES	YES	YES

Notes: This table presents difference-in-differences regression results from the Eq. (1) regression with either the innovation input measure *Explore-to-Exploit Salary Ratio*, *Exploratory Employee Salary Ratio*, or *Exploitative Employee Salary Ratio* as the dependent variables. Column (1) includes the baseline regression with *Explore-to-Exploit Salary Ratio* and firm and year fixed effects. Column (2) is the baseline regression with firm and year fixed effects except with *Exploratory Employee Salary Ratio*, and Column (3) is the baseline regression with firm and year fixed effects except with *Exploitative Employee Salary Ratio.* Column (4-6) adds the vector of appropriate control variables to the regressions run in Columns (1-3). The unit of observation is at the firm-year level. The standard errors are clustered by firm. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Table 7

Panel A: Descriptive Statistics for SMOTE Sample

	N	*Mean*	*Std. Dev.*	*25%*	*Median*	*75%*
Exploratory Patent Portfolio	5,992	0.250	1.765	0	0.002	0.042
Affected by GDPR	5,992	0.271	0.445	0	0	1
EU Rev Exposure	5,992	0.500	0.500	0	0.500	1
Post-GDPR	5,992	0.532	0.499	0	1	1
Assets	5,992	7.729	2.206	6.154	7.743	9.301
Leverage	5,992	0.243	0.186	0.085	0.236	0.356
Book-to-Market	5,992	0.451	0.356	0.217	0.373	0.594
Employees	5,992	1.436	2.099	0.021	1.591	2.991
R&D	5,992	3.010	2.551	0	3.235	4.708
Sales	5,992	7.257	2.257	5.919	7.477	8.837
PPE	5,992	6.394	2.526	4.755	6.484	8.134

Notes: This table presents descriptive statistics for the main dependent variable and control variables used in regressions run on the innovation output test dataset, balanced through data expansion using the synthetic minority over-sampling machine learning technique (SMOTE).

Table 7

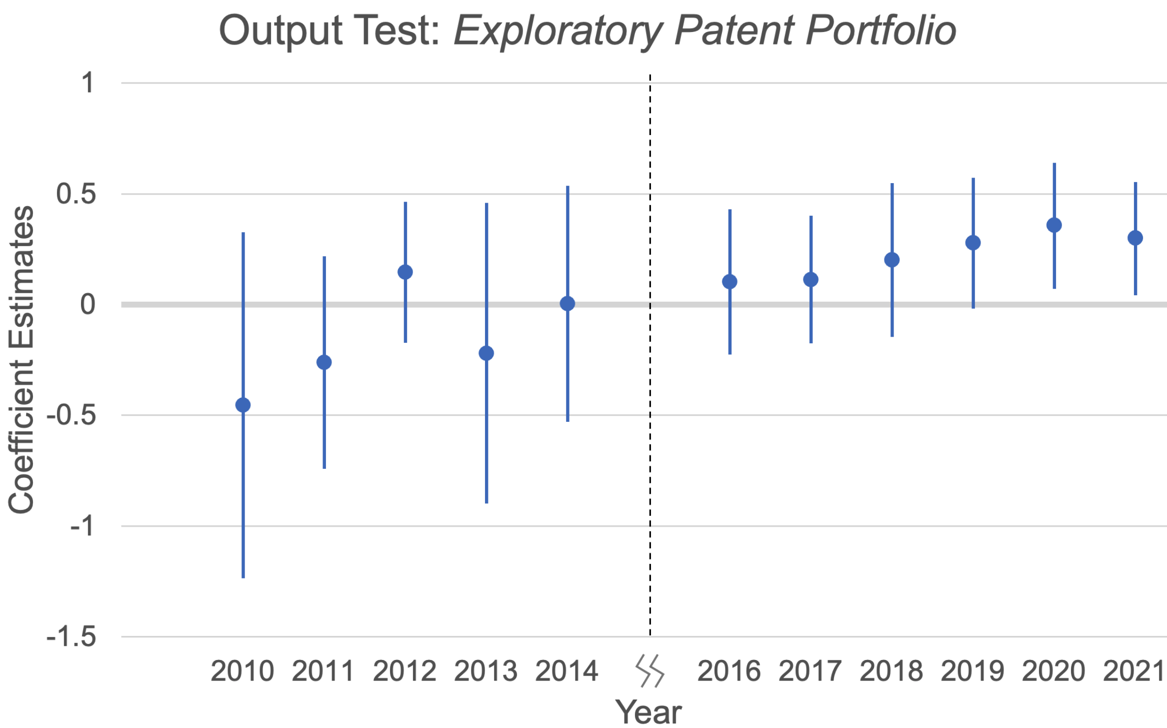
Panel B: Results with SMOTE-generated dataset

	(1) *Exploratory Patent Portfolio*	(2) *Exploratory Patent Portfolio*
Affected by GDPR	0.180**	0.184**
	(1.98)	(2.03)
EU Rev Exposure	-0.317***	-0.274***
	(-4.78)	(-4.08)
Post-GDPR	-0.317***	-0.292***
	(-4.93)	(-4.52)
Assets		0.058*
		(1.74)
Leverage		-0.306**
		(-2.22)
Book-to-Market		-0.100
		(-1.47)
Employees		-0.072**
		(-2.31)
R&D		-0.078***
		(-7.63)
Sales		0.080**
		(2.12)
PPE		-0.021
		(-0.76)
Observations	5,992	5,992
R-squared	0.009	0.020

Notes: This table presents difference-in-differences regression results from estimating the Eq. (2) regression with *Exploratory Patent Portfolio* as the dependent variable, run on the dataset balanced through data expansion using the synthetic minority over-sampling machine learning technique (SMOTE). Columns (1) and (2) study the innovation output variable *Exploratory Patent Portfolio* without and with appropriate control variables, respectively. The unit of observation is at the firm-year level. The values in the parentheses represent t-statistics. ***, **, * indicates statistical significance at 1%, 5%, and 10% respectively (two-tailed). Detailed definitions of all variables are provided in Appendix B.

Figure 1

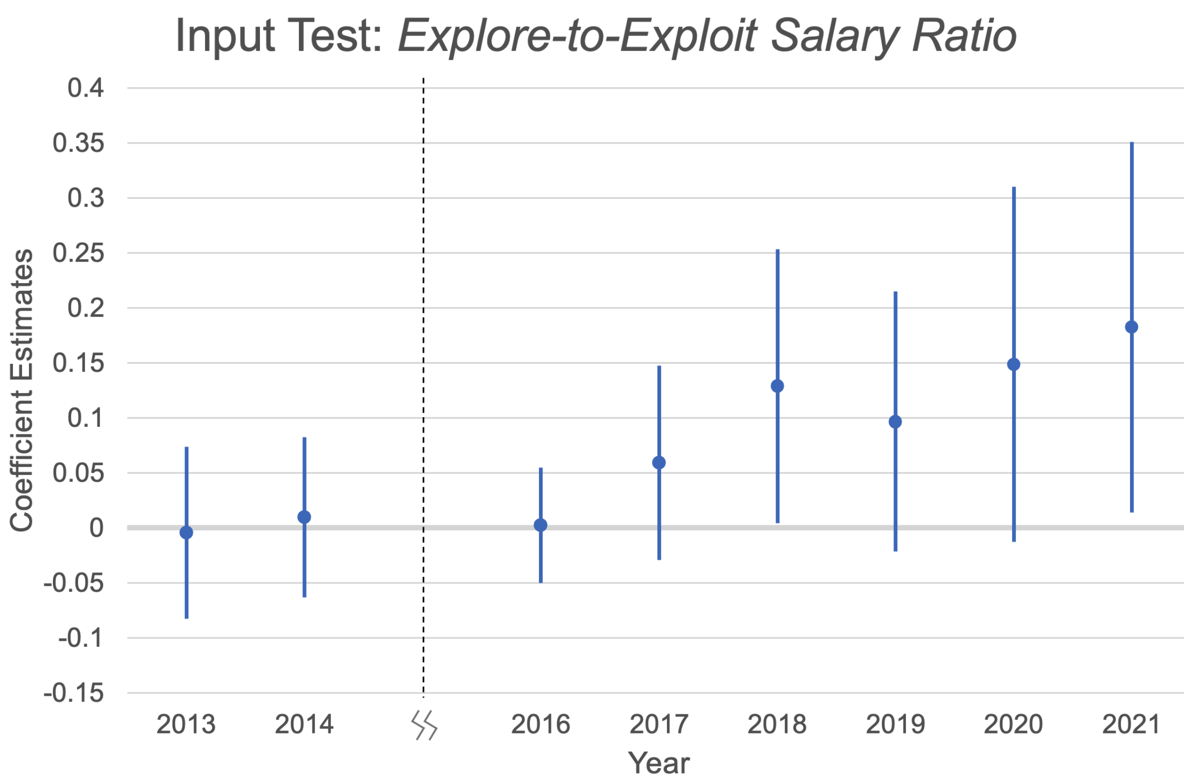
Output Test: *Exploratory Patent Portfolio*



Notes: This figure displays the year-by-year coefficients from estimating the Eq. (1) difference-in-differences regression model with *Exploratory Patent Portfolio* as the dependent variable, with all appropriate controls, firm and year fixed effects, and standard error clustering by firm. The omitted year is 2015. The definition of *Exploratory Patent Portfolio* is in Appendix B.

Figure 2

Input Test: *Explore-to-Exploit Salary Ratio*



Notes: This figure displays the year-by-year coefficients from estimating the Eq. (1) difference-in-differences regression model with *Explore-to-Exploit Salary Ratio* as the dependent variable, with all appropriate controls, firm and year fixed effects, and standard error clustering by firm. The omitted year is 2015. The definition of *Explore-to-Exploit Salary Ratio* is in Appendix B.

Appendix A. Sample Selection Criteria

This table presents the sample selection criteria for my main analyses.

Criteria	Firm-year observations	Number of firms
Firm-year observations of public U.S. firms on CRSP/Compustat from 2010-2021	**65,925**	**9,647**
Firm-year observations of public U.S firms with e-commerce or analytics technologies on websites from 2010-2021	**10,235**	**1,814**
Innovation output test (patent-based):		
After merging with Kogan et al. (2017) extended patent data to construct the main dependent variable:	5,183	868
After keeping only observations that adhere to the innovation output regression test design:	4,662	533
Innovation input test (workforce-based):		
After merging with Revelio Labs workforce sample:	6,532	978
After keeping only observations that adhere to the innovation input regression test design:	2,838	383

Appendix B. Variable Definitions

Variable	Definition
Exploratory Patent Portfolio	One minus the Balsmeier et al. (2017) variable that calculates the similarity between the distribution of patents across 3-digit CPC technology classes applied by a given firm in year t and the same firm's prior distribution of patents across technology classes. The distribution is of the number of patents (in year of application) per technology class and firm. The variable ranges from 0 and 100, where the 0 end indicates exploitation and the 100 end indicates exploration. Patent data from PatentsView and Kogan et al. (2017).
Exploratory Patenting	The natural log of one plus the number of patents filed in a new technology class by a firm in a given year. Patent data from PatentsView and Kogan et al. (2017).
Exploitative Patenting	The natural log of one plus the number of patents filed in a technology class previously filed in by a firm in a given year. Patent data from PatentsView and Kogan et al. (2017).
Explore-to-Exploit Salary Ratio	The total salaries paid to exploratory innovation role employees divided by the total salaries paid to exploitative innovation role employees in a firm within a year. Workforce data from Revelio Labs.
Exploratory Employee Salary Ratio	The total salaries paid to exploratory innovation role employees divided by the total salaries paid to all employees in a firm within a year. Workforce data from Revelio Labs.
Exploitative Employee Salary Ratio	The total salaries paid to exploitative innovation role employees divided by the total salaries paid to all employees in a firm within a year. Workforce data from Revelio Labs.
EU Rev Exposure	A dummy that equals 1 if a firm earns significant percentage of revenues from the EU in 2015, 0 otherwise, where significance is determined by whether revenues are disclosed in the 10-K footnotes as from the EU. Data for revenue significance by geography is collected from Compustat Segments.
Post-GDPR	A dummy that equals 1 if a firm-year observation is in the year or after GDPR passage in 2016, 0 otherwise.
Affected by GDPR	The interaction term of *EU Rev Exposure* with *Post-GDPR*.
Assets	The natural logarithm of total assets (AT) from Compustat.
Leverage	Total liabilities divided by total assets (DLTT+DLC)/AT from Compustat.
Book-to-Market	Book value of equity divided by market capitalization (CEQ+TXDB)/(PRCC_F*CSHO) from CRSP/Compustat.
Employees	The natural logarithm of employees (EMP) in the prior year from Compustat.

R&D	The natural logarithm of research and development expense (XRD) in the prior year from Compustat, with missing values replaced with 0, in accordance with Koh and Reeb (2015).
Sales	The natural logarithm of sales (REVT) in the prior year from Compustat.
PPE	The natural logarithm of total gross property, plant and equipment (PPEGT) in the prior year from Compustat.
B2C Dummy	A dummy that equals 1 for a firm in a B2C 4-digit SIC industry, 0 for a firm in a B2B 4-digit SIC industry, based on classification from Tacheva et al. (2020).
Customer Demand Volatility	The standard deviation of revenues of firms within an SIC 2-digit industry in a given year. Data on revenues (REVT) from Compustat.
Market Reaction to GDPR Approach Plan	The stock price return to GDPR-affected treatment firms upon the event of the European Council first reaching a general approach on GDPR on June 15, 2015. Defined as the price on the event date minus the price the day before the event, divided by the price the day before the event. Data from CRSP.
Market Reaction to GDPR Implementation	The stock price return to GDPR-affected treatment firms upon the implementation or enforcement of GDPR on May 25, 2018. Defined as the price on the event date minus the price the day before the event, divided by the price the day before the event. Data from CRSP.

**All continuous unbounded variables are winsorized at the 1st and 99th percentile.*

Appendix C. Discussions of Data in the Media

Below are quotes that support common positive sentiments about data:

- *The Economist* article from 2017/05/06 (The Economist, 2017): "The world's most valuable resource is no longer oil, but data."
- *New York Times* article from 2018/05/28 (Abrahamian, 2018): "Data is currency; creating and holding it is power."
- *New York Times* article from 2021/02/19 (Deming, 2021): "[Data has] increasing value as an economic resource…"; "'Data is the new oil.'"
- *New York Times* article from 2022/05/12 (Ovide, 2022): "Tech companies… mostly unknown data middlemen, and even the local supermarket harvest any morsel of data on us that might help their businesses."; data is good for all types of business and the economy.
- Laura Veldkamp (Veldkamp, 2023a): "[Data has] central importance to our modern economy"; the most valuable firms today are valuable because of their data.

Appendix D. Anecdotal Validation of Customer Data's Value

I present anecdotal evidence from Fossil Group's 2018 10-K that discusses its use of customer data to generate insights, innovate, and succeed.

<u>"Owned Brands"</u> (page 1):

- "Our **consumer-first mindset** drives every decision we make. By capitalizing on major fashion trends and **leveraging proprietary data and insights**, we are able to deliver **relevant, high-value product and experiences** to consumers across a diverse range of price points, **style preferences** and **geographies**."

<u>"Building Strong Brands"</u> (page 3):

- "Our **product designs are fueled** by a combination of **creativity**, fashion trends and **consumer insights**. Over the past 30 plus years, we have built an incredible in-house design team that works in partnership with our **consumer insights** and trend teams to **ideate, design, test and deliver new product concepts to market**. We also employ more than 200 research and development ("R&D") team members who focus on **innovation and product development** across our watch and smartwatch categories...
- ...In order to respond to and capitalize on fast-paced changes in the global marketplace, we have created a process that allows us to **design and develop consumer insight driven product** in as little as 30 days. We have found speed coupled with **insight-driven product** to be a true differentiator and **key revenue driver** across our business...
- ...We are also able to deliver a **high level of personalization** through the **consumer insight and predictive analytics capabilities** we have built over the past few years and through our partnerships with leading **online** third-party retailers."

<u>"Operating Strategy"</u> (page 4):

- "Our goal is to **drive shareholder value** by **increasing earnings** and making a positive impact on our people, planet and communities. While we currently operate in a challenging business environment we are leveraging our business strengths while continuing to lead a significant internal transformation to strengthen our business model. We plan to achieve our **business strategy** by focusing on the following strategic initiatives...

- ...We are focused on improving our overall profitability through revenue-management strategies to price and position our products optimally and most effectively...
- ...We are driving innovation across every aspect of our business. We continue to form new partnerships with leading brands, which helps us leverage our vertical structure, size and scale. We are bringing new and innovative functions to smartwatches across both our hybrid and display platforms—as well as expanding our distribution and increasing our addressable market. We are also **driving innovations** in traditional watches and our accessory categories **through our investment** in R&D and **data analytics**...
- We are investing in our **digital infrastructure** and commerce capabilities across our owned and third-party **e-commerce sites**. We plan to continue to expand our **digital capabilities** for **consumer insight, analytics and the use of data** throughout our organization, as well as shifting to a new marketing and commerce platform to drive greater personalization and a better consumer experience."

"Any material disruption of our information systems could disrupt our business and reduce our sales" (page 17):

- "We are **increasingly dependent on information systems to operate our websites, process transactions, manage inventory, monitor sales and purchase, sell and ship goods on a timely basis**...
- ...In addition, we have **e-commerce** and **other websites in the U.S. and internationally**. In addition to changing consumer preferences and buying trends relating to Internet usage, **we are vulnerable** to certain additional risks and uncertainties associated with the Internet, including changes in required technology interfaces, website downtime and other technical failures, security breaches, and **consumer privacy concerns**. Our **failure to successfully respond to these risks and uncertainties could reduce e-commerce sales, increase costs and damage the reputation of our brands**."

Appendix E. Anecdotal GDPR Validation

I present anecdotal evidence that validates GDPR as a plausibly exogenous and significant negative shock to affected firms' data value.

Exhibit 1. Annual report excerpts about GDPR's effect on the collection and analysis of consumer information

<u>Activision Blizzard 2018 10-K:</u>

- "We **collect and store information about our consumers**, including consumers who play these games. In addition, we collect and store information about our employees. We are **subject to laws from a variety of jurisdictions regarding privacy and the protection of this information, including the E.U.'s General Data Protection Regulation (the "GDPR")**... Failure to comply with any of these laws or regulations may increase our costs, subject us to expensive and distracting government investigations, and result in substantial fines."

<u>Groupon 2018 10-K:</u>

- "**We are subject to a variety of federal, state and international laws and regulations governing consumer data**. The General Data Protection Regulation ("GDPR"), which was recently adopted by the European Union became effective in May 2018, **requires companies to satisfy new requirements regarding the handling of personal and sensitive data, including its collection, use, protection and the ability of persons whose data is stored to correct or delete such data about themselves. Complying with the GDPR caused us to update certain business practices and systems**. Non-compliance with GDPR could result in proceedings against us by governmental entities or others and fines up to the greater of €20 million or 4% of annual global revenue... As a result of GDPR, in particular, we may also experience **difficulty retaining or obtaining new European or multi-national customers**..."

<u>Twitter 2022 10-K:</u>

- "A number of proposals have recently been adopted or are currently pending before federal, state and foreign legislative and regulatory bodies that could significantly affect our business... For example, the **GDPR imposes stringent operational requirements for entities processing personal information** and significant penalties for non-compliance, including fines of up to €20 million or 4% of total worldwide revenue, whichever is higher...Moreover, the **GDPR and other similar regulations require companies to give specific types of notice and in some cases seek consent from consumers and other data subjects before collecting or using their data for certain purposes**..."

Exhibit 2. Annual report excerpts about awareness and anticipation of GDPR as early as its 2016 passage

Activision Blizzard 2016 10-K (with fiscal year end 12/31/2016):

- "For example, the **E.U.'s General Data Protection Regulation (the "GDPR")**, which will come into effect in May 2018, imposes a range of new compliance obligations for us and other companies with European users, and increases financial penalties for noncompliance significantly."

Exhibit 3. Annual report excerpts about enforcement of GDPR

Activision Blizzard 2018 10-K:

- "The laws and regulations concerning data privacy are continually evolving. **Failure to comply with these laws and regulations could harm our business**.
- ...We are subject to laws from a variety of jurisdictions regarding privacy and the protection of this information, including the E.U.'s General Data Protection Regulation (the "GDPR")...
- ...If we fail to comply with our posted privacy policies, EULAs, or terms of service, or if we fail to comply with existing privacy-related or data protection laws and regulations, it **could result in proceedings or litigation against us by governmental authorities or others, which could result in fines or judgments against us, damage our reputation, impact our financial condition, and harm our business**. If regulators, the media, consumers, or employees raise any concerns about our privacy and data protection or consumer protection practices, even if unfounded, this **could also result in fines or judgments against us, damage our reputation, negatively impact our financial condition, or damage our business**."

<u>Groupon 2018 10-K:</u>

- "**Failure to comply with** federal, state and **international privacy laws and regulations**, or the expansion of current or the enactment of new privacy laws or regulations, **could adversely affect our business**.
- ...**Noncompliance could result in proceedings against us by governmental entities or others and fines. For example, fines under GDPR could be up to the greater of €20 million or 4% of annual global revenue and damage our reputation and brand**.
- ...**Any failure, or perceived failure, by us to comply with our posted privacy policies or with any data-related consent orders, Federal Trade Commission requirements or orders or other federal, state or international privacy or consumer protection-related laws, regulations or industry self-regulatory principles could result in claims, proceedings or actions against us by governmental entities or other third-parties or other liabilities, which could adversely affect our business. In addition, a failure or perceived failure to comply with industry standards or with our own privacy policies and practices could result in a loss of subscribers or merchants and adversely affect our business**."

<u>Twitter 2018 10-K:</u>

- "...the European Union, or EU, and its member states traditionally have taken broader views as to types of data that are subject to privacy and data protection, and have imposed greater legal obligations on companies in this regard. For example, the GDPR has been adopted and went into effect in May 2018. The GDPR includes **more stringent operational requirements** for entities processing personal information and **significant penalties for non-compliance, including fines of up to €20 million or 4% of total worldwide revenue, whichever is higher**."

Exhibit 4. Meta Conference Call Transcript Excerpts

Before GDPR:

- "*...with regards to GDPR and other initiatives around data usage...we believe that European MAU and DAU may be flat to slightly down sequentially in Q2 as a result of the GDPR roll out...that's just based on what we're expecting, given that you're having to bring people through these consent flows*" - David Wehner, CFO, (2018 Q1 earnings call transcript on April 25, 2018)

After GDPR:

- "*GDPR was an important moment for our industry. We did see a decline in monthly actives in Europe – down by about 1 million people as a result.*" - Mark Zuckerberg, CEO, 2018 Q2 earnings call transcript on July 25, 2018)

Appendix F. Manual Classification of Innovation Job Roles

I present my classification, through manual textual analysis, of different types of job roles into innovation strategy types.

Job Roles (50 Role Granularity)	**Job Roles (150 Role Granularity)**	**Job Category**	**Dummy for Exploratory Job**
Legal	Compliance	Admin	.
Legal	Fraud Analyst	Admin	.
Legal	Legal	Admin	.
Recruiter	Recruiter	Admin	.
Coordinator	Coach	Admin	.
Coordinator	Coordinator	Admin	.
Coordinator	Student Intern	Admin	.
Coordinator	Corporate Trainer	Admin	.
Development Manager	Training Facilitator	Admin	.
Development Manager	Development Manager	Admin	1
Operations Administrator	Operations Administrator	Admin	0
Operations Administrator	Support Staff	Admin	.
Operations Administrator	Information Specialist	Admin	.
Operations Administrator	Facilities Manager	Admin	.
Human Resources Specialist	HR Business Partner	Admin	.
Human Resources Specialist	Payroll Specialist	Admin	.
Human Resources Specialist	Human Resources Specialist	Admin	.
Human Resources Specialist	Benefits Specialist	Admin	.
Cashier	Cleaner	Sales	.
Cashier	Conseiller commercial	Sales	.
Cashier	Pharmacy Technician	Sales	.
Cashier	Cashier	Sales	.
Crew Member	Crew Member	Sales	.
Crew Member	Restaurant Manager	Sales	.
Merchandiser	Stylist	Sales	.
Merchandiser	Merchandiser	Sales	.
Receptionist	Security Specialist	Sales	.
Receptionist	Pilot	Sales	.
Receptionist	Receptionist	Sales	.
Retail Sales	Genius	Sales	.
Retail Sales	Branch Manager	Sales	.
Retail Sales	Sales Service Representative	Sales	0
Retail Sales	Loss Prevention	Sales	.
Retail Sales	Retail Sales	Sales	.
Product Manager	Product Manager	Sales	1

Product Manager	Corporate Strategy	Sales	1
Product Manager	Market Research	Sales	1
Sales Associate	Customer Success Specialist	Sales	0
Sales Associate	Sales Engineer	Sales	0
Sales Associate	Account Manager	Sales	1
Sales Associate	Inside Sales	Sales	.
Sales Associate	Commercial Manager	Sales	1
Sales Associate	Sales Associate	Sales	0
Customer Service	Sales Support	Sales	0
Customer Service	Customer Support	Sales	0
Customer Service	Customer Service	Sales	0
Customer Service	Vendor Management	Sales	0
Customer Service	Customer Experience Specialist	Sales	0
Customer Service	Subject Matter Expert	Sales	0
Sales Representative	Sales Representative	Sales	.
Sales Representative	Sales Training Specialist	Sales	.
Solutions Specialist	Solutions Specialist	Sales	.
Accountant	Accountant	Finance	.
Accountant	Auditor	Finance	.
Accountant	Financial Controller	Finance	.
Accountant	Financial Analyst	Finance	.
Client Services	Client Services	Finance	.
Client Services	Business Support	Finance	.
Claims Specialist	Collections Specialist	Finance	.
Claims Specialist	Claims Specialist	Finance	.
Financial Advisor	Financial Advisor	Finance	.
Financial Advisor	Wealth Manager	Finance	.
Financial Advisor	Agent	Finance	.
Financial Advisor	Property Manager	Finance	.
Financial Advisor	Realtor	Finance	.
Financial Advisor	Banker	Finance	.
Billing Specialist	Billing Specialist	Finance	.
Investment Specialist	Investment Specialist	Finance	.
Investment Specialist	Economist	Finance	.
Investment Specialist	Risk Analyst	Finance	.
QA Tester	QA Tester	Engineer	0
Technician	Technical Support Engineer	Engineer	0
Technician	Technician	Engineer	0
Data Analyst	Data Scientist	Engineer	0
Data Analyst	Data Analyst	Engineer	0
Data Analyst	Business Analyst	Engineer	1

IT Specialist	Technical Support	Engineer	0
IT Specialist	Network Specialist	Engineer	0
IT Specialist	IT Specialist	Engineer	0
IT Specialist	Database Administrator	Engineer	0
IT Specialist	IT Analyst	Engineer	0
IT Specialist	Application Support	Engineer	0
Delivery Manager	Business Process Specialist	Engineer	0
Delivery Manager	Service Delivery Manager	Engineer	0
Delivery Manager	Delivery Manager	Engineer	0
Delivery Manager	Transformation Specialist	Engineer	0
Machine Operator	Machine Operator	Engineer	0
Machine Operator	Foreman	Engineer	0
Machine Operator	Mechanic	Engineer	0
Quality Assurance	Laboratory Technician	Engineer	0
Quality Assurance	Quality Assurance	Engineer	0
Software Engineer	Technology Analyst	Engineer	0
Software Engineer	Software Developer	Engineer	1
Software Engineer	Systems Engineer	Engineer	1
Software Engineer	Software Engineer	Engineer	0
Software Engineer	Technology Lead	Engineer	1
Software Engineer	DevOps Engineer	Engineer	0
Software Engineer	Web Developer	Engineer	.
Software Engineer	Data Engineer	Engineer	0
IT Project Manager	SAP Consultant	Engineer	0
IT Project Manager	IT Project Manager	Engineer	1
Mechanical Engineer	Automation Engineer	Engineer	0
Mechanical Engineer	Mechanical Engineer	Engineer	1
Mechanical Engineer	Structural Engineer	Engineer	0
Mechanical Engineer	Process Engineer	Engineer	1
Mechanical Engineer	Electrical Engineer	Engineer	.
Production Operator	Production Operator	Engineer	0
Production Operator	Manufacturing Associate	Engineer	0
Production Operator	Quality Engineer	Engineer	0
Technical Architect	Documentation Specialist	Engineer	0
Technical Architect	Construction Manager	Engineer	0
Technical Architect	Contracts Specialist	Engineer	0
Technical Architect	Technical Architect	Engineer	1
Technical Architect	Planning Manager	Engineer	0
Application Engineer	Test Engineer	Engineer	0
Application Engineer	Application Engineer	Engineer	1
Infrastructure Engineer	Infrastructure Engineer	Engineer	0

Infrastructure Engineer	Information Security	Engineer	.
Sustainability Specialist	Sustainability Specialist	Engineer	.
Sustainability Specialist	Safety Officer	Engineer	.
Designer	Graphic Designer	Marketing	1
Designer	Technical Writer	Marketing	.
Designer	UX Designer	Marketing	.
Designer	Designer	Marketing	1
Producer	Writer	Marketing	.
Producer	Content Specialist	Marketing	.
Producer	Producer	Marketing	.
Marketing	Digital Marketing Specialist	Marketing	.
Marketing	Brand Manager	Marketing	.
Marketing	Marketing	Marketing	.
Communications Specialist	Communications Specialist	Marketing	.
Communications Specialist	Public Relations	Marketing	.
Geologist	Geologist	Scientist	.
Scientist	Scientist	Scientist	.
Medical Rep	Case Manager	Scientist	.
Medical Rep	Medical Rep	Scientist	.
Clinical Research Associate	Regulatory Affairs Associate	Scientist	.
Clinical Research Associate	Clinical Research Associate	Scientist	.
Logistics	Procurement Specialist	Operations	0
Logistics	Logistics	Operations	0
Project Manager	Project Manager	Operations	1
Project Manager	Project Administrator	Operations	0
Operations Manager	Operations Manager	Operations	1
Operations Manager	AM	Operations	1
Operations Manager	Officer	Operations	1
Operations Manager	MD	Operations	1
Business Operations	Business Operations	Operations	0
Distribution Specialist	Operations Coordinator	Operations	0
Distribution Specialist	Distribution Specialist	Operations	0
Distribution Specialist	Driver	Operations	0

Appendix G. Examples of Exploratory and Exploitative Jobs

I present examples of job postings for a firm in my sample, Coca-Cola, that represent jobs that contribute to exploratory and exploitative innovation.

Exploratory Job Role: Coca-Cola Scientist IV

Scientist IV

The Coca-Cola Company · Atlanta, GA · 4 days ago · **Be an early applicant**

On-site · Full-time

10,001+ employees · Food and Beverage Services

Skills: Cell Biology, High-Performance Liquid Chromatography (HPLC), +8 more

About the job

Duties

The Coca Cola Company has an opening for a Scientist IV in Atlanta, GA. Duties are to be responsible for leading all aspects of new product development from concept to commercialization. Work closely with several cross-functional groups (Marketing, Knowledge & Insights, Technical Operations, Quality, etc.) to lead and influence new product innovation in Retail & Food Service Channels. The position will perform the following:

- Responsible for planning, organizing, and executing new product development activities to support business growth and continuity. Designs, tests and execute activities/processes to
- ensure that all cycles of product development process are executed successfully and on time.
- Provide technical leadership and expertise to projects from inception through commercialization and launch. Supports other development projects, operations and related activities as necessary.
- Responsible for creating and managing technical timeline, ensuring product brief is complete and aligned upon, ensures risks analysis is complete and communicated. Executes projects within given timelines to meet desired business objectives (consumer, financial, operational, etc.). Exercises deep cross-functional involvement and alignment with project teams and management.
- Apply scientific, engineering and consumer insights principles in research, formulation, processing and commercialization of beverages.
- Identify, evaluate, and select new ingredients, developments, trends & technologies in food and beverage industry to guide product development initiatives. Partners with internal and external parties to stay abreast of our consumer's needs and identifies actions plans to address those needs. Drives and leverages internal and external suppliers to deliver ingredient and product innovation.

Education

Requires a minimum of a Master's Degree, or foreign equivalent, in Food Science, Chemical Engineering, or related field plus three years of experience in job offered, related position, or research assistant experience while pursuing a post-bachelor's degree.

Experience

Experience must include 3 years of experience developing and launching beverage or food products for a food or beverage company; 3 years of experience evaluating the chemistry of flavors, food ingredients, processing, packaging, nutrition, and stability testing. 3 years of experience working within a food science laboratory. 3 years of experience working with cross-functional teams ; 3 years of experience leading a food science laboratory and junior scientists.

Skills

Product Development; Leadership; Chemistry; Influencing; Continual Improvement Process; Environmental Science; Sensory Processing; Researching; organization; Microbiology Laboratory; Project Management; Food Sciences; Food Technology; Communication; Laboratory Testing; Data Compilation; Quality Control (QC); Food Safety Management; Green Solutions

Exploitative Job Role: Coca-Cola Advisor for Customer Logistics and Supply Chain

Advisor, Customer Logistics and Supply Chain

The Coca-Cola Company · Atlanta, GA · 19 hours ago

Full-time

10,001+ employees · Food and Beverage Services

Skills: Attention to Detail, Social Influence, +8 more

About the job

This role is responsible for providing dedicated support for our Retail, Bottler, Distributor, McDonald's customers and Business partners by processing orders and inquiries within the Order To Cash (OTC) Supply Chain organization. The Advisor, Customer Logistics and Supply Chain Specialist will research, influence and resolve issues for our Customers and Business partners using Coca-Cola North America (CCNA) order management system & tools based on our established service level agreements.

Key Activities

- Single point of contact for our customers across Business units
- Partner with sales teams and brokers to address customer satisfaction needs related to pricing, delivery method changes, account management and strategic projects (product launches, packing changes etc.)
- Partner with Product supply, Supply planning, logistics and transportation teams to influence and resolve order flow concerns (late trucks, dwell time, refused deliveries)
- Responsible for managing phone calls and emails from customers, internal stakeholders and partners and accurately tracking and resolving the business need
- Customer order management – Acts as liaison between external departments and customers to process order changes, communicate all order changes, track and reschedule customer orders to meet customer requested delivery dates
- Apply best practices and business knowledge to make timely decisions and resolve issues with product orders to meet requested customer delivery dates
- Proactively manage order flow, communication of all In Full issues and partner with transportation to ensure delivery appointments and pick-up appointments are set timely to mitigate order failures
- Recognize and track trends with customer issues, evaluate and suggest process improvements for Product order management and our partners
- Understand Company goals and performance metrics and improve quality and speed to meet and exceed customer expectations
- Work collaboratively but often independently on daily tasks and resolve escalations that are diverse in scope using strategic thinking, people and company resources
- Build and leverage collaborative relationships with our customers, sales, logistics and other internal partners based on customer specific operations
- Analyze, coordinate and participation in implementation of design projects to support department and or key customer objectives.

Required Skills/Experience

- Strong customer service and relationship background, strategic thinking, effective communication and business writing skills
- Must have strong research or analytical skills, attention to detail, effective problem solver and influencing skills
- Must have a strong sense of urgency and be empowered to make timely and informed decisions
- Building collaborative relationships within Product Order Management (POM), Supply chain/OTC organization and our external partners
- Knowledge of the CCNA Product Supply system, Order Management and Salesforce & SAP a plus. Other systems used include Customer Relationship Management (CRM) Database, MS Office; Outlook, Word, Excel, SharePoint, Genesys
- Ability to excel and contribute in a fast paced and changing work environment with accuracy while meeting Service Level Agreement (SLA's) and deadlines
- Ability to understand overall Company objectives and manage competing project and tasks
- Roles within this organization include teleworking and remote working. Candidate must be able to work independently with minimal daily supervision

Types of additional activities managed

- Expedited Orders
- Customer Order Change Request
- Customer Pick Up
- Transportation Issues
- Dock Cuts
- Ship Withs
- General Product Information
- Plant Redirects
- Over, short and damaged process
- Transportation Method Change
- Duplicate, missing, or incorrect orders