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IMPRESSUM

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https://www.diw.de

ISSN electronic edition 1619-4535

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Competitors' Reactions to Big Tech Acquisitions: Evidence from Mobile Apps*

Pauline Affeldt† and Reinhold Kesler‡

December 9, 2021

Abstract

Since 2010, Google, Apple, Facebook, Amazon, and Microsoft (GAFAM) have acquired more than 400 companies. Competition authorities did not scrutinize most of these transactions and blocked none. This raised concerns that GAFAM acquisitions target potential competitors yet fly under the radar of current merger control due to the features of the digital economy. We empirically study the competitive effects of big tech acquisitions on competitors in a relevant online market. We identify acquisitions by GAFAM involving apps from 2015 to 2019, matching these to a comprehensive database covering apps available in the Google Play Store. We find that competing apps tend to innovate less following an acquisition by GAFAM, while there seems to be no impact on prices and privacy-sensitive permissions of competing apps. Additionally, we find evidence that affected developers reallocate innovation efforts to unaffected apps and that affected markets experience less entry post-acquisition.

JEL Classification: K21, L41, L86, G34

Keywords: mergers and acquisitions, digital markets, GAFAM, apps, innovation, privacy, event study

*We are grateful to Tomaso Duso, Axel Gautier, Shan Huang, Ulrich Kaiser, and Martin Peitz as well as participants of the workshop DIGECON2020, DIW IO Brown Bag Seminar, Paris Seminar on the Economics of Digitization, and CRC TR 224 Economics Seminar for their helpful comments.

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1. Introduction

Google, Apple, Facebook, Amazon, and Microsoft (GAFAM), often labeled as big tech, are among the most valuable companies worldwide. Some attribute the success of these five companies to the many and crucial acquisitions, where much of the discussion revolves around prominent cases like Google/DoubleClick, Facebook/Instagram, and Facebook/WhatsApp. Interestingly, not a single GAFAM acquisition has been blocked in the past. Further, most of these transactions were not reviewed by competition authorities at all based on current turnover thresholds for notification. For example, a report by the US Federal Trade Commission (FTC) shows that GAFAM made 616 unreported acquisitions at or above 1 million from 2010 to 2019, excluding hiring events or patent acquisitions.[1]

This led to numerous policy reports asking whether Big Tech pursues potentially anticompetitive acquisitions of nascent or potential competitors that are not reviewed at all or at least not rigorously enough (OECD, 2020; Australian Competition and Consumer Commission, 2019; Crémer et al., 2019; Furman et al., 2019; Scott Morton et al., 2019). In particular, firms in the digital economy often do not meet current turnover thresholds for merger investigation as they only start to monetize once they have acquired a large user base (Motta and Peitz, 2020). Furthermore, digital industries are typically characterized by multi-sidedness, (direct and indirect) network effects, access to data raising privacy issues, and often free provision of service to one side of the market (typically the user side while the advertising side pays). Firms then often compete on dimensions other than price, such as service quality, data collection, and innovation.

A particular worry is that incumbent high-tech companies might buy up start-ups solely to discontinue their innovation projects and to pre-empt future competition (so-called killer acquisitions, see Cunningham et al. (2021)). Relatedly, Caffarra et al. (2020) voice concerns over 'reverse' killer acquisitions: Instead of innovating themselves, large platforms buy young, innovative start-ups to acquire technology in complementary services into which the platforms want to expand. Finally, a study by Kamepalli et al. (2020) suggests that acquisitions by the incumbent may lower payoff prospects of new entrants and thus discourage them from investing ('kill zones'). Consequently, some reports conclude that merger control enforcement must be updated to properly account for the particular features of digital industries (Argentesi et al., 2019).

Indeed, several countries, most ambitiously Germany and the United Kingdom, have already implemented new rules, including the review of acquisitions for companies with paramount significance or strategic market status, respectively. On a broader scope, initiatives by the EU and US through the EU Digital Markets Act and the US Judiciary Committee's antitrust bills also target merger control procedures and big tech. Although definite changes regarding merger control remain to be determined, these efforts show an increasing willingness to change the approach towards big tech acquisitions.

Research on big tech mergers is primarily theoretical and focuses on effects on innovation.

[1] See https://www.ftc.gov/system/files/documents/reports/non-hsr-reported-acquisitions-select-technology-platforms-2010-2019-ftc-study/p201201technologyplatformstudy2021.pdf.

Motta and Peitz (2020) provide an overview of competitive effects from such acquisitions resulting in a call for stricter merger control, whereas Cabral (2020) stresses the importance of technology transfer through acquisitions and entrants' innovation incentives being discouraged due to strict merger policies. The latter is at the core of many papers providing guidance when to ban acquisitions (Letina et al., 2020; Fumagalli et al., 2020; Bryan and Hovenkamp, 2020; Katz, 2020). Relatedly, Cunningham et al. (2021) show for the pharmaceutical industry that incumbents buy entrants and subsequently shut them down. However, one has to account for the fact that digital markets are different in many regards, e.g., the amount of entrants, costs to develop and unpredictability (Cabral, 2020). Empirical research on big tech acquisitions is scarce. While Gautier and Lamesch (2020) as well as Parker et al. (2021) look at the acquisition strategies of GAFAM, Koski et al. (2020) and Prado (2021) consider the effects of big tech acquisitions on venture capital funding. We contribute to this by empirically looking into the competitive effects of GAFAM acquisitions at the product-level in a digital market, namely mobile applications.

In this paper, we focus on big tech acquisitions in the market for mobile applications. Examples include the large takeovers of WhatsApp and Instagram by Facebook. The complaint by the FTC against Facebook alleges that Facebook turned to unlawful acquisitions of innovative competitors after failing to compete in the mobile sphere.[2] The market for mobile applications is a good example of a relevant online market, in which innovation and privacy considerations are more important parameters of competition than price.[3] It is also a market that is, in principle, characterized by a competitive and dynamic environment with many apps and developers being active,[4] suggesting that acquisitions not only affect the acquirer and the acquired firm, but also competitors. We contribute to the scarce literature on the competitive effects of big tech mergers or acquisitions by empirically studying the impact of GAFAM acquisitions *on competitors* based on product-level data from the market for mobile applications.

Based on comprehensive lists of all GAFAM acquisitions from 2015 to 2019, we identify more than 50 acquisitions involving apps in the Google Play Store. We then match these with our dataset covering almost all apps in the Google Play Store. This allows us to not only observe the acquired apps along with GAFAM as a developer, but also gives us information on competing apps based on similarity, either suggested by Google or based on analyzing the textual description of apps. For the aforementioned features of digital industries, academic research on big tech mergers or acquisitions mainly focuses on innovation rather than price effects, while data is not traditionally at the core of most of the analyses. Relevant outcomes are thus updating behavior and requested privacy-sensitive permissions as measures of innovation and data collection.

We employ two-way fixed effects regressions to measure the impact of GAFAM app acquisitions on competitors. Specifically, we use observations from competitors of later acquired apps as control units for competitors of earlier acquired apps in order to account for calendar time

[2] See `https://www.ftc.gov/news-events/press-releases/2021/08/ftc-alleges-facebook-resorted-illegal-buy-or-bury-scheme-crush`.

[3] Less than 5 % of the apps in the Google Play Store are for pay (see `https://www.appbrain.com/stats`).

[4] Cabral (2020) argues that digital industries are typically characterized by many smaller firms that compete with one or two dominant firms like Google, Apple, or Facebook.

trends. This is complemented by various robustness checks related to the econometric setup along with different measures of competitors. Finally, we analyze the updating behavior of developers in order to measure possible spillovers onto other apps of a developer affected by an acquisition and study the effect of GAFAM app acquisitions on subsequent entry into the affected product markets.

Half of the acquired apps are discontinued, which tend to be smaller and less privacy-intrusive than apps that are continued. Following acquisition, acquired apps become free of charge but request more privacy-sensitive permissions. These developments have to be considered in concert with the impact on competing apps. We find no effect on competing apps' prices or requested privacy-sensitive permissions. In contrast, GAFAM acquisitions are related to a lower likelihood of an update by competitors, which is robust to various alternative specifications. Following a GAFAM app acquisition, competing apps' propensity to update decreases by 2.8 percentage points. Distinguishing the nature of the update, the evidence suggests that similar apps reduce the number of feature updates following a GAFAM acquisition, thereby substantiating that innovation is reduced. Finally, we find evidence that affected developers reallocate efforts of feature updates to unaffected apps and that developers shy away from launching new apps in markets affected by GAFAM acquisitions.

Our results reveal reduced innovation efforts in the market of acquisition, with competing developers shifting a part of their effort to their other apps and markets. This shows that the competitive effects of big tech acquisitions cannot be assessed by only looking at the acquirer and the target, but that we must also account for the impact on competing firms. In particular, we also have to consider potential spillovers to other markets in case of multi-product firms as well as effects on entry as more radical measures of innovation.

The rest of the paper is structured as follows. Section 2 presents the data and shows descriptive statistics. Section 3 outlines the empirical strategy. Sections 4 and 5 present the results and Section 6 concludes.

2. Data and Descriptives

2.1. Data

Play Store Data. We quarterly web-scraped apps available on the Google Play Store from October 2015 through October 2019, gathering all the publicly available information on the app and its developer. Since Google provides no registry of all the available apps, we used incomplete lists of apps from the website AndroidPIT providing information on the Play Store as a starting point.[5] In a next step, we found further apps by looking at the similar apps suggested in the Play Store by Google for each app from the initial list of apps. In subsequent steps, we repeated the process of adding similar apps of the newly found apps to the dataset until the similar apps did not

[5]See, as an example, `https://web.archive.org/web/20130819094306/http:/www.androidpit.de/de/android-market/paid-android-apps-BOOKS_AND_REFERENCE`.

yield any additional apps. The process of gathering similar apps for all previously found apps was repeated for the subsequent quarters. This resulted in 1 to 2.5 million apps observed each of the 17 quarters and more than 30 million observations for the full dataset from which we extract acquired as well as competing apps leaving us with a distinctively smaller sample.

The data contains many app characteristics such as the number of installations and ratings, the average rating, whether the app has a website or a privacy policy, the presence of a video description, as well as the category of the app.[6] In order to quantify the competitive effects of app acquisitions across several relevant outcomes, we primarily approximate dimensions of innovation and privacy.

Acquisition of Apps. In order to identify acquired apps, we systematically gather all acquisitions by GAFAM from October 2015 through October 2019 based on various sources, such as Gautier and Lamesch (2020), several policy reports, such as Argentesi et al. (2019), and comprehensive lists on Wikipedia (Affeldt and Kesler, 2021).[7]

This leads to a list of 203 identified acquisitions. For each acquisition, we follow a specific routine to determine whether the target company has or had an app on the Google Play Store and to identify its Google ID to match it back to our main dataset. This is complemented by Google searches, e.g., 'company name acquires app.' Acquisitions take place at different points in time, resulting in different pre- and post-acquisition periods, especially depending on the entry and exit of the acquired app.

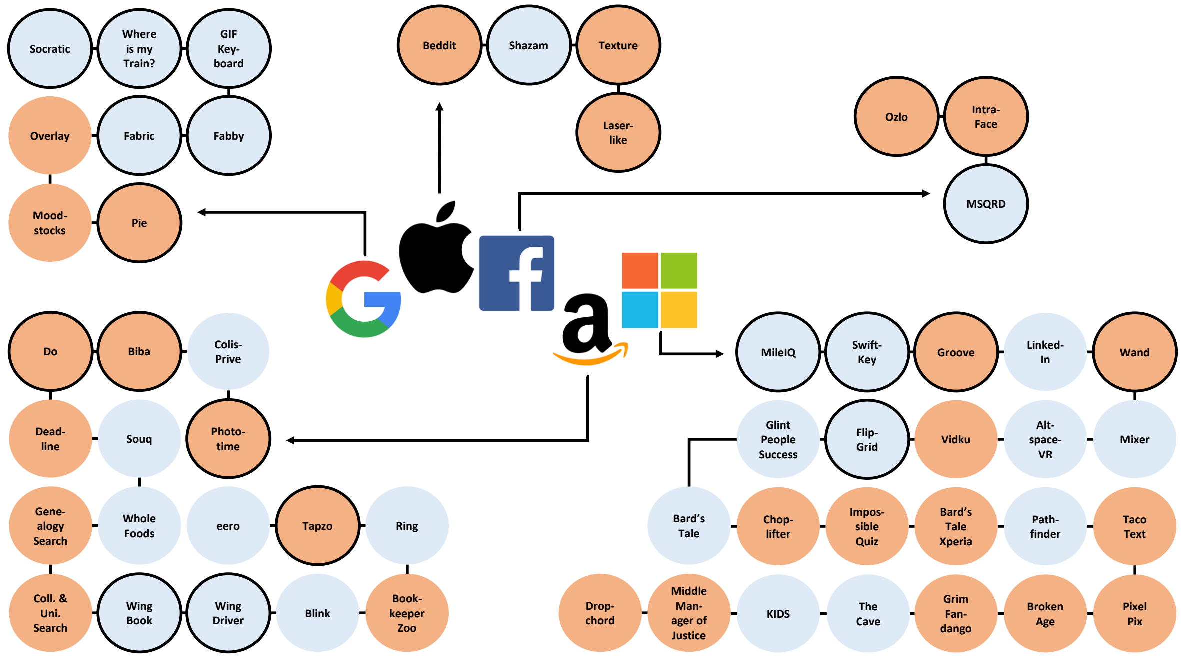
The routine involves first, whether news articles about the acquisition mention any apps. We then look at the target company's website (and its archives) as well as into articles reporting about the firm for indications about the presence of an app. If an app is mentioned anywhere, we search the name on the Play Store. In case the app is not available anymore, we try to retrieve links containing the Google ID from past news articles or search entries, as well as archived versions of the corresponding firm website. We managed to find 54 acquired apps that can also be successfully identified in our dataset. Figure 1 provides an overview of these acquisitions, showing them in the order of appearance with the arrow pointing toward the earliest takeover by the respective company in our observation period.

The acquisitions are classified into whether the acquired app is shut down (highlighted in orange in Figure 1) and whether the acquired app is the main part of the target company (outline in bold in Figure 1). For example, we consider the app as the main part of business for Shazam, while Whole Foods and LinkedIn have its main part outside the app. Besides these large takeovers, our sample also includes smaller companies that make it more difficult to assess the importance of the app. Although our observation period covers shutdowns of popular apps like Tapzo, which was covered by the media, the majority is inferred from the unavailability of the app in the Play Store and by looking up the unpublishing date on AppBrain. Unfortunately,

[6]For a detailed overview of all variables contained in the Play Store Data, see Kesler et al. (2019).

[7]See, as an example for Google, `https://en.wikipedia.org/wiki/List_of_mergers_and_acquisitions_by_Alphabet`.

Figure 1: Overview of GAFAM app acquisitions 2015-2019



Notes: The figure shows an overview of GAFAM acquisitions involving an app in the order of appearance for the 2015-2019 period. The arrow points toward the earliest takeover by the respective company in the observation period. The acquisitions are characterized by whether the acquired app is discontinued (highlighted in orange) and whether the acquired app constitutes the main part of the target company (outline in bold).

for most acquisitions, the transaction values are not disclosed, especially if the target company is small. A more detailed overview is provided in the Appendix in Table 7.

Competing Apps. The dataset allows us to approximate competitors, which is crucial for our empirical analysis. We define a market as the set of similar apps for the acquired app at the time of acquisition. Google suggested up to 24 and later 50 of them according to the similarity. While Google does not disclose the exact algorithm of how it identifies the set of relevant apps, the selection, also according to app developers, seems to be based on similarity in app characteristics (see Kesler et al. (2019) for a discussion). Although this can be considered quite narrow, we use this as our first definition of very close competitors following other studies (Kesler et al., 2019; Wen and Zhu, 2019).[8] Taking only the similar apps at the time of acquisition complicates the analysis, as some apps are not observed regularly pre- and post-acquisition due to late entry, early exit, and missings in our dataset. The latter also affects the observation of acquired apps, which might also be due to shutdowns several periods pre-acquisition. Moreover, for some, typically very small, apps, there are only a few or even no similar apps available.

All of this leads to some markets having no competitors defined, which results in 47 markets considered for the empirical analyses. This leaves us with an unbalanced panel of over 16,000 thousand app-quarter observations over 17 quarters. In a robustness check, we employ an al-

[8]We also looked whether the list of similar apps contain (potentially complementary) apps of the same developer. However, this is only the case for four of the acquired apps.

ternative approach to define similarity based on the textual description of apps (see section 4.3.2).

Measures. Our primary measure of innovation is based on updates. Specifically, we generate an indicator variable of whether the app has been updated in the previous quarter (corresponding to the last 90 days). However, an update might not necessarily indicate an innovation or change in the functionality of an app, but could also be related to fixing minor bugs in the app. Therefore, we capture the nature of the update by restricting the definition of the update dummy. In particular, we define three different dummy variables:

- *Update:* App has been updated in the previous quarter.
- *Feature Update: Update* accompanied by change in app features through more permissions excluding non-functional privacy-sensitive permissions.
- *Other Update: Update* without a change in any of the measurable characteristics (description length, number of screenshots, video, version number, number of clean permissions, and number of privacy-sensitive permissions related to functionality) and coming the closest to a minor update.[9]

Privacy can be approximated by the extent to which user data is accessed. This access to user data might serve as functionality or as a means of payment for the app, while privacy-intrusiveness is also affecting product's quality. One way to measure the access to user data is through Android's permission system. Specifically, one can classify the privacy-sensitive permissions an app requests upon installation. Based on Kummer and Schulte (2019), we identify a list of permissions that collect privacy-sensitive information of the user such as the access to the user's location, contacts, or browsing history.[10] In order to single out privacy-sensitive permissions that are necessary for functionality, we look at which permissions the majority (i.e., more than 50 percent) of paid apps in a category require. The assumption is that paid apps only request permissions that are necessary for functionality. One example may be a navigation app requesting the location of a user. All other privacy-sensitive permissions are deemed as non-functional and fulfill purposes other than functionality, thus, lowering the app quality for consumers.

We also observe app prices as well as prices of in-app products, giving us two indicator variables, equal to one if the respective monetization strategy is present.[11]

Finally, we are able to link each app to its developer, providing the possibility to look at multi-app developers. This enables us to measure possible spillovers regarding all of the aforementioned characteristics among apps of the same developer and the developer's behavior on a more aggregate level than just a single app.

[9] *Feature Update* and *Other Update* do not add up to *Update* as they constitute only a subset of updates besides other forms of possible updates.

[10] The list comprises permissions related to identities or accounts, records of messages, contacts, location, settings, logs, and control over device settings.

[11] Another important monetization strategy is advertising. However, we observe information about the presence of ads only from the seventh quarter onwards in our observation period.

2.2. Descriptives

We empirically study the effects of app acquisitions by GAFAM on competing apps. The final dataset contains information on over 16,000 thousand app-quarter observations belonging to 47 markets in which an app acquisition by GAFAM took place. In the following, we present descriptive statistics comparing acquired and competing apps.[12]

In Table 1, summary statistics of acquired and competing apps are shown for the pre-acquisition period and all variables used in the econometric analysis. Compared to acquired apps, competing apps are more often free of charge. They update more and request fewer privacy-sensitive permissions than acquired apps. In general, GAFAM app acquisitions seem to target markets that are more innovative in terms of updates when compared to the full Play Store dataset (Affeldt and Kesler, 2021).

Table 1: Acquired and Similar Apps Pre-Acquisition

	Acquired Mean	Similar Mean	Difference
Days Since Last Update	358.37	128.28	230.09***
Update in Last Quarter (1=Yes)	0.59	0.69	-0.10***
Feature Update in Last Quarter (1=Yes)	0.11	0.12	-0.01
Other Update in Last Quarter (1=Yes)	0.36	0.41	-0.05*
P-S Permissions (Number)	2.47	2.03	0.44***
P-S Permissions (1=Yes)	0.61	0.67	-0.06**
Non-Functional P-S Permissions (Number)	2.34	1.95	0.40***
Non-Functional P-S Permissions (1=Yes)	0.61	0.67	-0.06**
App Price (1=Yes)	0.29	0.10	0.19***
In-App Product (1=Yes)	0.17	0.35	-0.18***
Ratings (k)	148.98	285.27	-136.29
Average Rating	4.12	4.24	-0.12***
Clean Permissions (Number)	8.62	8.40	0.22
Privacy (1=Yes)	0.66	0.71	-0.05*
Video (1=Yes)	0.47	0.36	0.11***
Website (1=Yes)	1.00	0.89	0.11***
Observations	301	8,981	
Number of Apps	45	1,370	

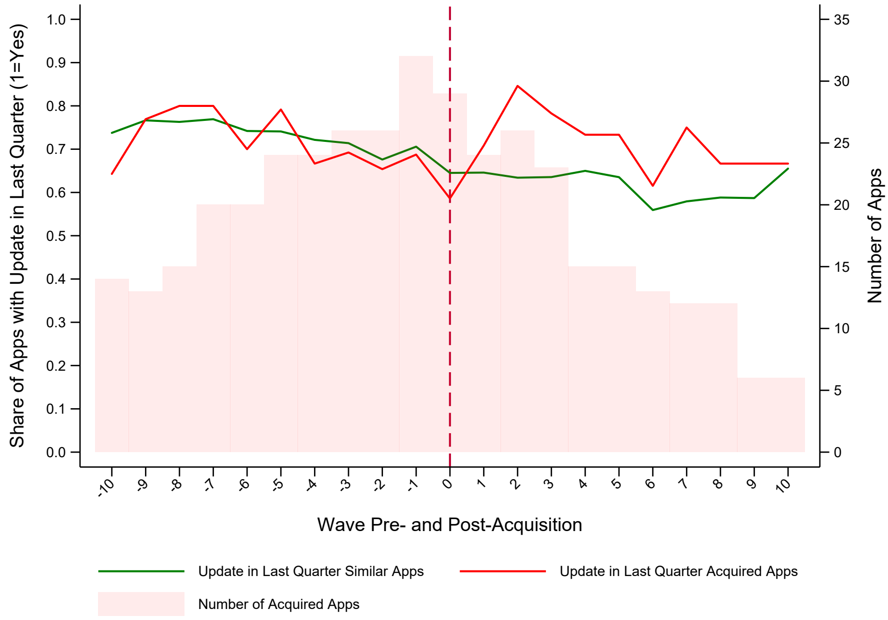
Notes: The means for acquired and similar apps are computed based on all pre-acquisition observations. Since acquisitions take place at different points in time and apps can enter, exit or not be observed in every period, the number of observations per app differs. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Before presenting the empirical strategy, we descriptively look at the development of competing apps in response to GAFAM acquisitions. A simple comparison of the development over calender time of key outcome variables for acquired and similar apps might be flawed as sometimes different post-acquisition periods and trends overlap. Thus, we study the development

[12]For more details on the 54 app acquisitions, see Affeldt and Kesler (2021). For a discussion of GAFAM's acquisitions strategies in general, see Gautier and Lamesch (2020); Parker et al. (2021).

relative to the time of acquisition of each acquired app. In Figure 2, we look at the development of the share of apps with an update in the last quarter for the acquired and similar apps. If we focus on the periods with at least ten acquired apps, post-acquisition, acquired apps seem to be more likely to be updated while there seems to be a slight decrease in the propensity to update for similar apps.

Figure 2: Comparing Acquired and Similar Apps Before-After: Updates

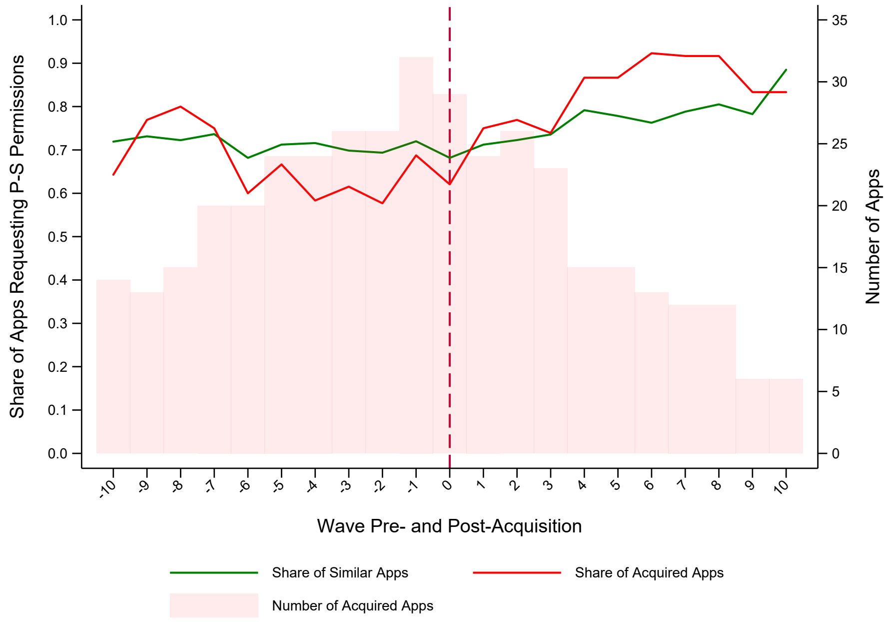


Notes: The plot for the acquired apps is based on 33 acquired apps for which we have pre- and post-acquisition data and at least one similar app. The plot for the similar apps is based on 1,143 similar apps to the 33 acquired apps included.

In Figure 3, we look instead at the development of the share of apps requesting privacy-sensitive permissions for acquired and similar apps. Both acquired and similar apps are more likely to request privacy-sensitive permissions post-acquisition, which may reflect a more general trend.

In addition to our main outcome measures, one can also look at more drastic responses by competitors such as the exit from the market of the acquisition. Table 2 shows that, on average, only 2 out of 25 competitors exit up to half a year subsequent to an acquisition by GAFAM.

Figure 3: Comparing Acquired and Similar Apps Before-After: Privacy-Sensitive Permissions



Notes: The plot for the acquired apps is based on 33 acquired apps for which we have pre- and post-acquisition data and at least one similar app. The plot for the similar apps is based on 1,143 similar apps to the 33 acquired apps included.

Table 2: Mean Exits of Similar Apps Post-Acquisition

Acquirer	Number Similar Apps at Acquisition	Exits up to 1 Quarter Post-Acquisition	Exits up to 2 Quarters Post-Acquisition	Developer Exits up to 1 Quarter Post-Acquisition	Developer Exits up to 2 Quarters Post-Acquisition
Google	22.67	0.83	1.17	0.67	1.00
Apple	37.00	1.67	3.67	2.00	3.67
Facebook	7.00	1.00	1.33	0.33	0.67
Amazon	21.92	1.31	2.54	1.00	1.77
Microsoft	30.69	1.08	1.92	1.00	1.85
Total	25.05	1.16	2.11	0.97	1.74

Notes: An app is considered to have exited the market one or two quarters post-acquisition if the app is observed for the last time one respectively two quarters post-acquisition. Acquistions taking place in the last three quarters are excluded from the analysis so that competing apps can in principle be observed for at least two quarters post-acquisition.

3. Methodology

3.1. Competitive Effects of App Acquisitions on Competitors

We want to empirically study the competitive effects of app acquisitions by GAFAM *on competitors*. Following the descriptive statistics, the question remains which effects on competitors are to be expected if a given app acquisition is pro- or anti-competitive.

By studying the effects of app acquisitions on competitors, we borrow from the literature on the effects of horizontal mergers on competitors' prices or profits.[13] As argued previously, we do not expect significant price effects. However, in the context of the digital economy, where many products are provided free of charge, merger effects on product quality and innovation incentives may be particularly important. Additionally, the quality of a (digital) product may also be determined by the user data collected, thereby raising privacy issues. For example, even if the product or service is provided for free both pre- and post-merger, product quality might decrease if the acquired entity collects more (privacy-sensitive) user data post-merger.[14] Translating this into the specific context of the app market, we study the effects of GAFAM acquisitions on apps competing in the same market as the acquired app. In particular, we primarily consider the effect on competitors' updating behavior and user data collected.

Updating Behavior. We would expect competitors to innovate less post-merger, if a given GAFAM app acquisition is anti-competitive.[15] However, it is arguably difficult to measure innovation in the context of the app market. We approximate it by the presence of updates in the previous quarter that are accompanied by app feature changes (see section 2 for the discussion of the different update measures).

Data Collected. As explained in section 2, we can measure the access to user data based on the number of privacy-sensitive permissions. However, the effect of an anti-competitive acquisition on the number of privacy-sensitive permissions is ambiguous: they could either increase because functionality (and app quality) is increasing or because more data is collected without an increase in functionality (and app quality). Therefore, we also measure privacy-sensitive permissions requested by an app that are not necessary for functionality. If an app acquisition is anti-competitive, we would expect that competing apps increase the user data they

[13] While the first papers to look at stock market returns of rivals, when horizontal mergers are announced, were Eckbo (1983) and Stillman (1983), more recent papers using event studies of competitors' abnormal returns to identify anti- and pro-competitive mergers include Duso et al. (2007) and Duso et al. (2013). Gugler and Szücs (2016) instead study the impact of horizontal mergers on competitors' profits. Stiebale and Szücs (2019) investigate the impact of horizontal mergers on rivals' markups, where mark-ups are first estimated via production function estimation.

[14] Even if the merging parties do not collect more user data post-merger, they might be able to combine the user data from the previously two distinct companies. Thus, app acquisitions might provide GAFAM with additional user data.

[15] While the theoretical literature is inconclusive about whether the overall impact of a merger on innovation is positive or negative (see for example Jullien and Lefouili (2018) for a comprehensive discussion), recent empirical studies mostly find a negative effect of mergers on innovation (Igami and Uetake, 2019; Haucap et al., 2019). Igami and Uetake (2019) find a plateau-shaped relationship between optimal R&D investment and the number of firms in the market. Haucap et al. (2019) find that mergers reduce innovation, measured by average patenting and R&D expenses, of both merging and competing firms, due to the reduction of competition in affected technology fields.

request without increasing functionality (and by this quality) post-acquisition.[16]

Lastly, while many apps are free of charge, many have in-app advertisements. As a result, users might not pay, but are exposed to (targeted) advertising instead, which lowers quality in case it is considered a nuisance. Thus, if an app acquisition is anti-competitive, in-app advertising might increase. Unfortunately, our data on in-app advertising is incomplete as outlined in section 2, which makes an analysis impossible. This is amplified by the fact that we cannot observe the advertiser side of the app market and developers interacting with it (in terms of prices).

3.2. Empirical Strategy

3.2.1. Static Specification

We study the competitive effects of GAFAM app acquisitions using an event study approach. Each of the 47 GAFAM app acquisitions is considered an event. Furthermore, in our setting, we use a dataset consisting only of apps competing with apps that are acquired by GAFAM at some point during the sample period. Therefore, the treatment is being exposed to a GAFAM acquisition as a competitor app. We use the terms pre-/post-treatment and pre-/post-acquisition interchangeably. We have no never-treated control group. Instead, competing apps that have not yet been exposed to a GAFAM acquisition serve as control observations. In the staggered treatment framework, these control observations are used to construct the counterfactual to treated observations of competing apps after they have been exposed to a GAFAM acquisition.

Consequently, we compare competitors of acquired apps pre- and post-acquisition, controlling for app and time fixed effects as well as time-varying app characteristics that measure demand, functionality, and quality. This is widely used in the literature and known as a two-way fixed effects regression (see, for example, Angrist and Pischke (2009) or Cameron and Trivedi (2005)).

We estimate the following two-way fixed effects (TWFE) regression for competing app i, in market m, at time t:

$$Y_{imt} = \beta_0 + \beta_1 Acq_{mt} + X_{it} + \eta_i + \eta_t + \varepsilon_{it} \tag{1}$$

A market m is defined as the set of similar apps competing with the acquired app at the time of acquisition. Acq_{mt} is an acquisition dummy, which is equal to one for market m as of the period in which an app in market m is acquired by GAFAM and all subsequent periods. X_{it} are time-varying app characteristics and η_i as well as η_t are app and quarter fixed effects, respectively.

The outcome variables Y_{imt} of competing app i, in market m, at time t are the different variables measuring innovation, quality, and, to a lesser extent, prices. In the main results, we present regressions on the different update dummy variables, the privacy-sensitive permissions dummy

[16] There are some theoretical papers suggesting that more market power leads to less privacy and more data collection (Casadesus-Masanell and Hervas-Drane, 2015; Dimakopoulos and Sudaric, 2018), while there is only scarce empirical evidence confirming this positive correlation (Preibusch and Bonneau, 2013; Kesler et al., 2019).

variable, as well as the non-functional privacy-sensitive permissions dummy variable. Results on the price dummy variable and the in-app purchase dummy variable are only reported in the Appendix.

The app characteristics X_{it} include the logarithm of the number of ratings as a measure of demand, the number of clean permissions as a proxy for functionality, along with variables approximating quality that involve the average rating and indicator variables for whether the app has a website, has a privacy policy, and has a video. Other measurable characteristics, such as the content rating, description length, or the number of screenshots are not included as these vary little over time and, thus, are mostly captured in the app fixed effects.

We corrected the error term by clustering standard errors at the app-level. Furthermore, we also ran all regressions using market rather than app fixed effects and clustering the standard errors at the market-level.

In order for β_1 to represent the causal effect of GAFAM app acquisitions on the outcome variables of interest for competing apps affected by an acquisition (average treatment effect on the treated, ATT), we must assume that the common trend assumption holds conditional on the app fixed effects, the time fixed effects, as well as the time-varying app characteristics X_{it}. Thus, conditional on the covariates, absent treatment, treated and untreated apps would follow the same trend. Furthermore, we need to assume that competitors do not anticipate a GAFAM acquisition, as this could affect the counterfactual trend, and that treatment effects are constant across apps. While app acquisitions by GAFAM are arguably endogenous and represent a selection into certain app markets, our analysis is solely based on those that get treated at some point in time. Thus, as we only consider apps as the control group that are not yet treated rather than never treated, endogeneity is partially accounted for. Nevertheless, claiming causality would rely on including all characteristics X that could explain trend differences between treated and not yet treated observations. Thus, we do not claim to estimate causal effects.

3.2.2. Dynamic Specification

Equation 1 is a static specification in the sense that the indicator for the acquisition is equal to one for the whole post-acquisition period. Instead, we can estimate a dynamic specification by including dummy variables for specific periods pre- and post-acquisition. The two-way fixed effect regression with leads and lags is then the following:

$$Y_{imt} = \beta_0 + \sum_{l=-K}^{-2} \beta_l Acq_{mt}^l + \sum_{l=0}^{L} \beta_l Acq_{mt}^l + X_{it} + \eta_i + \eta_t + \varepsilon_{it} \tag{2}$$

where Acq_{mt}^l is an indicator for being l time periods away from the initial treatment (the app acquisition is at $l = 0$), while η_i and η_t are app and quarter fixed effects, as before. The period before treatment is excluded. K and L are the most distant periods relative to the treatment included. Excluding some relative period from the dynamic specification is necessary to avoid multicollinearity among the relative period indicators or with app and quarter fixed effects.

This specification allows for checking whether there are dynamic treatment effects, i.e., different treatment effects depending on the time since treatment, but also whether there are some anticipation effects, i.e., whether competitors in the market anticipate the acquisition by GAFAM and, thus, might already react to the acquisition in advance.

3.2.3. Staggered Treatment

In our setting, treatment occurs at different points in time, i.e. the app acquisitions by GAFAM in the different markets take place at different points in time. While the TWFE model explained above is still widely used, several papers (see for example Borusyak and Jaravel (2018), Chaisemartin and D'Haultfoeuille (2020), Goodman-Bacon (forthcoming), Sun and Abraham (2021)) show that the estimated coefficient β_1 on the acquisition dummy variable in equation 1 is a weighted average of many different treatment effects and that these weights can even be negative if treatment effects vary over time. In general, bias can arise because treatment effects may vary across units and/or because the treatment effect may be time-varying within a treated unit (dynamic treatment effects). We are aware that both issues might arise in our application, since the effects of an app acquisition might change over time or could be heterogeneous depending on, for example, characteristics of the acquired app, the acquirer, or the market affected. Therefore, we check the robustness of our results by explicitly taking these issues into account when estimating treatment effects.

Goodman-Bacon (forthcoming) shows that the estimated β_1 actually is a weighted average of all possible two-group/two-period difference-in-difference estimators, where the weights are proportional to group sizes and the variance of the treatment indicators in each pair. This implies that units treated in the middle of the panel get the highest weights. Furthermore, panel length alone can change the difference-in-difference estimates. Additionally, in our application, we have no never-treated units and use the not yet treated units as control group. However, Goodman-Bacon (forthcoming) also shows that some of the two-group/two-period difference-in-difference estimators use not yet treated units as the control group while others actually use the earlier-treated group as a control after treatment begins. This can lead to negative weights on these treatment effects if treatment effects change over time.

While Goodman-Bacon (forthcoming) proposes a series of tests to check the robustness of the TWFE results, Callaway and Sant'Anna (2021) and Sun and Abraham (2021) propose solutions to estimate unbiased treatment effects in case of multiple time periods, variation in treatment timing, and when the parallel trends assumption may only hold after conditioning on observables. The estimator by Sun and Abraham (2021) assumes that the parallel trend assumption holds unconditionally, while the estimator developed by Callaway and Sant'Anna (2021) allows for conditioning on covariates. As the estimator developed by Callaway and Sant'Anna (2021) allows for using not yet treated observations as the control group and can be applied to a panel unbalanced in calendar time, we believe that Callaway and Sant'Anna (2021) is best suited for our application (see Appendix A.2 for details).

4. Main Results

4.1. Static Specification

Table 3 presents the results of the static two-way fixed effects regressions for the different outcome variables of interest. We find a negative relationship between GAFAM app acquisitions and the indicator for whether a competing app had any update in the past 90 days. Thus, subsequent to a GAFAM acquisition, competing apps in the affected markets tend to innovate less. In particular, the likelihood that a competing app has been updated in the previous quarter decreases by 2.8 percentage points post-acquisition. Compared to an unconditional mean probability of competing apps to update of 69% pre-acquisition, this is a decrease of around 4%. As discussed before, an update might not necessarily indicate an innovation or change in the functionality of an app, but could also be related to fixing minor bugs. Therefore, we also show the results for regressions with the feature update and other update indicator variables. The acquisition dummy is only statistically significant and negatively correlated with the feature update dummy, while it is insignificant in the regression with other updates. Thus, the negative relationship between GAFAM app acquisitions and competitors' updating behavior seems to be driven by changes in app features. Therefore, competing apps seemingly decrease their innovative efforts following GAFAM app acquisitions rather than decreasing their efforts to maintain the app. This negative association between GAFAM acquisitions and competitors' updating behavior is robust to the inclusion of market fixed effects instead of app fixed effects (see Appendix A.4).

GAFAM app acquisitions neither affect the percentage of competing apps that have privacy-sensitive permissions nor the percentage of competing apps that ask for non-functional privacy-sensitive permissions. This is robust to using market fixed effects instead of apps fixed effects (see Appendix A.4).[17]

For completeness, we also report the regressions on the indicator variables for whether the app is for pay or has in-app purchases in Appendix A.3. As expected, we do not find an effect of GAFAM app acquisitions on competitors' monetization strategies. In contrast, the robust negative relationship between the acquisition dummy and the update measure suggests that while GAFAM app acquisitions have no short-term competitive effects on prices or permissions, they seem to have a negative effect on the innovation incentives of competitors. If competitors update less following an app acquisition by GAFAM, it is not surprising that prices or permissions do not change.

4.2. Dynamic Specification and Staggered Treatment

In the baseline results, we measure the effects of GAFAM app acquisitions with a simple acquisition dummy that is one for every post-acquisition period. However, the estimated effect

[17]When running the same regressions with the number of privacy-sensitive permissions and the number of non-functional privacy-sensitive permissions as a dependent variable, the acquisition measure is also not statistically significant.

Table 3: Static Two-Way Fixed Effects Regression with App Fixed Effects

	Update	Feature Update	Other Update	P-S Perms.	Non-F. P-S Perms.
Acquisition (1=post-acquisition)	-0.028**	-0.019**	-0.020	-0.000	-0.000
	(0.011)	(0.009)	(0.013)	(0.007)	(0.007)
Number of Ratings (log)	-0.029***	0.011***	-0.071***	-0.001	-0.002
	(0.006)	(0.004)	(0.007)	(0.005)	(0.005)
Average Rating	0.114***	-0.024*	0.131***	0.009	0.011
	(0.022)	(0.015)	(0.025)	(0.015)	(0.016)
Number of Clean Permissions	0.016***	0.041***	-0.010***	0.024***	0.026***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Constant	0.331***	-0.284***	0.767***	0.514***	0.495***
	(0.107)	(0.075)	(0.114)	(0.078)	(0.080)
Further Controls	Yes	Yes	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.652	0.111	0.389	0.694	0.691
Observations	16535	16535	16535	16535	16535
Num. of Groups	1477	1477	1477	1477	1477
Adjusted R^2	0.46	0.09	0.17	0.84	0.83

Notes: The table shows the baseline estimations, when using alternative outcome variables to study the competitive effects of GAFAM app acquisitions. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. The dependent variable in column 4 is a dummy variable that takes the value of one if an app collects *any* privacy-sensitive permissions, and in column 5, we use context-specific criteria based on the app categories to determine which permissions are privacy-sensitive and not necessarily functional. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficient of interest is the one on the acquisition dummy.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

is a weighted average of potentially different effects over time. Thus, we also estimate a dynamic specification, where we deviate from the basic setup outlined in 3.2.2 and include two lead dummy variables (which are equal to one for two quarters and one quarter pre-acquisition, respectively), a dummy variable that is only one in the acquisition period, as well as two lag dummy variables (which are equal to one for two quarters and one quarter post-acquisition, respectively) as well as an indicator variable aggregating all time periods more than two periods post-acquisition. The estimated coefficients therefore show the effect on the outcome variables relative to the reference category of competing apps more than two quarters pre-acquisition. We do not include further leads and lags, as we have fewer observations the further away we move from the treatment period. The app acquisitions happen at different points in time which implies that we do not observe the same pre- and post-treatment periods for all competing apps. In particular, for acquisitions taking place early in our sample period, we will not observe many pre-treatment periods, while for acquisitions taking place late in our sample period, we have few post-treatment periods. The more leads and lags we include, the fewer competing apps will be observed in these periods, leading to imprecise estimates on the respective leads and lags.

Table 4 shows the results of these dynamic two-way fixed effects specifications. Most coefficients for the lead variables are statistically insignificant in the regressions for all outcome

Table 4: Dynamic Two-Way Fixed Effects Regression with App Fixed Effects

	Update	Feature Update	Other Update	P-S Perms.	Non-F. P-S Perms.
2 Quarters Pre-Acquisition	-0.006	-0.008	0.033*	0.008	0.007
	(0.014)	(0.012)	(0.018)	(0.007)	(0.007)
1 Quarter Pre-Acquisition	-0.009	-0.015	0.027	-0.007	-0.007
	(0.015)	(0.012)	(0.018)	(0.009)	(0.009)
Quarter of Acquisition	-0.015	-0.028**	0.012	-0.004	-0.006
	(0.016)	(0.012)	(0.019)	(0.010)	(0.010)
1 Quarter Post-Acquisition	-0.049***	-0.012	-0.041**	0.002	0.002
	(0.018)	(0.014)	(0.021)	(0.011)	(0.011)
2 Quarters Post-Acquisition	-0.044**	-0.048***	0.037	-0.002	-0.002
	(0.020)	(0.015)	(0.023)	(0.013)	(0.013)
more than 2 Quarters Post-Acquisition	-0.044*	-0.031*	0.000	0.023	0.023
	(0.023)	(0.016)	(0.026)	(0.016)	(0.016)
Number of Ratings (log)	-0.028***	0.012***	-0.072***	-0.001	-0.001
	(0.006)	(0.004)	(0.007)	(0.005)	(0.005)
Average Rating	0.113***	-0.024*	0.131***	0.011	0.013
	(0.022)	(0.015)	(0.025)	(0.015)	(0.016)
Number of Clean Permissions	0.016***	0.041***	-0.010***	0.024***	0.026***
	(0.003)	(0.004)	(0.003)	(0.003)	(0.003)
Constant	0.334***	-0.287***	0.775***	0.505***	0.485***
	(0.107)	(0.075)	(0.114)	(0.077)	(0.079)
Further Controls	Yes	Yes	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.652	0.111	0.389	0.694	0.691
Observations	16535	16535	16535	16535	16535
Num. of Groups	1477	1477	1477	1477	1477
Adjusted R^2	0.46	0.09	0.17	0.84	0.83

Notes: The table shows the dynamic estimations, when using alternative outcome variables to study the competitive effects of GAFAM app acquisitions. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. The dependent variable in column 4 is a dummy variable that takes the value of one if an app collects *any* privacy-sensitive permissions, and in column 5, we use context-specific criteria based on the app categories to determine which permissions are privacy-sensitive and not necessarily functional. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficients of interests are on the leads and lags of the acquisition dummy variables. More than two periods pre- and post-acquisition are regrouped into one dummy variable respectively.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

variables, except for one weakly significant lead for the other update outcome variable that vanishes completely with market fixed effects. Insignificant leads are reassuring for two reasons. First, they indicate that there are no anticipation effects. Thus, it seems plausible to consider a GAFAM app acquisition as an event not anticipated by competitors.[18] Secondly, even if the app acquisitions would not be anticipated by competitors, there is some imprecision in the acquisition dates we identified. For many of the app acquisitions, it is impossible to find information on the exact acquisition date. The fact that the lead dummy variables are insignificant in the regressions makes us confident that in most cases the actual acquisition date and the announcement

[18]This is actually in line with our desk research on the GAFAM acquisitions, where often these acquisitions are announced only after they took place.

date fall within the same quarter.

The dynamic specifications confirm the results of the static specification: GAFAM app acquisitions have a negative effect on the likelihood that competing apps are updated. The dynamic effects are even larger than those identified in the static specification, reducing the likelihood that a competing app was updated by about 4-5 percentage points, one, two and more than two quarters post-acquisition. We also find a negative association between GAFAM app acquisitions and updates of app features. However, the results cannot be compared directly to the baseline regressions, as the reference category is not the same and, in the baseline specification, we estimate an average effect post-acquisition while the immediate effects in the periods close to the acquisition period might be larger. As in the static specification, we find no effect of GAFAM app acquisitions on competing apps' (non-functional) privacy-sensitive permissions. The results are qualitatively similar when employing market rather than app fixed effects (see Appendix A.4).

The estimated coefficients in the dynamic specification in Table 4 show the effect on the outcome variables relative to the reference category of competing apps more than two quarters pre-acquisition. However, we also find one weakly significant coefficient on the lead variables. This may be due to composition effects. Besides the dataset being an unbalanced panel, we look at time relative to treatment when specifying pre- and post-acquisition periods. Given that GAFAM app acquisitions happen at different points in time, we do not observe the same pre- and post-treatment time periods for all competing apps in the sample. Thus, the composition of the sample varies over absolute and relative time periods. Therefore, in Appendix A.5, we report estimation results of dynamic specifications *keeping the sample constant*. In particular, we only keep competing apps in the dataset if we observe them at least from two periods prior to two periods after a GAFAM app acquisition, which reduces the number of observations considerably. The results for the update measure are robust and even larger in magnitude. In the balanced panel, GAFAM app acquisitions reduce the likelihood that a competing app was updated by about 6 percentage points one and two quarters post-acquisition. With this balanced panel, the previously found statistically significant lead turns insignificant, suggesting the results on leads to be driven by composition rather than anticipation. Again, we find no effect on non-functional privacy-sensitive permissions.

Lastly, we also check the robustness of our main result accounting for the timing of the treatment as in Callaway and Sant'Anna (2021). Aggregating the group-specific average treatment effects to an overall average effect, we find that GAFAM app acquisitions reduce the likelihood of competing apps being updated by on average 5 percentage points in a specification without further control variables (see Appendix A.6).

Summarizing, we find the probability to update by competitors to be affected by a GAFAM app acquisition across all the specifications. Since we find no significant effects on privacy-sensitive permissions, we only report results of the following analyses for the different update measures.

4.3. Robustness

4.3.1. Considering More Relevant Similar Apps

In the baseline results, we consider the relevant market of an acquired app to be comprised of similar apps provided by the Play Store at the time of acquisition. This set includes up to 50 similar apps. However, when browsing exemplary lists of similar apps, one might argue that the first apps being suggested are closer substitutes. When web-scraping, we also save the order in which the apps appear in the list of similar apps. Thus, we can assign a rank from 1 to 50 to the competing app based on its position in the list of similar apps. As outlined, we would expect that apps being closer substitutes (translating to a lower rank) can be considered more relevant competitors to the GAFAM app acquisition, which we aim to capture. In addition, at the beginning of our sample period until December 2016, Google only suggested up to 24 similar apps.

In Table 14 in Appendix A.7, we present estimation results, where we restrict the sample to competing apps with a rank of at most 24. First, this allows for a consistent market size over time and second it should get rid of less relevant competing apps at the end of the list of similar apps. Our results are robust to this change in the market definition: an app acquisition by GAFAM reduces the likelihood that a competing app is updated by around 3 percentage points. This shows that the result is driven by apps in the first part of the list of similar apps provided by Google.

4.3.2. Market Definition Based on Text Analysis

Another possibility to assess the robustness of the results is to adopt an entirely different market definition that is not based on the list of similar apps provided by the Google Play Store. For this, we developed an alternative definition of the market, i.e. the relevant set of apps competing with the app acquired by GAFAM, based on text analysis.

Specifically, we used the app description of each app in the Play Store. In a first step, we went through the app descriptions of all acquired apps at the time of acquisition and identified up to 10 keywords that best describe the app in descending order of importance.[19]

We then consider an app to be a similar app of an acquired app if it is in the same app category as the acquired app and contains at least 5 of the keywords in its app description. From this set of competing apps, we remove all apps that exited the Play Store up to one quarter before a GAFAM app acquisition in the relevant market took place. We report the baseline results based on these 5 keywords. However, the results are qualitatively similar if we require the competing app's description to contain at least 3 or all 10 keywords to qualify as a competitor of the acquired

[19]Each of the two authors as well as one research assistant identified up to 10 keywords for each acquired app. We kept a keyword if at least two people agreed on the keyword. This led to a list of keywords for each acquired app. After cleaning, removing stopwords, and stemming, we searched for these keywords in the app description text of all apps included in the dataset. The list of keywords for each acquired app is provided in Table 8 of the Appendix.

app.

This market definition based on text analysis has two advantages. First, it is not based on Google's black box algorithm for defining similar apps. If the baseline results are robust to this change in market definition, we are confident in using Google's set of similar apps. Second, the market definition based on text analysis allows to study entry (see section 5.2.2). The market definition based on similar apps does not contain entry: a market is defined as the set of similar apps of the acquired app at the time of acquisition. We then follow this constant set of apps over time. To reproduce the baseline result with the text analysis market definition, we do the same: we follow those apps that are competing with the acquired app at the time of acquisition by GAFAM over time.

Table 15 in Appendix A.7 reports the baseline results based on this alternative market definition. The acquisition dummy is negative and statistically significant in the regression on the update dummy. An acquisition by GAFAM decreases the likelihood that a competing app has been updated in the previous quarter by 2.1 percentage points. The acquisition dummy variable is statistically insignificant in the regressions on feature updates, while it suggests a statistically significant and negative relationship with other updates as in Table 14.

5. Analysis of Developers

5.1. Empirical Strategy

As outlined in section 2, we are able to link each app to its developer, which enables us to measure possible spillovers among apps of the same developer. Therefore, we extend our analyses on the competitive effects of a GAFAM app acquisition from affected apps to affected developers, looking at whether the developer's behavior changes also with respect to (seemingly) unaffected apps. This is similar to Wen and Zhu (2019), who find that after Google's entry threat increases, affected developers shift innovation to unaffected and new apps. In order to investigate this, we create a second dataset, where in addition to the apps competing with apps acquired by GAFAM (the previous sample), we add all other apps owned by the developers of the affected apps. Accordingly, we regress the different outcomes on a sample comprising the similar app of an affected developer and its remaining, unaffected apps, distinguishing through an interaction effect how the response by the developer differs between affected and unaffected apps.

As a more radical measure of innovation, one may consider the number of (new) apps in a product market. Accordingly, a related research question is then whether an app acquisition by GAFAM changes the decision of other app developers to enter into the respective product market. Based on the aforementioned theoretical and empirical studies, the direction is *a priori* not clear. To answer this question, we need to measure entry (and exit) of competing apps over time. Thus, rather than taking the set of similar apps at the time of acquisition and following this constant set over time, we allow the similar apps of an acquired app to change over time employing text analysis (see section 4.3.2). The markets based on the textual app description allow us to identify apps that appear in the Play Store after the acquisition and enter into a market post-acquisition (i.e. because their app description contains the relevant keywords). This changing market definition allows for measuring entry and the number of apps in each market. Specifically, for each period and acquisition, we then sum up the number of apps in the product market of the acquired app. This measure of active apps in a given market is the dependent variable in our regression, which is explained by a dummy variable equal to one for post-acquisition periods (our coefficient of interest) and time fixed effects accounting for general trends as the app market experienced a strong growth until 2018. This analysis can provide an insight into whether developers launch or refrain from launching new apps in product markets targeted by GAFAM acquisitions.

5.2. Results

5.2.1. Affected Developers' Behavior

In all previous results, we show that competing apps reduce their innovative efforts, as measured by updates following a GAFAM app acquisition. However, it could be the case that developers divert their innovative efforts to their other apps. Therefore, following Wen and Zhu (2019), we investigate in this section, whether app developers shift their innovation effort to unaffected apps after reducing it for apps that are directly competing with an acquired app.

Table 5 shows estimation results with the same setup as before with the only difference being that we regress the update and permission measures on a sample comprising the similar app of an affected developer and its remaining, unaffected, apps. The coefficients of interest are the acquisition dummy variable, which is the baseline acquisition effect for affected developers (equal to one from the first GAFAM acquisition onwards) and the interaction term of the acquisition dummy, where the similar app dummy variable corresponds to an additional impact for the similar apps of a developer.

While affected developers' increase updates related to changes in functionality for unaffected apps, they decrease these updates for apps that are directly affected by a GAFAM acquisition. In particular, the likelihood that an affected developer updated an unaffected app in the past 90 days, including feature changes through changes in permissions, increases by about 2.4 percentage points. For affected apps, the negative coefficient on the interaction effect with 5.3 percentage points surpasses the baseline effect and suggests a decrease in the likelihood of feature-changing updates for these apps in the past 90 days. This suggests that developers shift their innovative efforts to apps that are unaffected by GAFAM app acquisitions.

5.2.2. Entry Decisions of Developers

Besides updates as a proxy of innovation, another possible measure may involve the entry of new apps into the market. By this, we study whether GAFAM app acquisitions have an impact on any app developers' choices to exert further effort in the acquired apps' markets. For this, we

Table 5: Affected Developers' Updating Behavior

	Update	Feature Update	Other Update
Acquisition (1=post-acquisition)	-0.009***	0.024***	-0.040***
	(0.003)	(0.002)	(0.003)
Acquisition x Similar App	0.027***	-0.053***	0.110***
	(0.010)	(0.006)	(0.010)
Number of Ratings (log)	-0.075***	0.015***	-0.116***
	(0.003)	(0.002)	(0.003)
Average Rating	0.030***	-0.004*	0.032***
	(0.005)	(0.002)	(0.005)
Number of Clean Permissions	0.016***	0.052***	-0.025***
	(0.001)	(0.003)	(0.002)
Constant	0.497***	-0.382***	0.950***
	(0.034)	(0.026)	(0.036)
Further Controls	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes
Mean Dep. Var.	0.331	0.052	0.226
Observations	209966	209966	209966
Num. of Groups	29358	29358	29358
Adjusted R^2	0.46	0.12	0.26

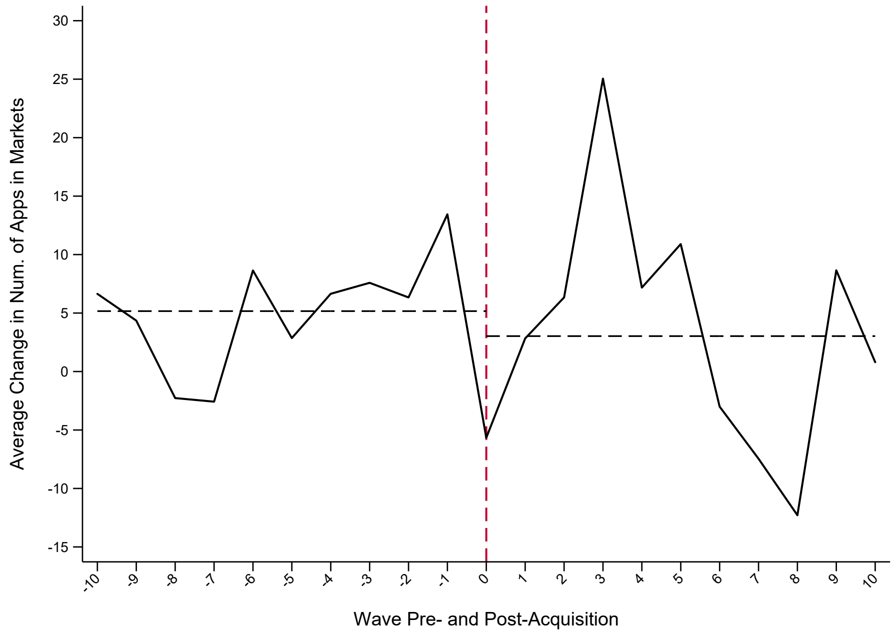
Notes: The table shows estimations, when using alternative update measures and comparing apps affected by a GAFAM acquisition with apps non-affected by a GAFAM acquisition for affected developers. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficients of interests are the one on the acquisition dummy as well as the interaction term indicating that an app was directly affected by a GAFAM acquisition, i.e. was a competing app of an acquired app at the time of acquisition.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

use the markets defined based on the textual description, which allow the competitors to vary over time and choose, as before, those apps containing at least 5 keywords in common with the acquired app. For each acquired app, we aggregate the number of competing apps in each wave corresponding to the respective market. In Figure 4, the average quarterly change in the number of apps active in the market is depicted relative to the acquisition period.[20] One can observe that, on average, there is a larger increase in the number of apps before a GAFAM acquisition, while at the time of acquisition there is a distinctive decrease suggesting exit. Additionally, post-acquisition there are also fewer apps active in the market on average, although it is more volatile.

We run a regression explaining the number of apps active in a market on an indicator variable taking the value one in case of a post-acquisition period, while also including time fixed effects as there may be a general change in certain periods. Table 6 shows the results. As one can hypothesize that an acquisition has a more immediate impact around the time of acquisition and it is harder to attribute the impact to the event after many quarters, we restrict the period of observation to certain waves around the acquisition successively. Accordingly, we look only

[20] This does not specifically distinguish whether it is a new app, but rather looks at the number of active apps.

Figure 4: Change in Average Number of Apps in Market around GAFAM acquisition



Notes: The dashed black line shows the pre- and post-acquisition average change in the number of apps in the markets.

into 10, 5, and 3 quarters around an acquisition in columns 2 to 4. Zooming into the relevant quarters around the acquisition makes the negative relationship between the GAFAM acquisition and the number of apps active in the market of the acquired app more apparent and statistically significant. As a result, app developers seem to shy away not only from updating remaining apps but also launching new ones in the affected markets.

Table 6: Explaining Number of Apps in Affected Markets

	All	$-10 \leq t \leq 10$	$-5 \leq t \leq 5$	$-3 \leq t \leq 3$
Acquisition (1=post-acquisition)	2.132	-3.130	-17.684*	-16.926*
	(8.989)	(5.476)	(9.823)	(9.055)
Constant	18.125	11.531	-26.914	-22.854
	(14.873)	(19.404)	(41.682)	(34.336)
Quarter FE	Yes	Yes	Yes	Yes
Mean Num. of Apps	79	78	80	76
Observations	676	606	392	202
Num. of Groups	43	43	43	43
Adjusted R^2	0.80	0.79	0.79	0.94

Notes: The table shows estimations explaining the number of apps active in a market before and after a GAFAM acquisition. The dependent variable is the number of apps in a market based on the textual description, which necessitate 5 keywords from the acquired app. Columns 2 to 4 restrict the sample to an observation period of 10, 5, and 3 quarters around the acquisition. The coefficients of interests is the one on the acquisition dummy, while time fixed effects are controlled for.
Standard errors clustered at the market-level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Conclusion

In this paper, we provide empirical evidence on the competitive effects of acquisitions by big tech, also known as GAFAM, on competitors in terms of innovation and data collection based on product-level data from the Google Play Store. We do this by studying the impact of GAFAM app acquisitions on competing apps using an event study approach.

We find that about half of the acquired apps are discontinued, typically these tend to be smaller and less privacy-intrusive than those apps that are continued. Following the acquisition, acquired apps become free of charge but also request more privacy-sensitive permissions. In contrast, we do not find any effect on competing apps' prices or requested privacy-sensitive permissions. However, GAFAM acquisitions are related to a lower probability of competitors updating their apps. Distinguishing by the nature of the update, the results suggest that similar apps reduce the number of feature updates, thereby substantiating that innovation is reduced. Finally, we find evidence that affected developers reallocate efforts of feature updates to unaffected apps and that developers are less likely to launch new apps in markets affected by GAFAM acquisitions.

Overall, our results suggest that big tech acquisitions impact the strategic behavior of competitors in the respective product market. Specifically, innovation efforts measured both by updates and entry are reduced post-acquisition in the market of acquisition pointing toward anti-competitive effects of these takeovers. At the same time, competing developers shift part of their effort to unaffected apps. These results further contribute to research suggesting acquisitions by an incumbent to shape a start-up's innovation and investment portfolio (Dijk et al., 2021), while they also raise the question on the net effect on innovation. As a consequence, the assessment of competitive effects of big tech acquisitions must look at competitors along with the acquirer and target company, and, in case of multi-product firms, potential spillovers or reallocation of efforts to other product markets are to be considered. More generally, our evidence also points towards the importance of looking into dynamic effects on innovation and quality in digital markets rather than prices.

There are a few caveats and avenues for future research that we would like to mention.

Many digital markets are multi-sided. For the app market, we observe neither the developer (at least not prices) nor the advertiser side (neither prices nor quantities) and, therefore, we can only estimate acquisition effects on the user side. However, even if we estimate effects only on the user side of the market, we would ideally also consider the effects on in-app advertising quantities. Imagine a GAFAM app acquisition that neither changes the app price nor the app quality on the user side but increases the amount of in-app advertising. If users dislike advertising, this acquisition would decrease consumer surplus. Unfortunately, as we do not have a reliable measure for in-app advertising, we cannot account for these effects. Furthermore, as we only look at competitors of big tech acquisitions and do not consider the effort by the acquirer, assessments of the overall competitive effects on consumer surplus and total welfare are difficult. Relatedly, the phenomenon of 'reverse' killer acquisitions studied by Caffarra et al. (2020), where big tech acquirers would have innovated themselves absent the acquisition, is hard to verify without measuring efforts by the acquirer. One potential way of checking whether the acquirer integrated the target's technology would be to look at whether other apps owned by the acquirer become more similar in functionality to the acquired app over time.

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A. Appendix

A.1. Details on Acquired Apps

A.1.1. GAFAM Acquisitions Overview

Table 7: GAFAM Acquisitions Overview

Google ID	App Name	Acquirer	Announcement	Acquisition	Main	Disc.
com.piethis.pieandroid	Pie	Google		2/18/2016	1	1
com.moodstocks.scanner	Moodstocks	Google	7/6/2016		0	1
ms.overlay	Overlay	Google	7/6/2016		0	1
io.fabric	Fabric	Google		1/19/2017	1	0
com.fabby.android	Fabby	Google		8/16/2017	1	0
com.riffsy.FBMGIFApp	GIF Keyboard	Google	3/27/2018		1	0
com.whereismytrain.android	Where is my Train?	Google		12/10/2018	1	0
org.socratic.android	Socratic	Google	8/17/2019		1	0
com.beddit.beddit	Beddit	Apple	5/9/2017		1	1
com.shazam.android	Shazam	Apple	12/11/2017	9/24/2018	1	0
com.nim.discovery	Texture	Apple	3/12/2018		1	1
com.searchlike	Laserlike	Apple	3/13/2019		1	1
me.msqrd.android	MSQRD	Facebook		3/9/2016	1	0
com.intraface.intraface	IntraFace	Facebook		11/16/2016	1	1
com.ozlo.android	Ozlo	Facebook		7/31/2017	1	1
com.phototime	PhotoTime	Amazon		12/1/2015	1	1
com.colisprive.app	ColisPrive	Amazon	1/11/2016		0	0
com.biba.android.biba	Biba	Amazon	11/23/2016		1	1
com.domeetings.app.doapp	Do	Amazon		2/15/2017	1	1
deadline.mobile	Deadline	Amazon		3/6/2017	0	1
com.souq.app	Souq	Amazon	3/28/2017	7/3/2017	0	0
com.wholefoods.wholefoodsmarket	Whole Foods	Amazon	6/16/2017	8/28/2017	0	0
com.findthebest.android.genealogy	Genealogy Search	Amazon		7/20/2017	0	1
com.findthebest.android.colleges	Coll. & Uni. Search	Amazon		7/20/2017	0	1
com.finnetlimited.wings	Wing Book	Amazon	9/6/2017		1	0
com.finnetlimited.wingdriver	Wing Driver	Amazon	9/6/2017		1	0
com.immediasemi.android.blink	Blink	Amazon	12/22/2017		0	0
sqrrl.BookkeeperZoo	Bookkeeper Zoo	Amazon	1/23/2018		0	1
com.ringapp	Ring	Amazon		2/27/2018	0	0
com.akosha.directtalk	Tapzo	Amazon		8/28/2018	1	1
com.eero.android	eero	Amazon	2/11/2019	3/12/2019	0	0
com.mobiledatalabs.mileiq	MileIQ	Microsoft		11/5/2015	1	0
com.touchtype.swiftkey	SwiftKey	Microsoft	2/3/2016	3/1/2016	1	0
com.microsoft.xboxmusic	Groove	Microsoft	2/9/2016		1	1
com.linkedin.android	LinkedIn	Microsoft	6/13/2016	12/8/2016	0	0
com.wandlabs.wand	Wand	Microsoft	6/16/2016		1	1
com.mcprohosting.beam	Mixer	Microsoft	8/11/2016		0	0
com.altvr.AltspaceVR	AltspaceVR	Microsoft	10/4/2017		0	0
com.vidku.vidku	Vidku	Microsoft	6/18/2018		0	1
com.vidku.app.flipgrid	Flipgrid	Microsoft		6/18/2018	1	0
com.glintinc.app	Glint People Success	Microsoft	10/9/2018		0	0
com.inxile.BardTale	Bard's Tale	Microsoft	11/10/2018		0	0
com.inxile.Choplifter_HD	Choplifter	Microsoft	11/10/2018		0	1
net.inxile.tiq	Impossible Quiz	Microsoft	11/10/2018		0	1
com.inxile.sony.BardTale	Bard's Tale Xperia	Microsoft	11/10/2018		0	1
net.obsidian.pacg1	Pathfinder	Microsoft	11/10/2018		0	0
com.xoxco.tacostand	Taco Text	Microsoft	11/14/2018		0	1
com.xoxco.pixelpix	Pixel Pix	Microsoft	11/14/2018		0	1
com.doublefine.dfa	Broken Age	Microsoft	6/9/2019		0	1
com.doublefine.grimfandangoremastered	Grim Fandango	Microsoft	6/9/2019		0	1
com.doublefine.thecave	The Cave	Microsoft	6/9/2019		0	0
net.playables.kidsgame	KIDS	Microsoft	6/9/2019		0	0
com.doublefine.mmoj	Middle Manager of Justice	Microsoft	6/9/2019		0	1
com.doublefine.rad	Dropchord	Microsoft	6/9/2019		0	1

A.1.2. Markets Based on Textual Description

Table 8: Keywords of Acquired Apps

Google ID	App Name	Keywords
com.akosha.directtalk	Tapzo	cash, bank, recharg
com.altvr.AltspaceVR	AltspaceVR	virtual realiti, interact, live, event, activ, peopl, game, meet
com.beddit.beddit	Beddit	sleep, monitor, track, smart, measur, cycl, alarm
com.biba.android.biba	Biba	call, confer, meet, contact, busi, connect, messag
com.colisprive.app	ColisPrive	packag, realtim, deliv, follow, person, absent
com.domeetings.app.doapp	Do	meet, messag, schedul, product, agenda, note, share, followup
com.doublefine.dfa	Broken Age	game, adventur, teenag, anim, comingofag, live, stori
com.doublefine.grimfandangoremastered	Grim Fandango	game, adventur, agent, death, dead
com.doublefine.mmoj	Middle Manager of Justice	game, superhero, justic, team, crime, manag
com.doublefine.rad	Dropchord	game, arcad, dexter, music, challeng, finger, visual, dodg, score
com.doublefine.thecave	The Cave	game, adventur, puzzl, explor, charact, team, discov
com.eero.android	eero	wifi, access, system, network, manag, internet, secur
com.fabby.android	Fabby	selfi, style, mask, background, design, makeup, effect
com.findthebest.android.colleges	Coll. & Uni. Search	educ, colleg, school, univers, search, rank, inform, decis
com.findthebest.android.genealogy	Genealogy Search	record, genealog, ancestor, famili, histori, inform, origin, name
com.finnetlimited.wingdriver	Wing Driver	courier, deliveri, driver, transport, order, servic, locat, request, rate
com.finnetlimited.wings	Wing Book	deliv, courier, realtim, track, packag, ship
com.glintinc.app	Glint People Success	employe, analyt, human resourc, feedback, organ, team, success, result, manag, score
com.immediasemi.android.blink	Blink	home, monitor, alert, watch, motion, video, camera
com.intraface.intraface	IntraFace	face, detect, recogn, express, emot
com.inxile.BardTale	Bard's Tale	game, roleplay, funni, weapon, adventur, battl
com.inxile.Choplifter_HD	Choplifter	pilot, helicopt, rescu, save, mission, fantasi
com.inxile.sony.BardTale	Bard's Tale Xperia	game, roleplay, funni, weapon, adventur, battl
com.linkedin.android	LinkedIn	busi, connect, network, profession, profil, peopl, job, career
com.mcprohosting.beam	Mixer	stream, realtim, view, game, watch, channel, follow, chat
com.microsoft.xboxmusic	Groove	music, mp, playlist, album, download, song, discov
com.mobiledatalabs.mileiq	MileIQ	tracker, mileag, automat, busi, drive, log, report
com.moodstocks.scanner	Moodstocks	recognit, imag, index
com.nim.discovery	Texture	magazin, read, publish, content, download, issu, unlimit, articl, recommend, access
com.ozlo.android	Ozlo	artifici intellig, person, assist, plan, companion, want
com.phototime	PhotoTime	photo, organ, recognit, tag, automat, search, detect
com.piethis.pieandroid	Pie	messag, chat, work, team, share, cowork, client
com.riffsy.FBMGIFApp	GIF Keyboard	gif, video, share, send, emoji, respons, keyboard, search, express
com.ringapp	Ring	secur, safeti, alert, camera, home, realtim, neighborhood, watch, crime
com.searchlike	Laserlike	news, feed, person, brief, artifici intellig, interest, topic
com.shazam.android	Shazam	music, identifi, song, video, discov, stream, listen, share
com.souq.app	Souq	shop, product, buy, discount, brows, deal
com.touchtype.swiftkey	SwiftKey	keyboard, autocorrect, typo, artifici intellig, write, type, text, predict
com.vidku.app.flipgrid	Flipgrid	video, voic, discuss, social, learn, platform, student, communiti, respond
com.wandlabs.wand	Wand	chat, connect, share, convers, messag, app, control, servic
com.whereismytrain.android	Where is my Train?	train, status, timet, live, schedul, travel, locat
com.wholefoods.wholefoodsmarket	Whole Foods	food, coupon, sale, shop, offer, save, store
deadline.mobile	Deadline	render, job, administr, inform, monitor, manag, artist
io.fabric	Fabric	monitor, alert, user, stack, bug, inform, realtim, trace, metric
me.msqrd.android	MSQRD	selfi, record, video, chang, anim, look, friend
net.obsidian.pacg1	Pathfinder	card, game, roleplay, battl, deck, charact, adventur
net.playables.kidsgame	KIDS	interact, anim, move, crowd
org.socratic.android	Socratic	photo, explan, help, problem, learn, subject
sqrrl.BookkeeperZoo	Bookkeeper Zoo	financi, bookkeep, manag, realtim, report, account, busi, inform

A.2. Staggered Treatment Effect Estimation

For the Callaway and Sant'Anna (2021) estimator to produce unbiased estimates, the following assumptions need to hold: First, there is no anticipation so that the observed outcomes in the pre-treatment periods can be used as untreated potential outcomes. Secondly, the parallel trend assumption holds conditional on covariates X_{it}. Thirdly, treatment is irreversible. Fourthly, there has to be overlap in the probability of being treated between treated and control observations. Callaway and Sant'Anna (2021) then allow the treatment effect to be heterogenous across relative time to treatment and group (where a group is defined by the time when units are first treated, i.e. for example all apps in markets where a competing app was acquired by GAFAM in the second quarter of 2018).

The main causal parameter of interest is the group-time average treatment effect $ATT(g,t)$, defined as:

$$ATT(g,t) = \mathbb{E}[Y_t(1) - Y_t(0) | G_g = 1] \tag{3}$$

where G is a dummy variable equal to one when an individual is first treated in time period g and t is the time period. $Y_t(1)$ and $Y_t(0)$ are the potential outcomes at time t with and without treatment respectively. The group-time average treatment effects can then be aggregated by time t, relative time to treatment (to check whether there are dynamic effects), and by groups g.

Callaway and Sant'Anna (2021) then propose a two-step estimator for $ATT(g,t)$. In the first step, the generalized propensity scores $\hat{P}_{g,t}$ for the different g and t pairs are estimated with, for example, a probit or logit based on the observations treated at time g and those not yet treated at time $t \geq g$:

$$P_{g,t} = P(G_g = 1 | X, (G_g = 1 \cup D_t = 0)) \tag{4}$$

where the observations with $G_g = 1$ are the treated observations and the observations with $D_t = 0$ are the control observations not yet treated at time t. The generalized propensity score is the probability that an observation is treated conditional on having covariates X and being a member of group g or the control group of not yet treated observations. Note that, here, propensity scores have to be estimated for all different (g,t) pairs, while in the case with never treated units, propensity scores need only to be estimated for each treatment group g.

In the second step, the sample analog of $ATT(g,t)$ is computed as:

$$\widehat{ATT}_{n.yet}(g,t) = \mathbb{E}_n \left[\left(\frac{G_g}{\mathbb{E}_n\left[G_g\right]} - \frac{\frac{\hat{p}_{g,t}(X)(1-D_t)}{1-\hat{p}_{g,t}(X)}}{\mathbb{E}_n\left[\frac{\hat{p}_{g,t}(X)(1-D_t)}{1-\hat{p}_{g,t}(X)}\right]} \right) \left(Y_t - Y_{g-1}\right) \right] \tag{5}$$

where $\hat{p}_g(.)$ is the estimate of $p_g(.)$ and $\mathbb{E}_n[Z] = n^{-1} \sum_{i=1}^{n} Z_i$.

Essentially, this is a weighted average of the long difference in outcome variables $Y_t - Y_{g-1}$, where the weights depend on the propensity score. Each $ATT(g,t)$ only uses observations from the control group of not yet treated observations and group g, then giving higher weights to control observations that have similar characteristics to those frequently found in group g and gives lower weights to control observations that are not very similar to the observations in group g. In their “did” R-package, which we use, Callaway and Sant’Anna (2021) implemented an estimator that also provides bootstrapped standard errors and allows for aggregating the different $ATT(g, t)$ to the different average treatment effects of interest.

A.3. Baseline Regression Results for Prices

Table 9: Static Two-Way Fixed Effects Regression for Prices

	Price	Price	In-App Price	In-App Price
Acquisition (1=Yes)	-0.000	-0.009*	-0.002	0.004
	(0.001)	(0.005)	(0.004)	(0.006)
Number of Ratings (log)	-0.001	-0.018***	0.013**	0.027***
	(0.001)	(0.006)	(0.005)	(0.006)
Average Rating	0.002	0.046***	0.015	0.062**
	(0.003)	(0.017)	(0.014)	(0.030)
Number of Clean Permissions	0.000*	0.001	0.009***	0.001
	(0.000)	(0.001)	(0.003)	(0.003)
Constant	0.079***	-0.023	-0.061	-0.299**
	(0.018)	(0.050)	(0.081)	(0.142)
Further Controls	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Fixed Effects	App	Market	App	Market
Mean Dep. Var.	0.077	0.077	0.335	0.335
Observations	16369	16387	16535	16552
Num. of Groups	1476	47	1477	47
Adjusted R^2	0.99	0.37	0.89	0.35

Notes: The table shows the baseline estimations, when using outcome variables related to price to study the competitive effects of GAFAM app acquisitions. The dependent variable in columns 1 and 2 is a dummy variable that takes the value of one if an app has a positive price. The dependent variable in columns 3 and 4 is a dummy variable that takes the value of one if the app has in-app purchases. Columns 1 and 3 include app fixed effects, while columns 2 and 4 include market fixed effects. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficient of interest is the one on the acquisition dummy.
Standard errors clustered at the level of the app (columns 1 and 3) and market (columns 2 and 4) in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.4. Regression Results with Market Fixed Effects

Table 10: Static Two-Way Fixed Effects Regression with Market Fixed Effects

	Update	Feature Update	Other Update	P-S Perms.	Non-F. P-S Perms.
Acquisition (1=post-acquisition)	-0.051**	-0.022**	-0.038*	-0.002	-0.002
	(0.020)	(0.010)	(0.020)	(0.012)	(0.012)
Number of Ratings (log)	0.023***	0.004**	0.007**	0.012***	0.012***
	(0.004)	(0.001)	(0.003)	(0.004)	(0.004)
Average Rating	0.052**	0.008	0.024	-0.034*	-0.034*
	(0.020)	(0.008)	(0.019)	(0.018)	(0.017)
Number of Clean Permissions	0.015***	0.009***	0.005**	0.027***	0.027***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)
Constant	0.101	-0.138***	0.463***	0.411***	0.406***
	(0.097)	(0.035)	(0.090)	(0.092)	(0.092)
Further Controls	Yes	Yes	Yes	Yes	Yes
Quarter & Market FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.652	0.111	0.389	0.694	0.691
Observations	16552	16552	16552	16552	16552
Num. of Groups	47	47	47	47	47
Adjusted R^2	0.22	0.06	0.06	0.36	0.36

Notes: The table shows the baseline estimations, when using alternative outcome variables to study the competitive effects of GAFAM app acquisitions. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. The dependent variable in column 4 is a dummy variable that takes the value of one if an app collects *any* privacy-sensitive permissions, and in column 5, we use context-specific criteria based on the app categories to determine which permissions are privacy-sensitive and not necessarily functional. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficient of interest is the one on the acquisition dummy.
Standard errors clustered at the market level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Dynamic Two-Way Fixed Effects Regression with Market Fixed Effects

	Update	Feature Update	Other Update	P-S Perms.	Non-F. P-S Perms.
2 Quarters Pre-Acquisition	-0.016	-0.003	0.021	-0.007	-0.007
	(0.018)	(0.010)	(0.020)	(0.010)	(0.010)
1 Quarter Pre-Acquisition	-0.032*	-0.012	0.005	-0.018	-0.017
	(0.017)	(0.012)	(0.019)	(0.013)	(0.013)
Quarter of Acquisition	-0.038	-0.028*	-0.006	-0.014	-0.014
	(0.023)	(0.014)	(0.025)	(0.017)	(0.017)
1 Quarter Post-Acquisition	-0.077**	-0.010	-0.067**	-0.009	-0.009
	(0.030)	(0.013)	(0.028)	(0.017)	(0.017)
2 Quarters Post-Acquisition	-0.098***	-0.051**	-0.012	-0.016	-0.015
	(0.029)	(0.020)	(0.030)	(0.020)	(0.020)
more than 2 Quarters Post-Acquisition	-0.108***	-0.030*	-0.058*	0.020	0.021
	(0.032)	(0.016)	(0.031)	(0.024)	(0.024)
Number of Ratings (log)	0.023***	0.004**	0.007**	0.011***	0.012***
	(0.004)	(0.001)	(0.003)	(0.004)	(0.004)
Average Rating	0.051**	0.008	0.023	-0.033*	-0.033*
	(0.020)	(0.008)	(0.019)	(0.018)	(0.018)
Number of Clean Permissions	0.015***	0.009***	0.005**	0.027***	0.027***
	(0.002)	(0.001)	(0.002)	(0.004)	(0.004)
Constant	0.104	-0.138***	0.463***	0.411***	0.406***
	(0.098)	(0.035)	(0.090)	(0.092)	(0.092)
Further Controls	Yes	Yes	Yes	Yes	Yes
Quarter & Market FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.652	0.111	0.389	0.694	0.691
Observations	16552	16552	16552	16552	16552
Num. of Groups	47	47	47	47	47
Adjusted R^2	0.22	0.06	0.06	0.36	0.36

Notes: The table shows the dynamic estimations, when using alternative outcome variables to study the competitive effects of GAFAM app acquisitions. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. The dependent variable in column 4 is a dummy variable that takes the value of one if an app collects *any* privacy-sensitive permissions, and in column 5, we use context-specific criteria based on the app categories to determine which permissions are privacy-sensitive and not necessarily functional. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficients of interests are on the leads and lags of the acquisition dummy variables. More than two periods post-acquisition are regrouped into one dummy variable.
Standard errors clustered at the market level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.5. Dynamic Specification with Balanced Panel

Table 12: Dynamic Two-Way Fixed Effects Regression with App Fixed Effects - Balanced Panel

	Update	Feature Update	Other Update	P-S Perms.	Non-F. P-S Perms.
2 Quarters Pre-Acquisition	-0.008	0.015	0.025	0.006	0.003
	(0.024)	(0.022)	(0.032)	(0.012)	(0.012)
1 Quarter Pre-Acquisition	0.005	-0.017	0.061*	-0.008	-0.007
	(0.025)	(0.022)	(0.033)	(0.016)	(0.016)
Quarter of Acquisition	-0.042	-0.038*	-0.006	-0.004	-0.000
	(0.028)	(0.021)	(0.035)	(0.017)	(0.018)
1 Quarter Post-Acquisition	-0.062**	0.006	-0.033	-0.012	-0.007
	(0.030)	(0.026)	(0.039)	(0.019)	(0.020)
2 Quarters Post-Acquisition	-0.058*	-0.035	0.019	-0.016	-0.010
	(0.034)	(0.027)	(0.040)	(0.020)	(0.021)
more than 2 Quarters Post-Acquisition	-0.067	-0.027	-0.019	0.012	0.017
	(0.042)	(0.029)	(0.048)	(0.027)	(0.028)
Number of Ratings (log)	-0.030***	0.013**	-0.065***	-0.009	-0.010
	(0.012)	(0.006)	(0.012)	(0.008)	(0.008)
Average Rating	0.097**	-0.020	0.128***	0.023	0.028
	(0.038)	(0.025)	(0.039)	(0.024)	(0.026)
Number of Clean Permissions	0.015***	0.032***	-0.008**	0.022***	0.024***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.006)
Constant	0.432**	-0.304**	0.751***	0.656***	0.622***
	(0.168)	(0.123)	(0.192)	(0.104)	(0.111)
Further Controls	Yes	Yes	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes	Yes	Yes
Mean Dep. Var.	0.676	0.107	0.419	0.759	0.752
Observations	5115	5115	5115	5115	5115
Num. of Groups	397	397	397	397	397
Adjusted R^2	0.45	0.07	0.18	0.83	0.83

Notes: The table shows the dynamic estimations with a balanced panel, when using alternative outcome variables to study the competitive effects of GAFAM app acquisitions. In particular, we only keep competing apps in the dataset if we observe them at least from two periods prior to two periods following a GAFAM app acquisition in its market. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. The dependent variable in column 4 is a dummy variable that takes the value of one if an app collects *any* privacy-sensitive permissions, and in column 5, we use context-specific criteria based on the app categories to determine which permissions are privacy-sensitive and not necessarily functional. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficients of interests are on the leads and lags of the acquisition dummy variables.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.6. Group-Time Average Treatment Effect

One possibility to aggregate the group-time average treatment effects is to compute a weighted average of all group-time average treatment effects with weights proportional to the group size. While this aggregation avoids the negative weights problem of the TWFE regression, it tends to overweight the effect of the groups treated earlier as they are observed for more post-treatment periods. An alternative is to aggregate the group and time specific effects to group-specific average treatment effects. Thus, these are the average effects of participating in the treatment for observations in each treatment group averaged across all post-treatment time periods. The overall ATT then averages the group-specific treatment effects across groups. Callaway and Sant'Anna (2021) propose to report this overall treatment effect as it measures the average treatment effect experienced across all observations participating in the treatment in any time period.

Table 13: Group-Time Average Treatment Effect - Aggregated across Groups

	Update	Feature Update	Other Update
Overall Average Treatment Effect	-0.0526*	-0.031	0.0072
Standard error	0.0256	0.0202	0.0314
95% Confidence Interval	[-0.1027; -0.0025]	[-0.0707, 0.0087]	[-0.0544, 0.0687]
Further Controls	No	No	No

Notes: The table shows the overall average treatment effect when aggregating the group-time average treatment effects first to group-specific treatment effects and then to an overall effect. The estimation is based on the did package in R provided by Callaway and Sant'Anna (2021). The control group are not yet treated units. We use the unbalanced panel option without further control variables. Standard errors are clustered at the app level and computed using the multiplier bootstrap based on 5000 bootstrap iterations. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.7. Robustness

Table 14: Considering up to 24 Competitors

	Update	Feature Update	Other Update
Acquisition (1=post-acquisition)	-0.032**	-0.004	-0.036**
	(0.014)	(0.011)	(0.017)
Number of Ratings (log)	-0.036***	0.007	-0.068***
	(0.008)	(0.005)	(0.009)
Average Rating	0.147***	-0.009	0.176***
	(0.028)	(0.018)	(0.031)
Number of Clean Permissions	0.016***	0.036***	-0.006
	(0.004)	(0.004)	(0.004)
Constant	0.290**	-0.297***	0.560***
	(0.145)	(0.093)	(0.144)
Further Controls	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes
Mean Dep. Var.	0.667	0.113	0.394
Observations	9845	9845	9845
Num. of Groups	853	853	853
Adjusted R^2	0.47	0.09	0.17

Notes: The table shows estimations, when using alternative outcome variables to study the effects of GAFAM app acquisitions on updating behavior. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficient of interest is the one on the acquisition dummy.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: Static Two-Way Fixed Effects Regression with App Fixed Effects - Text Analysis

	Update	Feature Update	Other Update
Acquisition (1=post-acquisition)	-0.021*	-0.008	-0.033***
	(0.012)	(0.007)	(0.012)
Number of Ratings (log)	-0.100***	0.005	-0.138***
	(0.014)	(0.006)	(0.014)
Average Rating	0.029	-0.005	0.030
	(0.019)	(0.008)	(0.019)
Number of Clean Permissions	0.012**	0.045***	-0.021***
	(0.006)	(0.004)	(0.005)
Constant	0.650***	-0.396***	1.113***
	(0.131)	(0.056)	(0.131)
Further Controls	Yes	Yes	Yes
Quarter & App FE	Yes	Yes	Yes
Mean Dep. Var.	0.312	0.041	0.212
Observations	12395	12395	12395
Num. of Groups	1450	1450	1450
Adjusted R^2	0.48	0.09	0.29

Notes: The table shows the baseline estimations, when using alternative outcome variables to study the effects of GAFAM app acquisitions on updating behavior and using a market definition based on text analysis. The dependent variable in column 1 is a dummy variable that takes the value of one if an app had any update in the past 90 days. The dependent variable in column 2 is a dummy variable that takes the value of one if an app had an increase in app features through more permissions (excluding non-functional privacy-sensitive permissions) in the past 90 days. The dependent variable in column 3 is a dummy variable that takes the value of one if an app had an update in the past 90 days without any change in the app characteristics including description length, number of screenshots, video, number of clean permissions, number of privacy sensitive permissions related to functionality, and first digit of the version number. Further controls include the indicator variables for whether the app has a privacy policy, has a website, and has a video. The coefficient of interest is the one on the acquisition dummy.
Standard errors clustered at the app level in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.