

# Impact of Privacy Regulation on Experimentation and Innovation \*

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## Abstract

Experimentation, particularly through A/B Testing is an increasingly common practice for many digital companies. Privacy regulations such as the General Data Protection Regulation (GDPR), limit the collection and processing of personal data making it more costly to perform experimentation for digital firms operating in the EU or firms with EU-based customers. Therefore, stricter privacy regulation may make it more costly for firms to perform A/B Testing. This might lead to a reduction in the innovative output of these companies as a consequence of not being able to perform this form of experimentation. Using a monthly dataset of mobile apps available on the Google Play Store from June 2017 to May 2019, we examine how the introduction of GDPR in May 2018 affected the use of A/B Testing tools, and the frequency of product updates. We find that the introduction of GDPR led to a reduction in the usage of third-party A/B Testing SDKs by 17%. Yet, we find that following GDPR regulation, the apps that keep using third-party A/B Testing SDKs were 0.3% more likely to make major updates per month, compared to the apps that do not use A/B Testing in the post-GDPR period. As a placebo check, we validated that there were no effects for mobile apps that operate outside the GDPR regime, and that effect is not driven by the use of other SDKs. These results have implications for policymakers, platforms and software developers, since they highlight the potential unintended impact and trade offs associated with privacy regulations.

*Keywords:* Mobile Apps, GDPR, A/B Testing, Innovation, Experimentation, Privacy

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## 1 Introduction

Experimentation is a critical part of how firms develop new products or improve existing ones. Previous studies highlighted numerous benefits of experimentation for innovation, such as evaluating and selecting competing ideas more easily (Luo et al., 2021), allocating resources optimally (Levinthal, 2007), generating and testing more (and riskier) ideas (Fleming and Sorenson, 2003; Koning et al., 2020). With the growing digitization of the economy and the growth of commerce through online platforms, techniques such as A/B Testing have emerged as a disciplined approach for experimentation to develop, test and refine product improvements (Thomke, 2001; Kohavi and Thomke, 2017). While experimentation may benefit consumers (in terms of better product), it often requires firms to collect user data for experimentation. Privacy regulations, such as the General Data Protection Regulation (GDPR), influences the ability of firms to collect and manage data on users (Jia et al., 2021; Goldfarb and Tucker, 2011). As a result, privacy regulations may impact both the decision of firms to use A/B Testing, and also the amount of subsequent experimentation that firms perform using data, which in turn affects their innovative output. In this paper, we investigate how the introduction of GDPR impacted the use of A/B Testing, measured through the use of a third-party A/B Testing Software Development Kit (SDK). We also investigate the impact of GDPR on the release of major product updates by products that use A/B testing SDK's, compared to those that don't.

Software applications need to be continuously revised and updated, and product updates are one of the primary ways that innovations to software products are introduced (Yin et al., 2014; Boudreau, 2012; Wen and Zhu, 2019). When new innovations or software features are created, they are first tested and refined through disciplined experimentation frameworks before it is finalized for the market release (Koning et al., 2020). In particular, A/B Testing enables firms to perform experiments regarding product features and then make data-driven decisions based on the results. However, performing such experiments requires collecting data on users and their actions. The quality, quantity and richness of data collected by firms directly affects their ability to perform experimentation through A/B Testing (Azevedo et al., 2020). Privacy protections, such as the GDPR which became enforced in the EU in May 2018, provides restrictions on how user data can be collected, stored, and managed. Such privacy regulations increase the cost of managing and collecting user data (Goldfarb and Tucker, 2019). As a result, a consequence of privacy regulation may be that it impacts the decision to use A/B Testing as

well as the innovation activity that results as a consequence of experimentation.

There is a growing literature exploring the implications of privacy regulation, particularly in relation to its unintended effects on the market structure of industries impacted by this regulation. For instance, [Peukert et al. \(2022\)](#) find that the enforcement of GDPR led to a greater concentration in the market for trackers. They demonstrate that as a consequence of a stricter privacy regulation, the market for trackers was concentrated in a few large players who could make the costly investment to ensure compliance. [Burford et al. \(2022\)](#) find that the enforcement of GDPR made it more difficult for firms to combine basic technological components, negatively impacting the performance of their products. [Zhao et al. \(2021\)](#) find that the enforcement of GDPR led to a concentration in web traffic among larger retailers, attributed to the increased frictions of customizing and targeting products, which are costly to deal with for smaller retailers. All of these results speak to the broader theoretical argument that while privacy regulations may protect consumers, they increase the costs of compliance which favors the firms with more resources that can bear the costs of compliance, in turn leading to a greater market concentration among those that can eventually use or manage these data ([Campbell et al., 2015](#)). One issue which has not yet been explored is whether privacy regulation impacts the use of experimentation, such as A/B Testing, and whether the use of A/B Testing under a stricter privacy regulation has implications for the consequent innovation itself.

In this paper, we study how the enforcement of a stricter privacy regulation impacted the adoption of experimentation via A/B Testing SDKs, and what implications this subsequently had for innovation. We theorize that the privacy regulation imposes considerable costs on firms to collect and manage user data, which in turn decreases the likelihood of adopting experimentation tools such as third-party A/B Testing SDKs. However, even though experimentation may be more costly under stricter privacy regulations, standardized A/B Testing SDKs ensure that firms are compliant with privacy regulations. As a result, having adopted these SDKs allow firms to experiment with greater ease than what would otherwise have been possible, and in turn to be more innovative (or at least innovate faster) than their competitors. We test these predictions using data from Google Play Store combined with proprietary data on the underlying components (SDKs) used by each of the titles. We study how the enforcement of GDPR, which strengthened privacy regulation for the developers established in the EU as well as the apps targeting European consumers, impacted the adoption of digital experimentation tools such

as A/B Testing SDKs, and what was the impact of stronger privacy regulation on the developers using these tools in terms of the number of product updates they would create. We exploit a number of additional checks, such as testing whether experimentation tools have higher returns contingent on the use of other, non A/B Testing SDKs, or testing whether effects differ for apps with higher quality of ratings or popularity. We also perform a series of placebo checks by comparing against products that are released in markets that are unaffected by GDPR. In line with our arguments, we find that those apps that did continue to use A/B Testing SDKs after the introduction of GDPR are 1.2% more likely to introduce product improvements than those which did not use these tools, only for those apps that should comply with GDPR (i.e., either a company established in the EU or a company that targets EU customers).

These results indicate how the use of privacy regulation has a potentially important impact on the practice of experimentation via A/B Testing tools, which is critical for innovation, especially in digital marketplaces and services. A fast-growing literature has begun to look at the impact of these privacy regulations on the market for digital service providers, online retailers and data stewards ([Peukert et al., 2022](#); [Burford et al., 2022](#); [Zhao et al., 2021](#); [Campbell et al., 2015](#)). Our results complement these studies by suggesting that privacy regulation does impede the adoption of experimentation tools which are critical to innovation. However, at the same time, we also find if A/B Testing SDKs are adopted (i.e., tools that ensure compliance with GDPR), then this can be beneficial for innovation even under heightened privacy regulation, because experimenting or developing new products with the use of these tools provides a greater level of consent ([Godinho de Matos and Adjerid, 2021](#)). This paper contributes to the debate around the impact of privacy regulation on technology ecosystems by demonstrating the impact of GDPR on experimentation and innovation. In addition, we contribute to the growing interest in experimentation ([Koning et al., 2020](#)) and data ([Hartmann and Henkel, 2020](#); [Gregory et al., 2022](#)) as critical assets and activities of digital firm strategy. The results of the present paper show the importance of basic functionality such as A/B Testing tools for experimentation and innovation in digital markets, and how this interacts with broader factors such as privacy regulation which relate to the way data is collected, stored and analyzed.

## 2 Literature Review

### 2.1 Digital Experimentation and Innovation

All firms, but particularly nascent or entrepreneurial ventures, need to make decisions about product and/or service design (Kerr et al., 2014). Since firms always need to make decisions with uncertainty among alternatives, they employ experimentation, which involves a series of trial-and-error changes over a short period of time, to optimize their product offering (Nicholls-Nixon et al., 2000; Agrawal et al., 2021). Specifically, firms generate ideas, test them, and make decisions according to the test results (Koning et al., 2020). By testing the ideas systematically, they can evaluate and select the best one (Thomke, 2001). The importance of an experimental approach to entrepreneurial strategy has been well established, particularly in relation to allowing firms to improve their learning, generate more innovations and in turn lead to greater performance (Camuffo et al., 2020; Gans et al., 2019; Levinthal, 2007; Davis et al., 2016; Thomke, 2001).

Despite its potential benefits, experimentation has traditionally been costly, which prevent many firms (especially smaller firms) from conducting experiments (Thomke, 2001). Over the last decade, the cost of conducting experiments declined significantly making this practice more widespread (Kohavi and Thomke, 2017). This was especially true for digital firms where experimentation has become very easy and affordable due to the availability of A/B Testing tools (Azevedo et al., 2020; Koning et al., 2020). By adopting A/B Testing, digital firms can easily conduct experiments (often several experiments at once) and optimize the design of their products. For example, A/B testing has been used to optimize the placement of web content (Lawrence et al., 2018), improve online advertising policies (Runge et al., 2020), or adjust the social features displayed on networking platforms (Bapna et al., 2016) to achieve higher usage or conversion of their products. The availability of low-cost testing tools does not only make the testing of potential product design ideas easier, but also motivates firms to generate more ideas and embrace data-driven decision-making further (Brynjolfsson and McElheran, 2016), which can translate to even greater performance and innovation for digital firms. For instance, Koning et al. (2020) find that startups adopting A/B Testing have more online page views and higher rates of launching new products.

## 2.2 Online Privacy Regulation

Data is increasingly being considered as a key strategic asset for companies (Gregory et al., 2022). This is particularly true for firms that want to employ data-driven decision making and experimentation as they develop new products and services, because this process inherently requires the collection of personal data (Berman and Israeli, 2022; Sun et al., 2021). In the past several years, privacy laws have begun to be introduced that regulate the collection and processing of personal data. There is a growing literature around the consequence of introducing and enforcing stricter privacy regulations on firms' abilities to obtain and use personal data.

Under the GDPR, informed consent is required from users before collecting data and users are given the right to access or delete the data which have been collected about them (Degeling et al., 2018). This makes it more costly for firms to collect, store and analyze personal data (Bessen et al., 2020). For instance, non-essential data collection which requires user's opt-in consent (e.g. for the purposes of app or site performance, analytics, advertising, etc.) became more difficult, as only 10% of users agreed to provide such consent (Snelders et al., 2020). An unintended consequence of increasing the costs of collecting and storing user data, is that it may have detrimental effects on the use of data-driven decision making. One example is the impact of privacy regulation on the ability to target users with digital advertising (Goldfarb and Tucker, 2011). The requirement for informed consent has also been shown to contribute to the decrease the amount of website pageviews of EU based users (Goldberg et al., 2021). Specifically, Lefrere et al. (2020) found that web traffic decreased 4% to European sites following GDPR in comparison to US Based websites.

The introduction of privacy regulation also impacts firms' operational costs, performance, and competitive environment. For example, Bessen et al. (2020) find that for AI startups which rely on large quantities of data for product development, GDPR increased their cost as training data is less available and more resources need to be allocated to ensure regulatory compliance. Relatedly, the number and amount of venture financing deals for European digital ventures decreased after the enforcement of GDPR (Jia et al., 2021). There is evidence from industries such as online advertising and health care, that stronger privacy regulations have been found to hamper data-based innovation (Goldfarb and Tucker, 2012). Similarly, in the Google Play Store, a third of mobile apps on the market exited

(left the market) after the enforcement of GDPR and the number of new apps entering the platform decreased in relation to before the introduction of GDPR (Janßen et al., 2022).

Despite the suggestion that privacy regulation may impact innovation, the findings are not always unanimous and other studies point out potential beneficial effects of privacy regulation. Through an analytical modeling approach, Gopal et al. (2020) demonstrate that consent-based policies on the websites may have unintended effect of increasing the number of third-parties and sharing of user information. Abis et al. (2022) find that conversational-AI firm with in-house data on users, compared with those purchasing external data, have better performance and can collect more data subsequently after the enforcement of privacy regulation. Zhao et al. (2021) find that EU users submit more search terms to access information and browse more pages and domains online after GDPR, as firms may fail to deliver information to users efficiently due to their inabilities to use user data. Aridor et al. (2020) find that although 12.5% users stop sharing their data due to the opt-in requirement after GDPR, the average value of remaining users to advertisers has increased, which offset the losses. In addition, the effectiveness of predicting user behavior did not worsen after GDPR. A similar result is reported by Godinho de Matos and Adjerid (2021) who found that the efficacy of marketing communications increased after consumers provided their consent.

### 3 The General Data Protection Regulation

With the stated goal to protect the privacy of its citizens online, the GDPR, one of the most well known and discussed privacy regulations, came into effect in the European Union (EU) on May 25, 2018 (European Union, 2016). The aims of GDPR were to strengthen and harmonize the privacy legislation in the EU and regulates the firms on processing including collecting, combining, and storing of personal data. It imposes regulations on the firms within the EU and the firms located outside the EU if they collect or process data from the individuals residing in the EU. As a penalty for failing to comply, large fines ( 4% of worldwide annual revenues or up to 20 million euros) could be imposed for GDPR infringement.

The enforcement of GDPR (after May 25, 2018) impacted the operation of mobile app developers in several ways. First, the territorial scope of GDPR is defined based on two main criteria: the “establishment” criterion and the “targeting” criterion (European Data Protection Board, 2019).

Thus, GDPR applies to the processing of personal data by an establishment of a controller or a processor in the EU (the “establishment” criterion). It also applies to the processing of personal data of individuals in the EU by a controller or a processor not established in the EU (the “targeting” criterion). Due to its increased territorial scope, mobile apps from EU firms should comply with GDPR, even their apps are only available for non-EU market. Moreover, mobile apps from non-EU firms should also comply with GDPR, if they are available in the EU market.

Second, users’ informed consent should be obtained before the collection and processing of personal data. In addition, personal data must be collected and processed only for the purposes stated (purpose limitation) and restricted to what is necessary for the stated purposes (data minimization). Mobile apps rely on personal data to deliver personalized content (Sutanto et al., 2013), optimize and monitor app performance, and monetize via targeted advertising (Wottrich et al., 2018). To do so, mobile app developers often depend on third-party services (e.g., advertising related SDKs, analytics SDKs, etc.). Since mobile apps are responsible for personal data collected via their apps, they are required to obtain users’ informed consent before activating third-party services and sending data to third-party SDKs, which means firms and third-parties are jointly responsible for the data processed by third-parties. Therefore, it may make data collection more costly and reduce a firm’s ability to obtain personal data and use third-party services.

Third, GDPR requires firms to take appropriate measures and imposes extra operating cost for compliance. GDPR aims to improve users’ rights to control their personal data (e.g., access, update, correct, delete, port, etc.). Therefore, firms processing personal data should invest in IT infrastructure to fulfill users’ rights. Moreover, they need data privacy professionals to oversee data management activities. For mobile app companies, especially for those relying on the processing of personal data, the compliance costs could be significant <sup>1</sup>.

## 4 Data & Methodology

To empirically analyze how GDPR influenced digital experimentation and innovation, we use a monthly dataset of the Google Play Store (6,854,724 distinct apps in total) from a mobile data provider that covers a period of 12 months before and after the enforcement of GDPR (from June 2017 to May

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<sup>1</sup>Peukert et al. (2022) provide detailed information on how GDPR affects the operations of digital firms



2019). The dataset contains the characteristics of the apps available on Google Play Store each month (e.g., app category, price, description, version, etc). In addition, we have the information about the SDKs those apps were using each month, and the types of those SDKs.

#### 4.1 Part 1: Impact of the GDPR on the use of A/B Testing

In order to measure the level of A/B Testing use before and after the enforcement of GDPR, we construct a balanced sample of apps that experience a change in the use of A/B Testing (either adopting or abandoning) during the 24 months of the observation window. Afterwards, we divided them into two groups: a treatment group which consists of the apps subject to GDPR , and a control group which consists of the apps not subject to GDPR . To do this, we checked whether the apps are available in the EU, as well as whether the app developers are located in the EU, since developer’s location also determines if an app is subject to GDPR regime ([Peukert et al., 2022](#)).

We defined an app as a GDPR app (an app that is subject to GDPR) if it has been available during the whole observation period of 24 months in at least one EU country. A NonGDPR app (an app that is not subject to GDPR), on the other hand, is an app that has not been available, for the whole period, in any EU country. For developer’s location, we go through 5 steps to automatically identify the country information from developer’s address, website, email, ID language and app ID. If it is impossible to determine developer’s location through above-mentioned processes for NonGDPR apps, we manually checked it (e.g., through developer’s website, developer’s Linkedin or Crunchbase page, etc.). We move NonGDPR apps to the group of GDPR apps if their developers are located in the EU (details of location identification can be found in [Appendix A](#)).

After completing the above exercise we ended up with 20,476 apps that used at some moment during this window of 24 months at least one A/B Testing SDK, and for which we have the geographical availability of the app and location information of the firm. 14,321 of the apps are subject to the GDPR privacy regulation, and 6,155 of them are not.

Our econometric model specification is at the app-month level of analysis, which permits us to capture the impact of GDPR and is given by:

$$Y_{at} = \alpha + \beta(\text{GDPR App}_a \times \text{Post GDPR}_a) + \gamma(\text{GDPR App}_a \times \text{Month}_t) + \mu_{at} + \varepsilon_{at}, \quad (1)$$

where  $Y$  is our dependent variable of interest. In this case the dependent variable is A/B Testing which is a binary variable that is 1 if the app  $a$  at month  $t$  is using at least one A/B Testing SDK, and otherwise 0. GDPR Apps is a binary variable that is equal to 1 if the app is subject to the GDPR and 0 otherwise. Post GDPR is a binary variable that is equal to 1 if the month  $t$  is after May 2018, when GDPR was enacted and enforced from that point onwards, and 0 otherwise. The model further includes app and time related fixed effects  $\mu$ , and a group-specific linear time trend  $\gamma$ , as in [Peukert et al. \(2022\)](#). The error term  $\varepsilon$  has the standard assumptions, and we report estimates clustered at the app level. Our coefficient of interest is  $\beta$ , which shows the change of use of A/B Testing apps that are subject to GDPR and the ones that are not, after the introduction of GDPR. The coefficients of GDPR App and Post GDPR variables are absorbed due to the use of app and time related fixed effects.

## 4.2 Part 2: Innovation performance in the Post-GDPR period

To measure the impact of GDPR on the relationship between experimentation and innovation we employ a diff-in-diff quasi-experimental design. Our control group is composed of apps that have never used any SDK, and consequently no A/B testing during the observed period of 24 months (503.920 apps), and our treated group consists of apps that have been using an A/B testing SDK the whole period of 23 months (27.002 apps). Later, we employed the CEM (Coarsened Exact Matching) matching so as to create comparable apps. We matched apps based on app characteristics (category, time in the market, number of total and sensitive permissions, price, average rating, total number of ratings, if it contains ads, and number of major updates during the last year), and developer characteristics (if it's top developer or not and number of other apps that each developer has published at Google Play Store). For the matching process, we used the values of these variables at one snapshot before GDPR came into force (i.e., May 2018). This process resulted in two samples, one based on 1 to 1 matching (13680 apps in each group), and the other one based on many to 1 weighted matching (99412 apps in the control group and 15076 in the treated group). Finally, we have decided to use a

balanced dataset because we know that GDPR had an impact on entry and exit of mobile apps (Janßen et al., 2022). To be able to infer apps’ innovation from their version number (Miric and Jeppesen, 2020; Wen and Zhu, 2019), we excluded the apps without explicit versioning (e.g., ”varies with device”) for the whole observation window, and also the apps without standardized version number (e.g., those that use an un-dotted number, use year/month to represent the version, etc.)

Our main econometric model specification is at the app-month level of analysis, which permits us to capture the impact of GDPR and is given by:

$$Y_{at} = \alpha + \beta(A/B\ Testing_a \times Post\ GDPR_a) + \gamma(A/B\ Testing_a \times Month_t) + \mu_{at} + \varepsilon_{at}, \quad (2)$$

where  $Y$  is our dependent variable of interest. In our analysis we employ two dependent variables, Major Update and Minor Update, by following the operationalization of innovation in the literature within a mobile app setting (Miric and Jeppesen, 2020; Wen and Zhu, 2019). Major Update is a binary variable that is 1 if the first digit of the version number of an app  $a$  in month  $t$  is different from the first digit(s) (the digit(s) just before the first dot of the version number) of the version number of app  $a$  in month  $t-1$ , and 0 otherwise. On the other hand, Minor Update is a binary variable that is 1 if the second digit(s) (the digit(s) just after the first dot of the version number) of the version number of an app  $a$  in month  $t$  is different from the second digit(s) of the version number of app  $a$  in month  $t-1$ , and 0 otherwise. Since the second digit is reset to zero when there is a major update and the first digit changes, in that specific case we count it as major update only. Major Update is associated with major and radical changes in the app such as refreshed user interface or a new section of the app, while Minor Update is associated with minor and incremental changes related to new features or functionalities. A/B Testing is a binary variable that is equal to 1 if the app  $a$  is using at least one SDK that belongs in the A/B Testing category, and 0 otherwise. Post GDPR is a binary variable that is equal to 1 if the month  $t$  is after May 2018, when GDPR was enforced, and 0 otherwise. The model further includes app and time related fixed effects  $\mu$ , and a group-specific linear time trend  $\gamma$ . The error term  $\varepsilon$  has the standard assumptions, and we report estimates clustered at the app level. Our coefficient of interest is  $\beta$ , which shows the change of the innovation output between apps that use

A/B Testing SDK and the ones that do not use it, after the introduction of GDPR. The coefficients of A/B Testing and Post GDPR variables are absorbed due to the use of app and time related fixed effects.

## 5 Results

### 5.1 Results: Impact of GDPR on Use of A/B Testing SDK(s)

**Descriptive Evidence.** In Figure 1, we provide a first model free evidence on how GDPR is associated with the adoption of experimentation tools in the universe of mobile apps in the Android ecosystem. As it can be observed, the number of apps using at least one A/B Testing SDK per month stopped to increase at the moment when GDPR was introduced. Furthermore, the number of apps per month that use A/B Testing SDKs decreased after the introduction of GDPR and stabilized in 2019, even though at an inferior level than May 2018. More specifically, the GDPR is associated with a reduction of 17% of usage of A/B Testing SDKs, at the extensive margin. This can be attributed to the impact of GDPR on the whole Android ecosystem via two mechanisms. First of all, to the exit of apps due to GDPR, and secondly to apps that either stop using A/B Testing SDK(s) or stop adopting it. In Figure 2, we demonstrate that GDPR lead to the exit of apps that have used at some point A/B Testing SDK(s), as Janßen et al. (2022) have also shown for the general app population of the Google Play Store. In Figure 3, we observe the apps that stop using A/B Testing SDK(s) per month, where we do observe a peak during the month of May 2018, which is the month when GDPR was introduced. Finally, in Figure 4 we present the number of apps that adopt A/B Testing each month for first time. After comparing those all above forces, it is clear that the reduction in the use of A/B Testing is mainly coming from apps that decide to exit the market, after the introduction of GDPR. Nevertheless, apps stopped using A/B Testing SDK or didn't adopt it most probably due to compliance risks and the uncertainty that surrounded the operations of digital firms at that moment.

**Regression Results.** In Table 1 we report our regression results for the use of A/B Testing after the introduction of GDPR (see Equation 1). We include Fixed Effects at the product level and therefore our results can be interpreted as being driven by the observations which adopted or stopped using A/B Testing SDK during our period of observation. We therefore limit our sample to only those observations. As we can see at Column (1) that apps which are under the GDPR regime had a 5%

less probability to use A/B Testing after the introduction of the GDPR compared to apps that are not subject to GDPR.

Digging more into which apps are more probable to not use A/B Testing we extend our base model described in Table 1 and we report the results of Equation 1, by using a triple interaction term and three different moderators. In Column (1) of the Table 2 we observe that the most popular<sup>2</sup> GDPR apps are less probable to use A/B Testing SDK after the introduction of GDPR. Similarly, in Column (2) of the same Table we observe that the GDPR apps with higher quality<sup>3</sup> are less probable to use an A/B Testing SDK. Finally, in Column (3) of this Table, we find that GDPR apps that use an ad-based business model<sup>4</sup> are less probable to use A/B Testing SDKs.

## 5.2 Results: Impact of GDPR and A/B Testing on Innovation

In Table 3, we present our regression results, and it can be observed that the probability of apps that have been using A/B Testing to be majorly updated after the implementation of the GDPR is positive and significant, independently of which sample is used for the regressions. This is an indication that apps that have externally outsourced the digital experimentation process (by using A/B Testing SDKs) are more capable to cope with the uncertainties of the complex environment that GDPR has created.

## 5.3 Robustness Checks

In order to validate the results previously presented, we will provide further evidence in the next subsections by conducting various robustness checks.

### 5.3.1 Parallel Trends

The first one is to check if the parallel trend assumption hold in this case. In Figure 5, we report coefficients for the monthly interaction coefficients (ie. A/B Testing x Month) as a way to test the parallel trend assumption. The model used to get these coefficients is the same econometric model that is used in Equation 2 but without any fixed effects or group related linear time trends, and the errors are clustered at the app level. At the left panel we report the results of the 1-to-1 matched

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<sup>2</sup>We use the number of ratings an app has received until May 2018 as a proxy for the popularity of the apps.

<sup>3</sup>We use the average rating an app has on May 2018 as a proxy for the quality of the apps.

<sup>4</sup>We use the label in the Google Play store which indicates if an app contains ads as a definition of the ad-based business model. If an app contains ads then it uses an ad-based business model, if it doesn't then not.

sample, while at the right panel the results of the many-to-1 sample. In both cases the dependent variable is Major Update. The results indicate that before GDPR the difference between control and treated groups regarding Major Update is statistically insignificant, meaning that the parallel trends assumption is satisfied.

### 5.3.2 Alternative sample: GDPR vs NonGDPR Apps

At the previous sections we provided a first evidence that apps that use third party A/B Testing SDKs, update more frequently compared to the ones that do not use, after the introduction of the GDPR. In the next sections, we will provide further evidence that this phenomenon observed around the time of the introduction of the GDPR is due to GDPR. We start by constructing two samples, one with the apps that should comply with GDPR, and a second one with the apps that are not under the GDPR regime, which means the app is not available in the EU market and its firm is not located in the EU. Those two samples are constructed by using the information we have on availability of apps and their location as explained in 4.1. And for each of those samples we employ the diff-in-diff design and the econometric model described by the Equation 2. So, our treated groups are composed of apps that have been using an A/B Testing SDK for the whole observation period of 24 months, and our control groups are composed of apps that have not used any A/B Testing SDK during the whole observation period. We exclude from the sample those apps that have used an A/B Testing SDK only for some months so as to have an as possible clean definition of the groups.

Our final balanced sample for this diff-in-diff approach consists of 32,613 apps in total. 19,684 of them are under the GDPR regime, while the other 12,929 are not. 2,105 apps in our sample use at least one A/B Testing SDK, while the rest 30,508 apps do not. Due to the low number of apps that use A/B Testing, we have decided to continue by not using a matched sample like explained in Section 4.2 and used in Table 3.

In Table 4, we present the regression results for the impact of GDPR on innovation, comparing those titles which used A/B Testing SDKs and those that did not (see equation 1). From Column (1), the probability of apps that have to follow to GDPR regulation and have been using A/B Testing is higher from the the control group that includes apps that also have to follow GDPR but did not use A/B Testing SDK(s). On average, apps that use A/B Testing SDK(s) have 1,2% higher probability

to update at a major level their app after the introduction of GDPR compared to the ones that do not use any A/B Testing SDK. In Column (2) of Table 4, we test the same econometric model but for a sample of apps that are not subject to GDPR. As it can be seen we find no significant results since there is no difference between apps that use A/B Testing SDK and apps that do not use it. This is an additional evidence that results that we provide at Table 3 are due to GDPR. In the next subsections we conduct extra robustness checks to support further our argument.

Furthermore, in Figure 6, we report coefficients for the monthly interaction coefficients (ie. A/B Testing x Month) as a way to test the parallel trend assumption. The model used to get these coefficients is the same econometric model that is used in Equation 2 but without any fixed effects or group related linear time trends, and the errors are clustered at the app level. At the left panel we report the results of the sample that includes apps that are under the GDPR regime, and at the right panel the results of the sample of the apps that are not. In both cases the dependent variable is Major Update. The results indicate that before GDPR the difference between control and treated groups regarding Major Update is statistically insignificant, meaning that the parallel trends assumption is satisfied.

### 5.3.3 Alternative Control Group: Apps that use SDKs but not A/B Testing

The control group of our main analysis consists of apps that don't any SDKs at all, including A/B Testing SDK(s), and apps that do not use A/B Testing SDK(s) but do use other SDK (ie. for app performance, or related to advertisement, like monetization, etc). This heterogeneity might cover fundamental differences between those apps, either in terms of the resources the firm behind the app has or the complexity of the app per se. In order to alleviate this concern, we rerun our econometric model described in equation 1, but using as control group only the apps that do use other SDKs but not A/B Testing. As it can be observed in Columns (1) and (3) of the Table 5 results regarding major update do not change compared to Table 4. In other words, we do observe a statistical difference between apps that use A/B Testing and the apps that do not use A/B Testing in the subsample of GDPR apps, while we do not observe any difference in the NonGDPR apps subsample. Moreover, going one step further our analysis we discover, as seen in Column (2), that the the more SDKs an A/B Testing app uses the more probable is to innovate more frequently after the introduction of GDPR. This is an indication that the more modular apps that use A/B Testing are more able to cope with

the burden imposed by GDPR and achieve to innovate more frequently after the introduction of the GDPR than the apps that do not use A/B Testing, but do use other SDKs. On the other hand we do not observe this at the subsample of the NonGDPR apps as seen in Column (4).

### **5.3.4 Alternative DV: Minor Update (Product Revisions)**

In Table 6, we present the results of the same econometric model as in Table 4 but for the Minor Update as dependent variable. The results remain consistent as seen in Column (1), and we observe a 1,4% higher probability for apps that use A/B Testing SDK to update at a minor level compared to the ones that do not use after the introduction of the GDPR. Also, in Column (2) we do not observe any difference between apps that use A/B Testing and don't use it in the subsample of apps that do are not under GDPR regime (NonGDPR Apps).

In addition, in Table 7, we used as control group only the apps that do use other SDKs but not A/B Testing, as we did in the previous subsection, but using now the Minor Update as DV. We can observe in Column (1) that we get statistically insignificant results, meaning that there is on average there is no difference regarding Minor Update between apps that use A/B Testing SDK and the ones that do not, but use other SDKs, independently if the app is under GDPR regime or not. The same applies also, and as expected, for the NonGDPR apps as seen in Column (3) of the same table. In continuation, we repeat the same exercise as for Major Update and we check for any heterogeneity due to the variance of the number of SDKs apps are using. As for Major Update, we do find that regarding Minor Update A/B Testing apps that use more SDKs are more probable to update at a minor level than the ones that do not use A/B Testing but do use other SDKs. This is an additional indication of the high complementary value of A/B Testing in a setting with stricter privacy regulation. Again as expected, we do not find any heterogeneity effects for the NonGDPR apps as seen in Column (4) of the same table.

### **5.3.5 Alternative Identification Strategy**

As another robustness check we decided to employ an alternative identification strategy. As a reminder, so far we have used in our diff-in-diff design as treated group the apps that use A/B Testing SDK and as control group apps that do not use this kind of SDK, and we compare those two groups of apps in



two different settings. One subject to the GDPR, and the second not. In this alternative diff-in-diff design we will use the identification strategy used in 4.1, where we compare apps that use A/B Testing SDK under GDPR regime to apps that also use A/B Testing but they are not subject to the GDPR regulation. Also, we will compare apps that do not use A/B Testing SDK but are under the GDPR privacy regime to apps that also do not use A/B Testing SDK but are not obliged to follow the GDPR regulation.

As we can see in Column (1) of the Table 8, the apps that use A/B Testing SDK(s) and have to follow the GDPR are updating at a major level with 1.8% higher probability compared to apps that also use A/B Testing but are not under the GDPR regime. In Column (2) of the same Table we do not observe any difference regarding the Major Update between the apps that use A/B Testing and do not use A/B Testing, and are not subject to GDPR. This is an indication of the importance of using A/B Testing SDKs to innovate under a stricter privacy regulation.

## 6 Discussion

Experimentation is critical to innovation, and it is an increasingly important activity for digital companies (Thomke, 2001). In practice, experimentation is increasingly being performed through frameworks such as A/B Testing which involves conducting structured experiments, observing information about customers and customer responses. Yet, privacy regulation which is intended to protect consumers' data, by requiring companies to manage customer data, gain informed consent and ensure data privacy, may impede the ability of companies to perform experimentation and in turn may impact innovation.

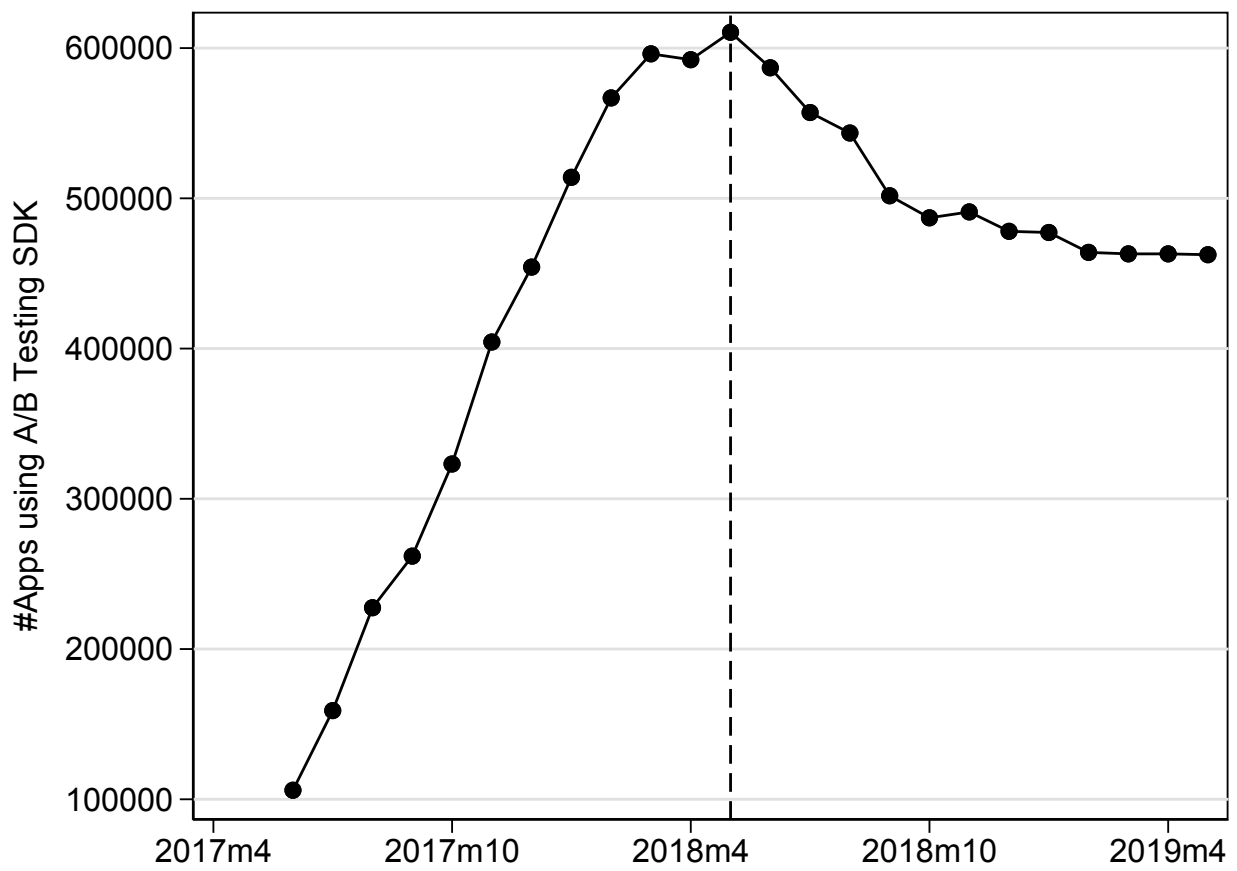
The results of our study provide insights into the consequences of the introduction of GDPR. First, our results show that GDPR had an overall negative impact on the use and adoption of third-party A/B Testing tools. Many of the products that continued to operate in the Android ecosystem stopped using third-party experimentation tools and in general it seems that apps were really hesitant in adopting A/B Testing SDK after the GDPR. As an additional check, we compared those titles which were required to comply with GDPR, to those that were not (outside of EU Domain) and we found that apps subject to GDPR were 5% more likely to stop using A/B Testing SDK after the GDPR, providing further evidence to this effect. Note that our unit of analysis was the app-month, and therefore this difference would be quite substantial over a period of several months. These findings

are consistent with the assertion that GDPR increased the costs of performing A/B testing and that this, in turn, reduces the use of A/B testing frameworks, especially in relation to third-party testing tools. However, our results also indicate some nuance in these results. We find that apps which were using A/B testing tools after GDPR, were 0.3% more likely (per month) to release an update compared to titles that did not use A/B testing tools. Even though this increase may appear small, if we take into account that product updates are rare events (and therefore a 0.3% increase in a month is quite substantial), then this may have a profound long term impact on innovation and potentially app performance (Rosenbusch et al., 2011). If we consider that those effects are on an individual product level, then in aggregate within a platform such as the Android platform, these effects are potentially very large and economically important. This suggests that after GDPR, once developers have legally compliant access to user data and informed consent of users to use the data, then firms are more likely to generate product improvements, consistent with the arguments that informed consent can actually enable greater experimentation for those that can jump through the hurdles of complying with privacy regulation.

As an additional check, we explored which titles were driving our empirical results. Our results point to the fact that the most pronounced impact is on titles which are already using some SDKs. This suggests that experimentation, A/B Testing SDK and privacy regulation are interrelated with other product architectures and characteristics. There may be considerable opportunities for future studies to explore how A/B Testing interacts with other technological components, and what this may mean for innovation overall.

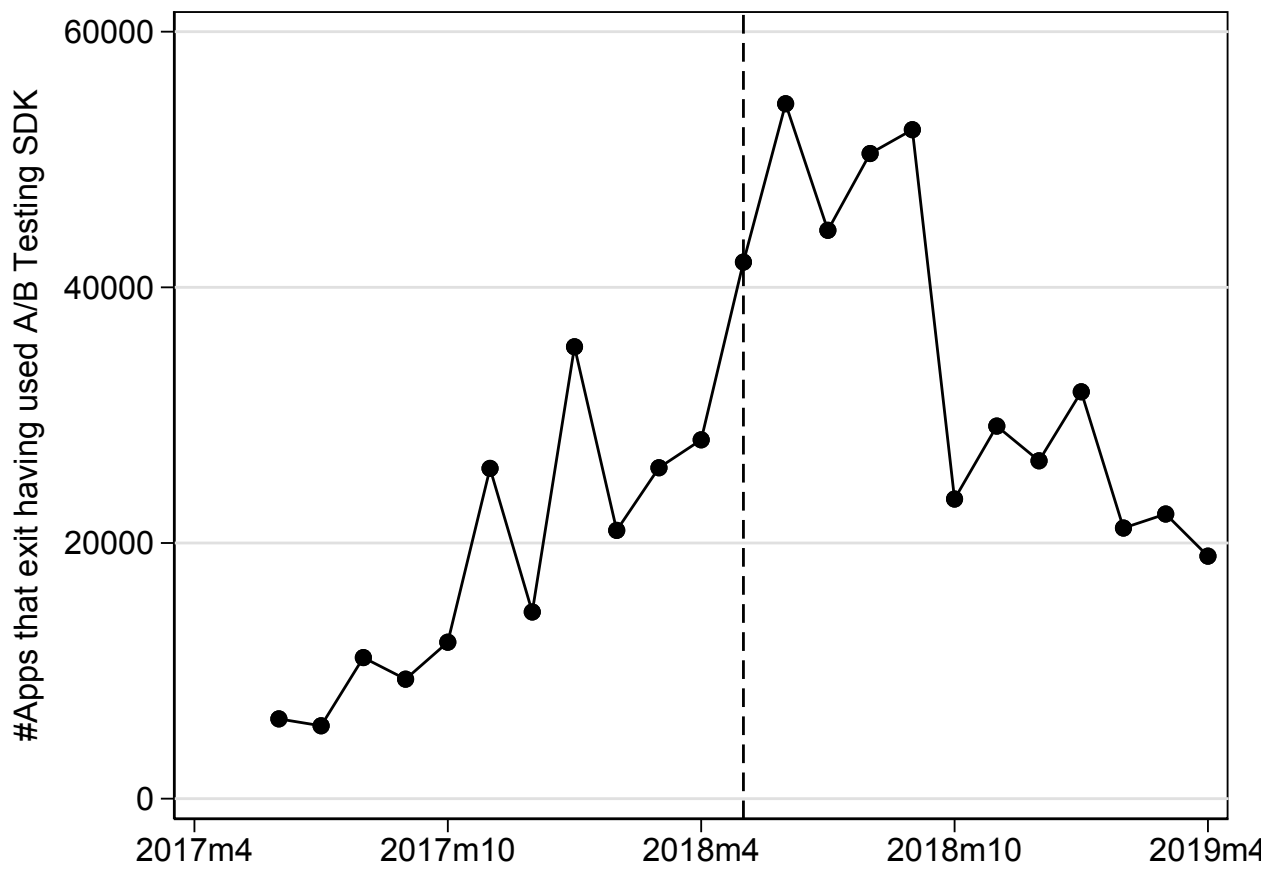
This paper contributes to the literature on privacy regulation (Godinho de Matos and Adjerid, 2021; Goldfarb and Tucker, 2019; Peukert et al., 2022), by showing how a potentially unintended consequence of privacy regulation may be the impact on experimentation and in turn on innovation. Our results highlight both conditions under which privacy regulation may hamper and encourage experimentation and innovation. This provides insights for policy makers to think about the optimal design and enforcement of privacy regulation to foster digital innovation.

**Figure 1:** Use of A/B Testing SDKs by all apps in the Google Play store



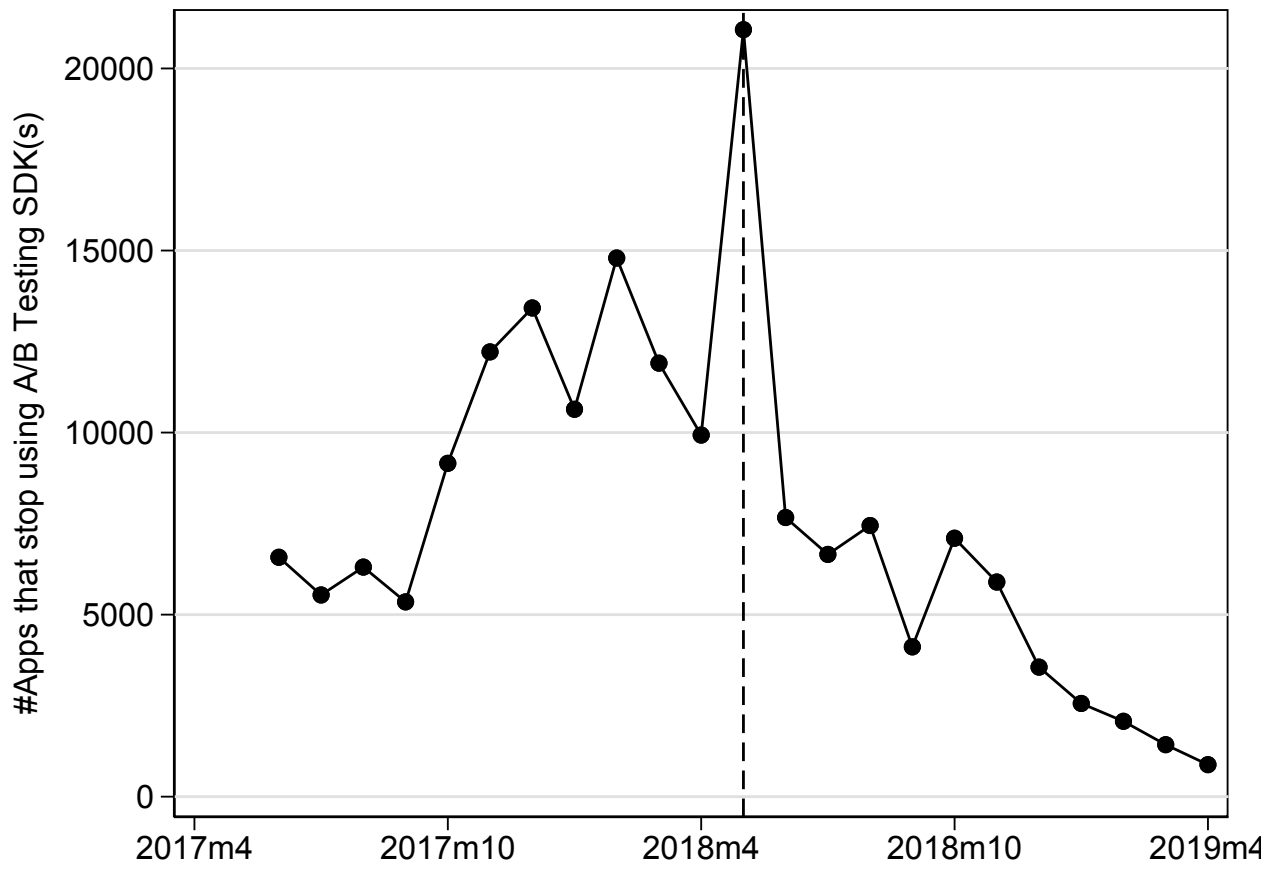
**Note:** The number of Apps per month that use at least one A/B Testing SDK. The dot vertical line represents when GDPR was introduced (May 2018)

**Figure 2:** Exit of apps which used at any moment at least one A/B Testing per month



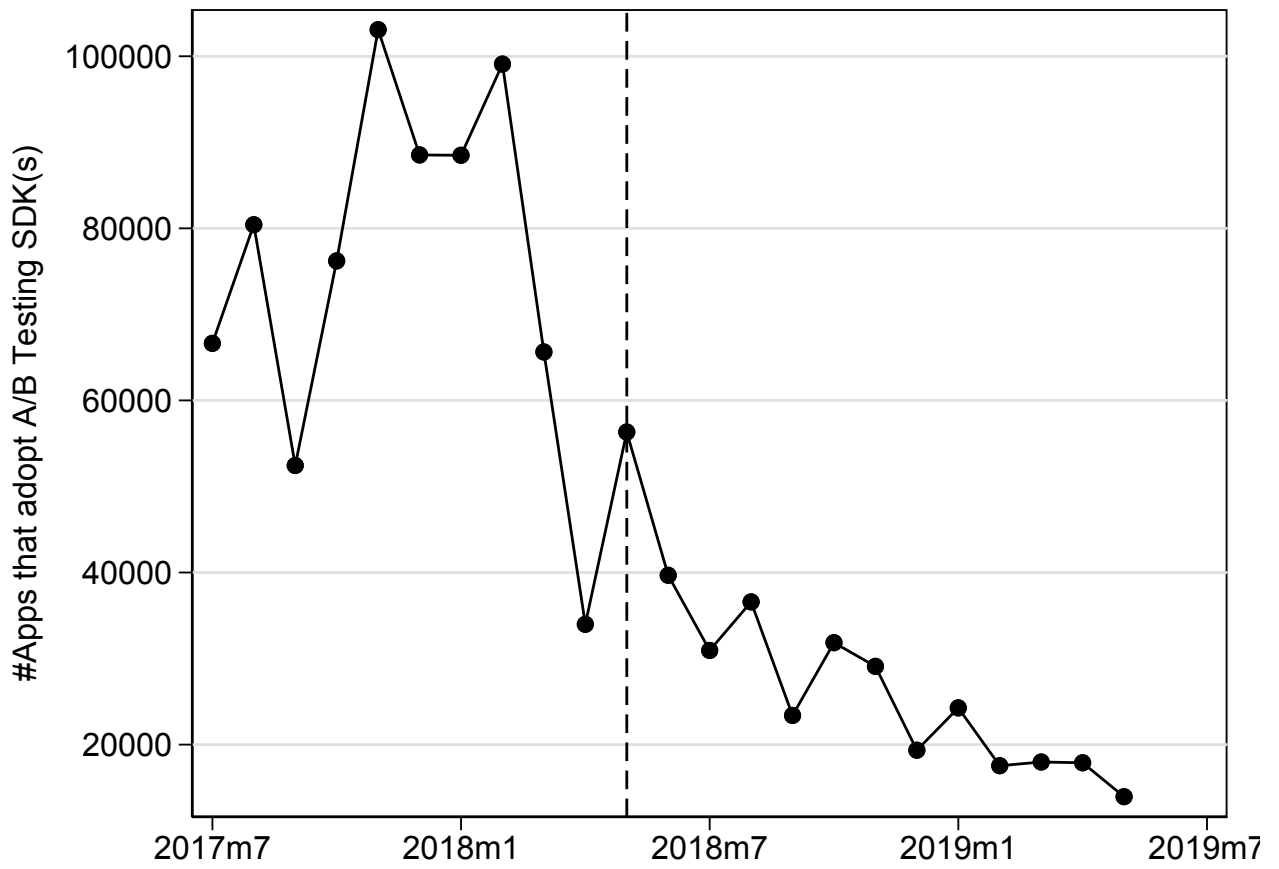
**Note:** The number of apps per month at the Google Play Store that have used at least one A/B Testing SDK and exit the market. We excluded the last month of our observation period. The dot vertical line represents when GDPR was introduced (May 2018)

**Figure 3:** Apps that stop using A/B Testing SDK(s) per month



**Note:** The number of apps per month at the Google Play Store that stop using A/B Testing SDK(S). Since some apps adopt and drop A/B Testing SDKs at various moments, we consider as "stop" the last time this happened. We excluded the last month of our observation period. The dot vertical line represents when GDPR was introduced (May 2018)

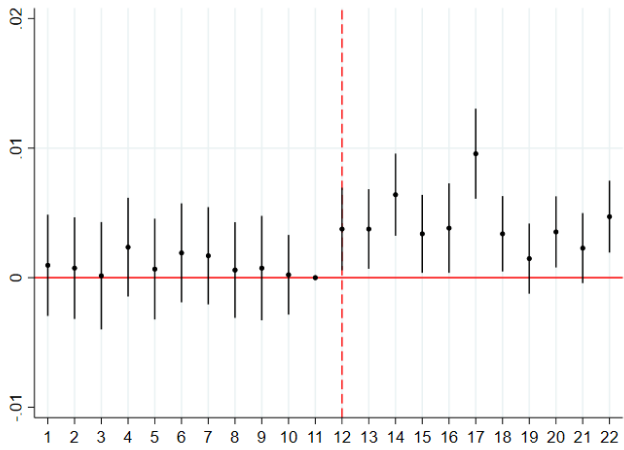
**Figure 4:** Apps that start using A/B Testing SDK(s) per month



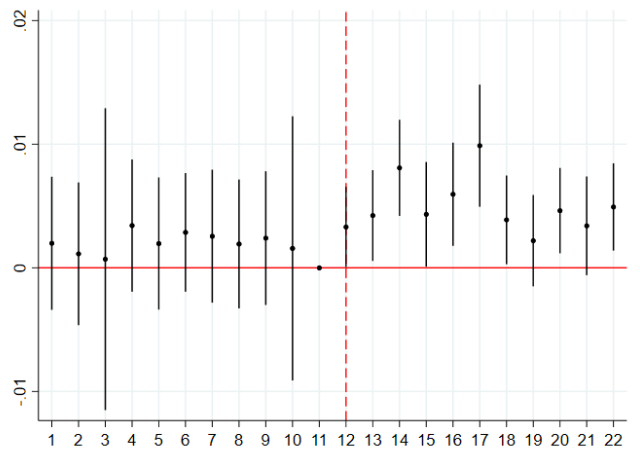
**Note:** The number of apps per month at the Google Play Store that start using A/B Testing SDK(S). Since some apps adopt and drop A/B Testing SDKs at various moments, we consider as "start" the first time this happened. We excluded the last month of our observation period. The dot vertical line represents when GDPR was introduced (May 2018)

**Figure 5:** Parallel Trends - Major Update

*Matched: 1-to-1*



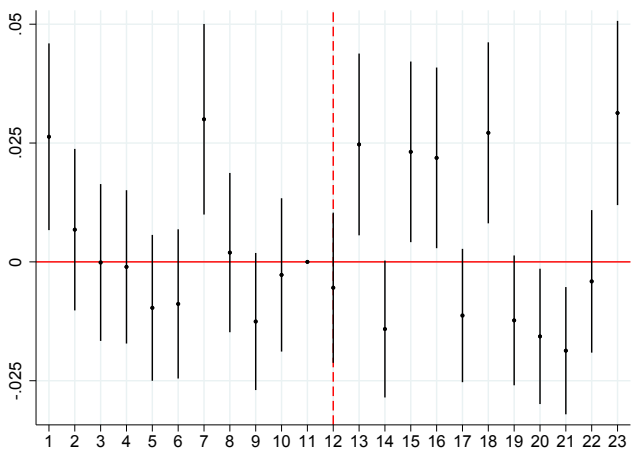
*Matched: Many-to-1*



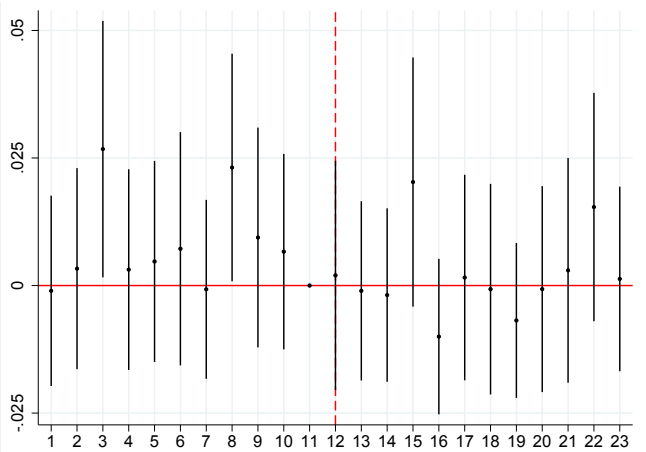
**Note:** On the left panel results from the the 1-to-1 sample, and on the right panel results from the many-to-1 sample. The reported confidence intervals are at the 95% level

**Figure 6:** Parallel Trends - Major Update

*GDPR Apps*



*NonGDPR Apps*



**Note:** On the left panel the GDPR apps, and on the right panel the NonGDPR apps. The reported confidence intervals are at the 99% level

**Table 1:** Use of A/B Testing

	(1) A/B Testing
GDPR App $\times$ Post GDPR	-0.050*** (0.006)
Observations	491424
$\overline{R^2}$	0.351
Apps FE	X
Month FE	X
Year FE	X
Group Time Trends	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 2:** Use of A/B Testing by Popularity, Quality and Business Model

	(1) A/B Testing	(2) A/B Testing	(3) A/B Testing
GDPR App $\times$ Post GDPR	0.107*** (0.023)	0.080 (0.051)	-0.015 (0.010)
Post GDPR $\times$ Log(No. of Ratings)	0.004 (0.003)		
GDPR App $\times$ Post GDPR $\times$ Log(No. of Ratings)	-0.020*** (0.003)		
Post GDPR $\times$ Avg. Rating		-0.052*** (0.010)	
GDPR App $\times$ Post GDPR $\times$ Avg. Rating		-0.030* (0.013)	
Post GDPR $\times$ Contains Ads			0.051*** (0.013)
GDPR App $\times$ Post GDPR $\times$ Contains Ads			-0.066*** (0.016)
Observations	488472	488616	471552
$\overline{R^2}$	0.352	0.352	0.349
Apps FE	X	X	X
Month FE	X	X	X
Year FE	X	X	X
Group Time Trends	X	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$



**Table 3:** Major Update

	Matched: 1-to-1	Matched: Many-to-1
	(1)	(2)
	Major Update	Major Update
A/B Testing $\times$ Post GDPR	0.003** (0.001)	0.003* (0.001)
Observations	625186	2617837
$\overline{R^2}$	0.213	0.249
Apps FE	X	X
Month FE	X	X
Year FE	X	X
Group Time Trends	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 4:** Major Update

	GDPR Apps	NonGDPR Apps
	(1)	(2)
	Major Update	Major Update
A/B Testing $\times$ Post GDPR	0.012** (0.004)	-0.007 (0.005)
Observations	452732	297367
$\overline{R^2}$	0.086	0.094
Apps FE	X	X
Month FE	X	X
Year FE	X	X
Group Time Trends	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 5:** Major Update - Apps that use at least 1 SDK

	GDPR Apps that use SDK(s)		NonGDPR Apps that use SDK(s)	
	(1) Major Update	(2) Major Update	(3) Major Update	(4) Major Update
A/B Testing $\times$ Post GDPR	0.011* (0.005)	-0.003 (0.006)	-0.005 (0.006)	-0.008 (0.010)
No. of SDKs		0.001** (0.000)		0.002*** (0.001)
A/B Testing $\times$ No. of SDKs		-0.002** (0.001)		0.000 (0.001)
Post GDPR $\times$ No. of SDKs		-0.000 (0.000)		-0.000 (0.000)
A/B Testing $\times$ Post GDPR $\times$ No. of SDKs		0.001* (0.000)		0.000 (0.000)
Observations	80914	80914	37651	37651
$\overline{R^2}$	0.124	0.124	0.143	0.144
Apps FE	X	X	X	X
Month FE	X	X	X	X
Year FE	X	X	X	X
Group Time Trends	X	X	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 6:** Minor Update

	GDPR Apps	NonGDPR Apps
	(1) Minor Update	(2) Minor Update
A/B Testing $\times$ Post GDPR	0.014* (0.007)	0.008 (0.010)
Observations	441853	291226
$\overline{R^2}$	0.249	0.224
Apps FE	X	X
Month FE	X	X
Year FE	X	X
Group Time Trends	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 7:** Minor Update - Apps that use at least 1 SDK

	GDPR Apps that use SDK(s)		NonGDPR Apps that use SDK(s)	
	(1) Minor Update	(2) Minor Update	(3) Minor Update	(4) Minor Update
A/B Testing $\times$ Post GDPR	0.003 (0.009)	-0.018 (0.014)	-0.005 (0.006)	0.017 (0.019)
No. of SDKs		0.007*** (0.001)		0.007*** (0.001)
A/B Testing $\times$ No. of SDKs		0.001 (0.001)		0.001 (0.002)
Post GDPR $\times$ No. of SDKs		-0.002*** (0.000)		-0.001 (0.000)
A/B Testing $\times$ Post GDPR $\times$ No. of SDKs		0.002** (0.001)		-0.000 (0.001)
Observations	79925	79925	37651	36685
$\overline{R^2}$	0.289	0.293	0.143	0.280
Apps FE	X	X	X	X
Month FE	X	X	X	X
Year FE	X	X	X	X
Group Time Trends	X	X	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

**Table 8:** Major Update - Alternative Identification Strategy

	A/B Testing Apps	No A/B Testing Apps
	(1) Major Update	(2) Major Update
GDPR App $\times$ Post GDPR	0.018** (0.007)	-0.001 (0.001)
Observations	48415	701684
$\overline{R^2}$	0.158	0.079
Apps FE	X	X
Month FE	X	X
Year FE	X	X
Group Time Trends	X	X

**Note:** Standard errors in parentheses, clustered at the app-level. \*  $p < 0.05$ , \*\*  $p < 0.01$  \*\*\*  $p < 0.001$

## References

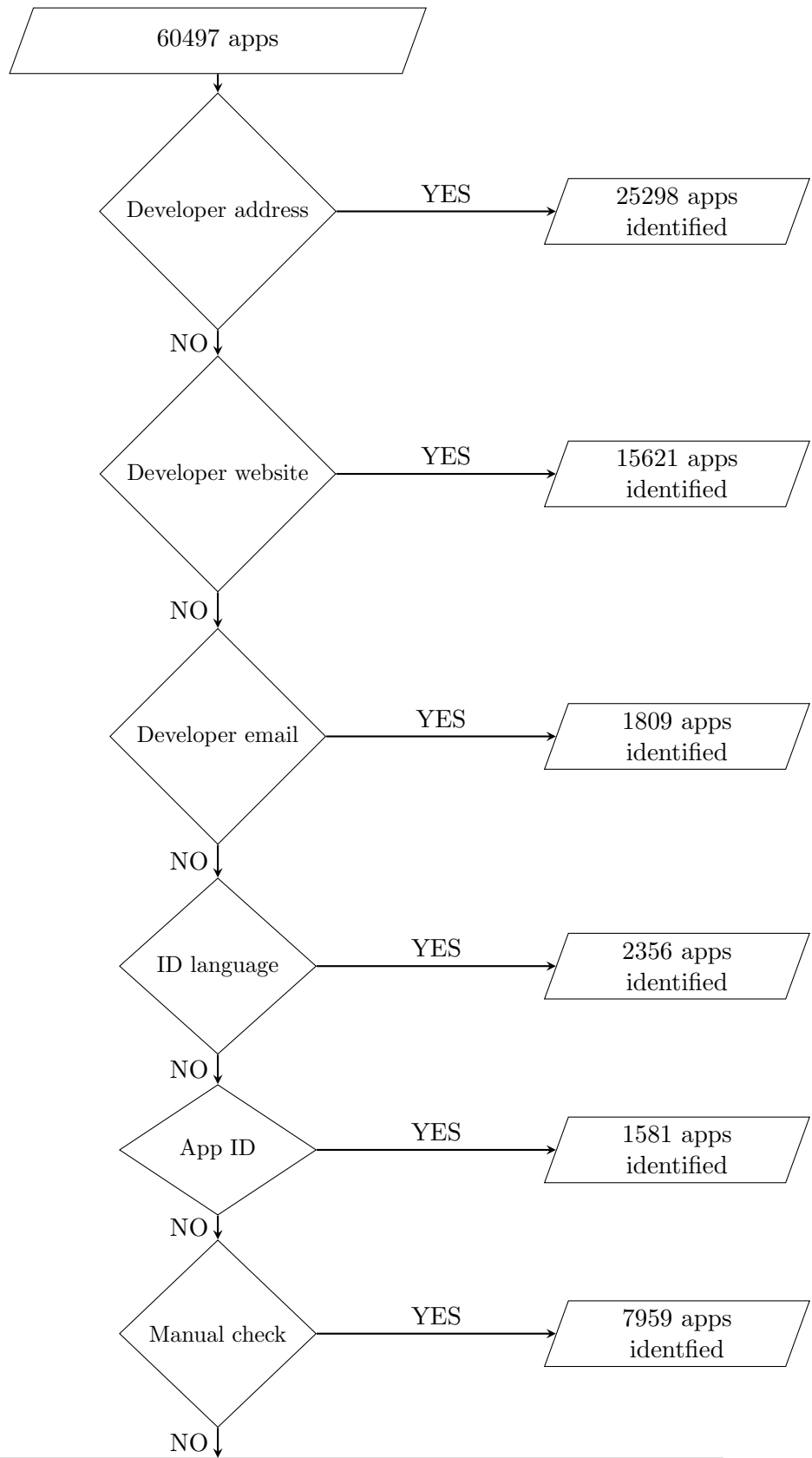
- Abis, S., Canayaz, M., Kantorovitch, I., Mihet, R., and Tang, H. (2022). “Privacy laws and value of personal data.” Tech. rep., EPFL.
- Agrawal, A., Gans, J. S., and Stern, S. (2021). “Enabling entrepreneurial choice.” *Management Science*, 67(9), 5510–5524.
- Aridor, G., Che, Y.-K., and Salz, T. (2020). “The economic consequences of data privacy regulation: Empirical evidence from gdpr.” *NBER working paper*, (w26900).
- Azevedo, E. M., Deng, A., Montiel Olea, J. L., Rao, J., and Weyl, E. G. (2020). “A/b testing with fat tails.” *Journal of Political Economy*, 128(12), 4614–000.
- Bapna, R., Ramaprasad, J., Shmueli, G., and Umyarov, A. (2016). “One-way mirrors in online dating: A randomized field experiment.” *Management Science*, 62(11), 3100–3122.
- Berman, R., and Israeli, A. (2022). “The value of descriptive analytics: Evidence from online retailers.” *Marketing Science*.
- Bessen, J. E., Impink, S. M., Reichensperger, L., and Seamans, R. (2020). “Gdpr and the importance of data to ai startups.” *NYU Stern School of Business*.
- Boudreau, K. J. (2012). “Let a thousand flowers bloom? an early look at large numbers of software app developers and patterns of innovation.” *Organization Science*, 23(5), 1409–1427.
- Brynjolfsson, E., and McElheran, K. (2016). “The rapid adoption of data-driven decision-making.” *American Economic Review*, 106(5), 133–39.
- Burford, N., Shipilov, A. V., and Furr, N. R. (2022). “How ecosystem structure affects firm performance in response to a negative shock to interdependencies.” *Strategic Management Journal*, 43(1), 30–57.
- Campbell, J., Goldfarb, A., and Tucker, C. (2015). “Privacy regulation and market structure.” *Journal of Economics & Management Strategy*, 24(1), 47–73.
- Camuffo, A., Cordova, A., Gambardella, A., and Spina, C. (2020). “A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial.” *Management Science*, 66(2), 564–586.
- Davis, J., Chhabra, Y., and Yin, P.-L. (2016). “Experimentation strategies and entrepreneurial innovation: Parallel and sequential innovation in the iphone app ecosystem.” Tech. rep., Working paper.
- Degeling, M., Utz, C., Lentzsch, C., Hosseini, H., Schaub, F., and Holz, T. (2018). “We value your privacy... now take some cookies: Measuring the gdpr’s impact on web privacy.” *arXiv preprint arXiv:1808.05096*.
- European Data Protection Board (2019). “Guidelines 3/2018 on the territorial scope of the gdpr (article 3), version 2.1.”
- European Union (2016). “Regulation (eu) 2016/679 of the european parliament and of the council of 27 april 2016 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing directive 95/46/ec.” *Official Journal of the European Union*, 119(1).

- Fleming, L., and Sorenson, O. (2003). “Navigating the technology landscape of innovation.” *MIT Sloan Management Review*, 44(2), 15.
- Gans, J. S., Stern, S., and Wu, J. (2019). “Foundations of entrepreneurial strategy.” *Strategic Management Journal*, 40(5), 736–756.
- Godinho de Matos, M., and Adjerid, I. (2021). “Consumer consent and firm targeting after gdpr: The case of a large telecom provider.” *Management Science*, 0(0), null.
- Goldberg, S., Johnson, G., and Shriver, S. (2021). “Regulating privacy online: An economic evaluation of the gdpr.” *Available at SSRN*.
- Goldfarb, A., and Tucker, C. (2012). “Privacy and innovation.” *Innovation policy and the economy*, 12(1), 65–90.
- Goldfarb, A., and Tucker, C. (2019). “Digital economics.” *Journal of Economic Literature*, 57(1), 3–43.
- Goldfarb, A., and Tucker, C. E. (2011). “Privacy regulation and online advertising.” *Management science*, 57(1), 57–71.
- Gopal, R. D., Hidaji, H., Kutlu, S. N., Patterson, R. A., and Yaraghi, N. (2020). “Economics of data protection policies.” *ICIS 2020 proceedings*.
- Gregory, R. W., Henfridsson, O., Kaganer, E., and Kyriakou, H. (2022). “Data network effects: Key conditions, shared data, and the data value duality.” *Academy of Management Review*, 47(1), 189–192.
- Hartmann, P., and Henkel, J. (2020). “The rise of corporate science in ai: Data as a strategic resource.” *Academy of Management Discoveries*, 6(3), 359–381.
- Janßen, R., Kesler, R., Kummer, M. E., and Waldfoegel, J. (2022). “Gdpr and the lost generation of innovative apps.” *NBER working paper*, (w30028).
- Jia, J., Jin, G. Z., and Wagman, L. (2021). “The short-run effects of the general data protection regulation on technology venture investment.” *Marketing Science*, 40(4), 661–684.
- Kerr, W. R., Nanda, R., and Rhodes-Kropf, M. (2014). “Entrepreneurship as experimentation.” *Journal of Economic Perspectives*, 28(3), 25–48.
- Kohavi, R., and Thomke, S. (2017). “The surprising power of online experiments.” *Harvard business review*, 95(5), 74–82.
- Koning, R., Hasan, S., and Chatterji, A. (2020). “Digital experimentation and startup performance: Evidence from a/b testing.” *Available at SSRN*, 3440291.
- Lawrence, A., Ryans, J., Sun, E., and Laptev, N. (2018). “Earnings announcement promotions: A yahoo finance field experiment.” *Journal of Accounting and Economics*, 66(2-3), 399–414.
- Lefrere, V., Warberg, L., Cheyre, C., Marotta, V., Acquisti, A., et al. (2020). “The impact of the gdpr on content providers.” In *The 2020 Workshop on the Economics of Information Security*.
- Levinthal, D. A. (2007). “Bringing selection back into our evolutionary theories of innovation.” *Perspectives on innovation*, 291–307.

- Luo, H., Macher, J., and Wahlen, M. (2021). “Judgment aggregation in creative production: Evidence from the movie industry.” *Management Science*.
- Miric, M., and Jeppesen, L. B. (2020). “Does piracy lead to product abandonment or stimulate new product development?: Evidence from mobile platform-based developer firms.” *Strategic Management Journal*, 41(12), 2155–2184.
- Nicholls-Nixon, C. L., Cooper, A. C., and Woo, C. Y. (2000). “Strategic experimentation: Understanding change and performance in new ventures.” *Journal of business venturing*, 15(5-6), 493–521.
- Peukert, C., Bechtold, S., Batikas, M., and Kretschmer, T. (2022). “Regulatory spillovers and data governance: Evidence from the gdpr.” *Marketing Science*, 0(0), null.
- Rosenbusch, N., Brinckmann, J., and Bausch, A. (2011). “Is innovation always beneficial? a meta-analysis of the relationship between innovation and performance in smes.” *Journal of Business Venturing*, 26(4), 441–457.
- Runge, J., Geinitz, S., and Ejdemyr, S. (2020). “Experimentation and performance in advertising: An observational survey of firm practices on facebook.” *Expert Systems with Applications*, 158, 113554.
- Snelders, E., Worp, L., and Song, S. (2020). “A future without advertising cookies? it’s possible.” Tech. rep., Technical report, Ster.
- Sun, T., Yuan, Z., Li, C., Zhang, K., and Xu, J. (2021). “The value of personal data in internet commerce: A high-stake field experiment on data regulation policy.” *Available at SSRN 3962157*.
- Sutanto, J., Palme, E., Tan, C.-H., and Phang, C. W. (2013). “Addressing the personalization-privacy paradox: an empirical assessment from a field experiment on smartphone users.” *MIS Quarterly*, 1141–1164.
- Thomke, S. (2001). “Enlightened experimentation. the new imperative for innovation.” *Harvard business review*, 79(2), 66–75.
- Wen, W., and Zhu, F. (2019). “Threat of platform-owner entry and complementor responses: Evidence from the mobile app market.” *Strategic Management Journal*, 40(9), 1336–1367.
- Wottrich, V. M., van Reijmersdal, E. A., and Smit, E. G. (2018). “The privacy trade-off for mobile app downloads: The roles of app value, intrusiveness, and privacy concerns.” *Decision support systems*, 106, 44–52.
- Yin, P.-L., Davis, J. P., and Muzyrya, Y. (2014). “Entrepreneurial innovation: Killer apps in the iphone ecosystem.” *American Economic Review*, 104(5), 255–59.
- Zhao, Y., Yildirim, P., and Chintagunta, P. K. (2021). “Privacy regulations and online search friction: Evidence from gdpr.” *Available at SSRN 3903599*.

## A Appendix

To identify the location of the developers offering those apps, we went through six steps. We started with 60497 apps for which we have their availability data for all 24 months. In addition, they are either available in at least one EU country for the whole period or never available in the EU. We first checked the field of developer address to determine the country name. If it is not possible to identify the country name from developer address, we examined the Top-Level Domain (TLD) from developer's website to see whether a country code TLD could be detected. We repeated the above process and checked the field of developer email address in the third step. Afterwards, we detected the language of developer ID for the rest of the apps. If a language (e.g., Chinese, Japanese, Korean, etc.) is only spoken outside the EU, we assigned non-EU or specific country code to that app. In the fifth step, we checked the country code from the field of App ID. Last, we manually checked the developer location, only for the apps which are not available in the EU. We searched for the information of developer's location on the Google Play Store, developer's website, LinkedIn or Crunchbase. At the end, we were able to identify developer's country information for 54624 apps. Developer's location of 183 apps, which are not available in the EU, could not be determined and we considered them as non-EU apps.



183 apps not available in the EU unidentified (5690 apps available in the EU not checked manually)