DOES PLATFORM OWNER'S ENTRY CROWD OUT INNOVATION? EVIDENCE FROM GOOGLE PHOTOS

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ABSTRACT

We study platform owner's decision to enter the market complementary to its platform with its own rival complement, and the consequences of such an entry on complementors' innovation behavior. We ask: if a platform owner like Google releases an app for its Android platform, does it keep app developers from innovating in the future? We investigate two mechanisms that suggest entry to stimulate complementor innovation: a racing effect, which prompts affected complementors to innovate due to "red queen" dynamics, and an attention spillover mechanism, which suggests increased innovation to result from spill over consumer demand and feedback to same-category complementors. We exploit Google's entry into the Android market for photography apps in 2015 as a natural experiment. Our difference-in-differences analyses of time-series data on a random sample of about 7,000 apps suggest strongly positive effects of entry on complementary innovation—further analyses lend support for the attention spillover effect.

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INTRODUCTION

In May 2015, Google released *Photos*, an all-purpose app for organizing, editing, and sharing digital photographs, to users of its smartphone platform Android (Google 2015). The various features of Photos were not new: Although it included a novel algorithm that was able to recognize people and objects in photos, a plethora of photo management apps had been available before (Mossberg 2015; NY Times 2015). From a theoretical perspective, however, the release of Photos is interesting because Google, in its role as the platform owner, entered the market space of app developers with an own product that competed with many of the apps complementors had contributed to the platform in the past.

In this paper, we exploit Google’s release of Photos as a quasi-experiment. The purpose of this paper is to shed light on the consequences of platform owner’s entry in complementary markets on complementary innovation. Entry into complementary markets, as in the case of Photos, is a popular yet not well-understood phenomenon. The landmark Microsoft antitrust trial sparked considerable interest of organizations, researchers, and policy makers regarding the behavior of platform owners toward their complementary markets (e.g., Gilbert and Katz 2001; Shapiro and Varian 1999). In the trial, the US government asserted that Microsoft’s entry in the market for Internet browsers, among other actions subject to the trial, was anticompetitive and to the detriment of complementors and consumers (Gilbert and Katz 2001). Whereas the claims against Microsoft remained difficult to untangle from legal and economic perspectives (Gilbert and Katz 2001), entry remains a common practice in the portfolio of platform owners, including Facebook (Li and Agarwal forthcoming), Intel (Gawer and Henderson 2007), and SAP (Iansiti and Lakhani 2009). Similarly, entry has not disappeared from regulators' awareness as the antitrust investigation against Google (Reuters 2016), for example, indicate.

Researchers have framed the decision to enter complementary markets as a trade-off in platform governance. Platform owners have strong incentives to enter (Farrell and Katz 2000), and may benefit from appropriating complementors' rents (Huang et al. 2013), increasing customer experience through integration (Eisenmann et al. 2011; Li and Agarwal forthcoming), and retaining control over platform evolution (Eaton et al. 2015; Gawer and Henderson 2007). Despite these incentives, entry may hurt complementors' revenues as they compete with the platform owner. Ultimately, complementors may hesitate contributing to the platform in the future. Thus, analyzing the consequences of entry for complementor innovations can help platform owners and policy makers determine the overall impact of this strategy.

Existing research on platform markets suggests different effects of entry on complementor innovations. The economics literature suggests that by entering complementary markets, platform owners appropriate complementors' rents and eventually reduce complementors' incentives to innovate (Choi and Stefanadis 2001; Farrell and Katz 2000). Oftentimes, platform owners are larger and possess more resources than complementors, which enables platform owners to squeeze complementors' rents (Farrell and Katz 2000). As a reaction to expropriation by the platform owner, complementors may invest available resources in mechanisms to protect their innovations or eventually affiliate with competing platforms (Ceccagnoli et al. 2012; Huang et al. 2013). Thus, entry may curb complementor innovation.

Whereas prior economics literature predicts entry to curb complementor innovation, management and marketing literature suggests that market entry may as well stimulate complementor innovation. First, studies on competitive dynamics suggest that entry may trigger a *racing effect*. According to this effect, entry puts complementors under direct competitive pressure, urging them to innovate in order to not lag behind (Barnett and Hansen 1996; Barnett and Pontikes 2008). Second, studies on consumer research suggest an alternative explanation, an *attention spillover effect*. According to this effect, entry stimulates innovation by attracting consumers to the focal market category and providing same-category complementors with new demand and feedback to innovate (Li and Agarwal forthcoming; Liu et al. 2014; Sahni forthcoming).

Despite these theoretical disagreements about the effects of entry on complementor innovation, there has been little empirical research on this phenomenon. Most literature on entry is descriptive and aims at providing insights into managerial practices of platform owners (Gawer and Cusumano 2002; Gawer and Henderson 2007). Models of platform owners' behavior toward complementors largely focus on pricing strategies (Choi and Stefanadis 2001; Farrell and Katz 2000; Parker and Van Alstyne 2005). Some studies investigated the consequences for platform owners when complementors fear appropriability (Ceccagnoli et al. 2012; Huang et al. 2013). Yet, these studies do not give insights into the impact of entry on existing complementors' innovation. Finally, none of these studies explains the mechanisms that affect complementors' innovation.

Our identification strategy is a quasi-experiment (Shadish et al. 2002), where we exploit Google's introduction of Photos. Our research design treats entry as an exogenous shock to complementors' innovation behavior, and helps us to isolate the effects of entry and to compare innovation outcomes to a control group not affected by entry. We avoid selection bias by using monthly time-series panel data on a random sample of apps, which we observe three months prior and after the release of Photos, and estimate the impact of entry on innovation using difference-in-differences (DID) analyses (Bertrand et al. 2004; Imbens 2004).

We model complementors' innovation as their decision to release a major update for their app, in terms of adding new features, functionalities or content. Updates constitute a growing portion of the innovation occurring in software industries. For example, the carmaker Tesla frequently rolls out "over-the-air" updates for its Model X cars, most recently introducing a feature that enables users to park their cars without having to be inside it. Apple, for example, annually stages publicized events, announcing new hardware products but also new updates for its iPhone and Mac operating software. We identify major updates by text-analyzing the release notes published by complementors.

Our difference-in-differences analyses of time-series data on a random sample of about 7,000 apps suggest strong and positive effects of entry on complementary innovation. Further analyses of rival explanations for this surprising finding suggest an "attention spillover" effect: Platform owner's entry increases consumer demand and feedback, which provides complementors with new ideas and opportunities to innovate.

BACKGROUND

Platform Owner's Entry and Complementary Innovation

Within the broader question of organizing the commercialization and development of products (Teece 1986), platforms have gained significant popularity among scholars and practitioners (El Sawy et al. 2015; Evans et al. 2006; Gawer and Cusumano 2002; Ghazawneh and Henfridsson 2013; Parker et al. 2016; Rochet and Tirole 2003). Platform owners' activities go beyond designing, developing, and distributing predefined products, but include the purposeful orchestration of an ecosystem of complementary innovation (Boudreau 2010, 2012; Cennamo and Santalo 2013). Prior research has mostly relied on analytical models to study the interactions between platform owners and complementors, largely based on pricing mechanisms (Farrell and Katz 2000; Hagiu and Spulber 2013; Rochet and Tirole 2003). These models regard the relationship between platform owners and complementors as that between an incumbent monopolist and actual or potential competitors. In these papers, entry—in terms of tying, first-party content, vertical integration or "squeezing"—is a means to extract rents from complementors. However, these studies have little to say about how entry alters complementary innovation. Models of entry that account for complementor innovation suggest entry to reduce or destroy complementors' incentives to innovate, given various assumptions of complete information and complementor behavior (Choi and Stefanadis 2001; Farrell and Katz 2000; Miller 2008). To the best of our knowledge, our paper is the first to evaluate the impacts of entry on complementary innovation empirically. Among related work, some studies investigated the influence of entry on platform adoption by prospective complementors (Ceccagnoli et al. 2012; Huang et al. 2013). The findings of Huang et al. (2013) illustrate platform owner's inability to commit not to squeezing complementors and show that complementors respond to these appropriability concerns by safeguarding returns from their innovations through patents, copyrights, and downstream capabilities. Gawer and Henderson (2007) use a deductive, qualitative approach to explore Intel's engagements in complementary markets. They offer insights into Intel's motivation to enter, outlining how Intel balanced its own strong incentives to enter against the risk of discouraging complementors' innovations. Ghazawneh and Henfridsson (2013) propose a theoretical model that focuses on resourcing and securing as two drivers behind boundary resources design and use and how they interact in third-party development in Apple's iPhone platform. These studies point to the challenges in platform governance for innovation (Benbya and Van Alstyne 2011; Parker et al. 2016).

Close to our study is Li and Agarwal's (forthcoming) study of Facebook's acquisition of Instagram, an existing, popular complement for sharing photos. Li and Agarwal (forthcoming) find Facebook's acquisition to increase the consumer demand not only for Instagram but also for other photography-sharing complements. Whereas Li and Agarwal (forthcoming) study consumer reactions to entry, we are the first to study how entry affects complementary innovation in a setting where we can control particularly well for endogeneity issues [1].

Mechanisms to Explain the Effect of Entry on Complementors' Innovation: Racing and Attention Spillover

Whereas the wider economics literature suggests entry to curb complementor innovation (Choi and Stefanadis 2001; Farrell and Katz 2000; Huang et al. 2013), the management and marketing literatures suggest two mechanisms that support the alternative hypothesis, namely that entry may indeed stimulate complementor innovation. We refer to these mechanisms as racing and attention spillover and discuss them in turn.

First, the racing mechanism suggests that increased innovation is a competitive response to entry (Barnett and Hansen 1996; Barnett and Pontikes 2008; Chen and Miller 2012). The rationale behind this argument stems from work on evolutionary competition (Barnett and

[1] Our review of prior literature suggests that platform owners' activities cause complex reactions by complementors and consumers, and that these reactions are subject to uncertainty and incomplete information (Eaton et al. 2015; Gawer and Henderson 2007; Wareham et al. 2014). Our conclusions derive from looking at both consumer and complementor reactions to entry.

Hansen 1996). It suggests performance differences among firms to be a function of a competitive arms race to secure profit margins (Chen and Miller 2012). Accordingly, increases in focal firms' innovation may be a response to other firms' competitive actions (Barnett and Hansen 1996; Barnett and Pontikes 2008). In the extreme scenario, competitors' achievements provide a continuously moving target for the focal firm, establishing "Red Queen" dynamics, in terms of the focal firm having to "run" just to stay in place (Barnett and Hansen 1996). The only way rival firms in such competitive races can maintain their performance relative to others is to increase their efforts (Barnett and Pontikes 2008). Thus, entry may increase complementor innovation by stimulating competition. In addition, if entry stimulates innovation by inducing racing behavior among complementors, platform owners may benefit from stimulating competition among complementors in general.

Second, an alternative attention spillover mechanism suggests that increased innovation may be the result of increased customer attention and feedback following the platform owner's market entry. Prior work on consumer attention has investigated attention spillover in the context of firms' marketing instruments, including decisions on pricing, promotions, and product introductions (Wansink 1994). Although such activities intuitively increase attention for a focal product and reduce consumers attention for competing products, more recent evidence indicates that marketing activities can have positive spillover effects on same-category products. Liu et al. (2014) show a positive spillover effect of advertising on same-category products in the refrigerated yogurt market. Sahni (forthcoming) observes a restaurant's advertising to cause positive spillover on similar competing restaurants. These studies attribute the positive spillover to consumers' awareness about the category.

Increases in consumers’ awareness about a category may affect complementors’ innovation behavior due to increased attention from customers and greater availability of customer feedback. Because of the increased attention about a category, complementors may decide to channel innovative efforts and resources toward this category. Li and Agarwal (forthcoming) observe, for example, that Facebook’s integration of Instagram, a popular photography app, substantially increased customer demand for the entire category of photography apps. In addition, increase in consumers’ awareness also means that complementors are equipped with resources that facilitate innovation. Specifically, attention spillover leads to a stream of customer feedback for complementors. Consumer feedback enables innovation by opening up new opportunities from which complementors can draw to innovate (e.g., Brown and Eisenhardt 1995; Leonard-Barton 1995; March 1991). We empirically assess the explanatory power of the above two mechanisms in how entry affects complementors' innovation behavior.

DATA AND METHOD

Empirical context: Google Android and the release of “Photos”

We investigate the consequences of Google’s 2015 entry into one of the categories in its “Android” platform. Google released Android in 2008 and subsequently opened the platform to third-party software applications (“apps”). Apps address various interests and functionalities, such as communicating with friends, playing games, or taking photos. Although a consortium of firms holds Android, Google exerts particular influence over Android by operating the largest marketplace for apps, Google Play. In Google Play, consumers can browse apps, obtain detailed information—including textual descriptions, prices, and reviews—and acquire the app (Salz 2014). At the time of our study, Google Play comprised more than 1.7 million apps provided by more than 150,000 independent third parties (AppAnnie 2015), available on four of every five smartphones shipped (The Wall Street Journal 2015).

On May 28th, 2015, Google published Photos in Google Play. Photos marked Google's market entry into its own ecosystem, in particular for complements addressing photography[2]. Google described Photos as an all-purpose app for organizing, editing, and sharing digital photographs. Photos addressed many of the needs of the "pic or it didn't happen" trend among smartphone users: First, the app promoted to decrease users' efforts in organizing pictures. It automatically grouped images by the individuals, landmarks, and objects shown in the images (The Wall Street Journal 2015). Second, the app comprised functionality to manipulate pictures, create animations, stories, and collages (Mossberg 2015). Finally, Photos gave users free, unlimited storage for pictures and videos (Levy 2015).

Google did not publicly announce Photos upfront. Photos received significant media attention. Not only the technology press covered the release of Photos but also major outlets picked up the news, including The Wall Street Journal, The New York Times, and The Washington Post. Technology writer Walt Mossberg (2015) described Photos as being "best of breed", highlighting its superiority compared to leading rival products. The New York Times (2015) featured Photos as "simple", "clean", and "impressive". In sum, Photos was perceived as a product that should be taken seriously by same-category complementors (Mossberg 2015).

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[2] This event provides a relatively unique setting: Google had largely refrained from entry in the past. Google offered several apps for their own services, including email, Internet search or calendar, in Google Play but these services had existed as stand-alone services before Android. By contrast, Google's platform competitor Apple had entered complementary markets several times, e.g. in the cases of iBooks (2010), Find My Frinds (2010), and Garage Band (2011). Whereas it is likely that Apple complementors considered entry before developing an app, it seems unlikely to make this assumption in our context.

Five months after its introduction, Photos was reported to have reached 100 million monthly users (Google 2015).

Research Design

We exploit Google's introduction of Photos by constructing a quasi-experimental design (Shadish et al. 2002). We compare innovation outcomes of complementors affected by entry with the innovation outcomes of complementors not affected by entry, both before and after the release of Photos. Our identification strategy uses the exogeneity of the event to complementors in order to assess the consequences of entry on complementor innovation.

Measuring innovation is complex and useful proxies are often context-specific. We model innovation as complementors' decision to release a major update for their app, in terms of introducing new content, new functionality, or new features to the app. One reason why we use updates as a proxy for innovation is that updates constitute a significant portion of the innovation in app markets, and the software industry in general. Software is technologically flexible, meaning that producers can redefine and shape software products after their market release. Whereas most prior work has investigated updates from a perspective of maintaining software (Kemerer and Slaughter 1999; MacCormack et al. 2001), we argue that updates can be highly innovative. To illustrate the significance of updates, consider the carmaker Tesla, which frequently rolls out "over-the-air" updates for its Model X cars. One update, for example, introduced autonomous parking, a feature that enables customers to park their car without having to be inside it. Another example is Apple, which annually stages publicized events, announcing updates for its iPhone and Mac operating system.

We chose updates as a proxy for innovation because updates allow isolating the decision to innovate more thoroughly. First, with updates as a dependent variable we can use app-level controls for potential heterogeneity that may influence the innovation decision. Second, unlike other measures of innovation (e.g., new app releases), updates allow inferring racing and attention spillover effects more directly. For example, we can observe app-level feedback of consumers and isolate how this feedback influences the likelihood of complementors to innovate. Prior work has not extensively adopted updates in their work. Exceptions include Boudreau (2012), who used a count of application updates to measure innovative behavior in the application marketplace for Palm devices, and Tiwana (2015), who used the frequency of updates to infer the speed of evolution of browser add-ons.

Sample

We collected data directly from Google Play. A big advantage of our dataset is that we are able to analyze app-level time-series data on a random sample of apps in Google Play, which helps to improve generalizability, account for time-invariant heterogeneity, and avoid potential selection bias that can arise by using data to apps listed in top rankings or by using a cross-sectional design. We began by compiling an initial database of all apps in Google Play between July and November 2014, and subsequently kept our database up-to-date by mirroring new app releases to Google Play. We selected a random sample of 100,000 apps from our database, for which we tracked app-specific information, including an app's average rating by customers, the number of reviews, updates, and prices over time[3][4]. In other words, we have panel data on a random sample of apps from Google Play. We compared descriptives of our sample of Google Play apps with population characteristics published by a major analytics firm. We did not observe significant differences, which increases confidence in the reliability of our data.

Difference-in-Differences Design and Control Group Construction

We employed a difference-in-difference (DID) framework for our empirical tests, comparing innovation among apps affected by entry (treatment) with a sample of apps not affected by entry (control), both before and after entry. To identify treatment and control apps we use the categorization system in Google Play. Categories group apps by their functional purpose. Categories are particularly suited for studying the effects of entry because they isolate complements that (1) share similar functionality and (2) compete for the same consumer attention. Regarding first, categories group apps of similar functionality. For example, "communications" labels apps that connect people, such as instant messaging and video conferencing, whereas "photography" is a label for apps that assist in capturing, editing, managing, storing, or sharing photos (Salz 2014). Regarding second, via categories, consumers blend in and out rival apps that serve a similar purpose (Ghose and Han 2011; Salz 2014), such as photography apps. Empirically, the use of categories to isolate the effects of entry helps

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[3] We filtered data as follows: Besides apps, Google Play lists content, including television shows, music, games, and books. Unobserved heterogeneity may arise from comparing functional apps with content. In order to ensure comparability, we excluded apps labeled as "books & references", "comics", "education", "libraries & demos", "news & magazines", "wallpaper", "widgets", and "games".

[4] We observe apps on a monthly base. In our context, complementors release one major update every two months, on average, which is similar to analyses in the business press (Business Insider 2015).

reducing heterogeneity among apps: user preferences, development costs, and prices of apps in the same category are likely to be correlated (Ghose and Han 2011).

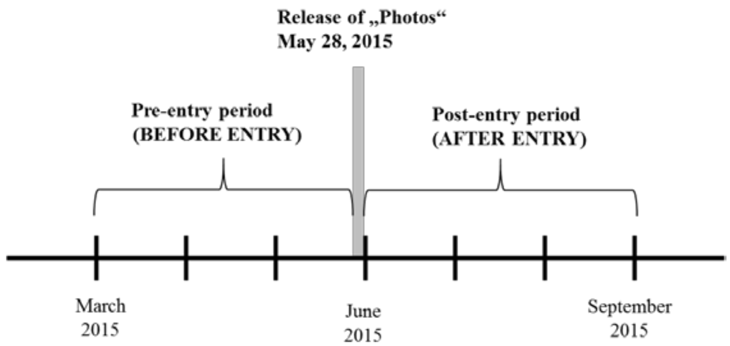
Google published Photos in the category “photography”, thus we define apps in the category “photography” as the treatment group. The selection of an appropriate control group is largely a theoretical question and depends on the context of the study. We define apps in the category “entertainment” as the control group. We selected entertainment apps because they have a comparably narrow functional purpose yet are unlikely to overlap with photography apps. Empirically, control and treatment groups must show similar observational characteristics in the pre-entry period (Angrist and Pischke 2009). Entertainment and photography apps show highly similar observational characteristics prior to entry, in particular regarding complementors’ decision to innovate as well as app ratings, reviews, and prices. By focusing on two categories, we believe we have substantially minimized the unobserved heterogeneity among the hundreds of thousands of apps in Google Play. We address potential concerns regarding our choice of the control group when assessing the robustness of our results.

Econometrically, our regressions follow the DID approach by comparing changes in complementors’ decision to update their apps over time between apps that are affected by entry and apps that are not affected by entry (Angrist and Pischke 2009; Bertrand et al. 2004). To allow enough time for estimating pre-entry differences, we define a three-month period—March 1, 2015 to May 27, 2015—as the pre-entry period. Correspondingly, we define the period from June 1, 2015 to September 1, 2015 as the post-entry period[5]. Our final sample includes 1,266

[5] Our choice of the pre-entry and post-entry periods is informed by prior work (Li and Agarwal forthcoming), but also the result of trading-off variance and standard errors. Longer periods may increase variance but may blur complementors’ reactions to entry. While still leading to significant estimates, shorter periods substantially introduce noise in our data.

treatment apps and 5,700 control apps, which we observed over a six-month period, resulting in a total sample of 41,796 app-month observations. Figure 1 plots the timeline of our study.

Figure 1: Timeline of the empirical study.



Dependent Variable

Our dependent variable is *MAJOR UPDATE*, which we constructed by text-analyzing the release notes complementors publish along with updates of their apps. We use text analysis because we want to identify updates that introduce new features, and exclude non-innovative updates, including bug fixes and efficiency improvements. Prior work relies on release numbers (e.g., 2.0, 2.1) to distinguish minor from major updates (e.g., Boudreau 2012; Tiwana 2015). Although it is an informal convention that integer increases in release numbers indicate major updates (Kemerer and Slaughter 1999), this standard is not enforced in many contexts and subject to certain ambiguity.

Following Kemerer and Slaughter (1999)'s arguments, we used release notes to gain richer insights into complementors' innovation. Release notes textually describe key aspects of an update. They provide detailed insights into the extent and novelty of changes made (Kemerer and Slaughter 1999). Release notes are visible to users of Google Play. They are displayed below the product description in a section entitled “What's new”, making them an important aspect of communication between complementors and consumers. Release notes are limited to 500 characters, which demands complementors to be precise in their description of changes (Salz 2014) and making release notes an accurate document for our analyses (see Table A1 for exemplary release notes).

Our approach to text analysis follows prior work that has used word lists (i.e., dictionaries) to objectively draw inferences from text (Bao and Datta 2014; Hoberg and Phillips 2010). Dictionaries use keywords or phrases to classify documents into categories or measure the extent to which documents belong to a particular category (Bao and Datta 2014). We constructed a dictionary for major updates by selecting a random subsample of 100 release notes from our sample and coded them into minor and major updates based on working definitions agreed upon by the authors. Subsequently, in an iterative procedure, we identified key words used in release notes of major updates. The final dictionary includes, among others, the words “feature”, “new”, “major”, and is available from the authors upon request. We then automated the dictionary-scoring using the Natural Language Toolkit in Python 2.7.

We implemented an algorithm that first removed filler words, punctuation, and stop words from the release notes. Lemmatization resulted in a list of unique words for each release note. We then scored the filtered release notes against our constructed dictionary, yielding a measure of “word hits”. Table A1 shows exemplary release notes and their classification. Finally, we included the dichotomous variable *MAJOR UPDATE* into our model, which we coded as 1 for apps that were updated with new features in a given month.

Independent Variables

Focal predictors (*PHOTOS* and *AFTER ENTRY*). The central predictor in our model is the dichotomous indicator *PHOTOS*, which is 1 if the focal app is affected by Google's release of Photos. DID analyses require a second indicator for distinguishing the periods before and after the event that is studied. Thus, we include the dichotomous indicator *AFTER ENTRY* in our models, which is 1 for the periods after the release of Photos. The DID estimator is then given by interacting *PHOTOS* with *AFTER ENTRY*.

Racing and difference in rating. The competitive dynamics literature explains innovation-enhancing effects by a competitive reaction of complementors caused by declines in their performance. If racing effects explain increased innovation by complementors, we should observe that apps experience a decline in consumer valuation after entry and, in addition, that declining consumer valuations increase the likelihood of updates. The app rating system on Google Play offers a unique opportunity to effectively capture different extents of consumer devaluation. To investigate potential racing effects, we created a measure *AVERAGE RATING* for each app in the sample, which captures consumers' mean rating of an app on a scale from 1 to 5 "stars", where 1 star represents a low rating and 5 stars represent a high rating. Apps with a high rating are perceived to fulfill user expectations, have an agreeable and engaging interface, and are well-suited to users' needs (Salz 2014). Decreases in app ratings are recognized as an important decision variable for complementors (Ghose and Han 2011; Tiwana 2015; Yin et al. 2014), thus allowing us to infer devaluations following entry. Thus, we added a variable *DIFFERENCE IN RATING*, which is the difference in the rating of an app in the post-entry months compared with the pre-entry months. According to the racing mechanism, the larger the

DIFFERENCE IN RATING following entry, the more likely it is that complementors will respond by increasing their efforts into innovation.

Attention spillover and difference in reviews. We assessed attention spillover effects using the number of consumer reviews for a focal app. On the one hand, the number of reviews is seen as a valid proxy for the popularity of an app in a certain category (Yin et al. 2014)—which will likely incentivize complementors to put more effort into innovating a particular app. On the other hand, reviews are valuable for complementors because they represent feedback from consumers of their app. Reviews provide complementors with evaluations of multiple attributes of their app and help complementors understand consumer needs (Salz 2014; Yin et al. 2014). We included the continuous variable *NUMBER OF REVIEWS* in our model, which is a count of the reviews for an app. We power-transformed *NUMBER OF REVIEWS* to account for its skewed distribution. To assess the attention spillover effect, we constructed the continuous variable *DIFFERENCE IN REVIEWS*, which is the difference in the number of reviews an app received in the post-entry period compared to the pre-entry period. According to the attention spillover effect, we should observe that complementors are more likely to increase their efforts into innovation when their apps show a higher *DIFFERENCE IN REVIEWS*.

Controls. We estimate our models with app-level fixed effects and time (i.e. month) fixed effects. In addition, we control for time variant changes in app prices. Table 1 reports summary statistics and correlations.

Table 1: Summary Statistics and Correlations

Variable	Mean	S.D.	Min.	Max.	1	2	3	4	5
1. Major update	.0183	.134	0	1	1				
2. Number of reviews (in thousands)	1.68	13.7	.011	818	.068***	1			
3. Average rating	3.61	.423	1.2	4.4	.039***	.060***	1		
4. Price	.114	.775	0	42.6	-.003	-.014*	-.051***	1	

5. Difference in rating	0	.13	-1.07	.8	.018**	.026***	.338***	-.005	1
6. Difference in reviews	.246	3.24	0	243	.079***	.825***	.054***	-.010	.035***
* p < .05, ** p < .01, *** p < .001									

Model

To estimate our main variable of interest, *MAJOR UPDATE*, we use the following specification.

$$\text{MAJOR UPDATE}_{i,t} = \beta_0 + \beta_1 \text{PHOTOS}_i \times \text{AFTER ENTRY}_t + V_i + T_t + p_{it} + \epsilon_{i,t}$$

where *MAJOR UPDATE*$_{i,t}$ is measured in month t for app i, *PHOTOS*$_i$ is an indicator variable for whether app i is in the treatment group, *AFTER ENTRY*$_t$ equals 1 if the current month is after the release of Photos, V_i are app fixed effects, T_t are time fixed effects, and p_{it} is app price. The DID coefficient of interest is β_1, which can be interpreted as the relative change of the treatment group compared to the control group, caused by the treatment. We cluster heteroskedasticity-robust standard errors at app level to adjust for the panel structure of the data. We also estimate continuous variables to assess the impacts of entry on price, reviews, and ratings. In these cases, the model specification is similar and follows the same notations as introduced before.

RESULTS

Effects of Entry on Innovation

To shed light on our core subject of investigation, whether entry crowds out complementor innovation, we investigate the change in the likelihood of update between treatment and control apps after the release of Photos. In Table 2, we show our estimations, specified as a linear probability model (LPM) in Model 1 and as a logit model in Model 2. In

Model 1 we observe a statistically significant positive coefficient of Photos x After entry, which indicates that the probability of a major update increases by 9.6% after entry in the treatment apps compared to that for the control apps. The increase in the likelihood to update confirms the hypothesis that Google's entry influenced complementors’ innovation efforts.

Table 2: Regression Models of the Consequences of Entry on Major Update

	Major update	
	Model 1	**Model 2**
Specification	LPM	Logit
Predictors		
Photos		.017 (.171)
Photos x After entry	.096*** (.009)	1.772*** (.182)
Controls		
App fixed effects	Yes	No
Time fixed effects	Yes	Yes
Constant	.005*** (.001)	-5.125*** (.090)
Adj. / Pseudo R-squared	.20	.107
N	41,616	41,616

* p < .05, ** p < .01, *** p < .001
Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

This finding is—as Model 2 in Table 2 shows—robust to a logit formulation, and consistent with the findings of Angrist and Pischke (2009) that there is typically little qualitative difference between the LPM and logit specifications. We focus on the LPM because it enables us to estimate a model using extensive app-level fixed effects, whereas estimating logit models using a large number of fixed effects is usually not efficient. Likely because our covariates are mostly, the predicted probabilities all lie between zero and one. Therefore, the potential bias of the LPM if predicted values lie outside of the range of zero and one (Horrace and Oaxaca 2006) is not an issue in our estimation.

We plot the marginal predicted probability of a major update in Figure 2. The vertical marks Google's release of Photos. First, we observe that both treatment and control apps are on nearly identical time trends before entry, which provides further evidence for the assumption of parallel pre-period trends in DID models. Second, we observe that the marginal predicted probability of update for treatment apps significantly increases after entry, whereas the time trend continues for control apps. Taken together, we find a significant shift in complementors' decision to innovate after entry: It is more likely that complementors release major updates for their apps following entry.

Analyses of Mechanisms

If entry does not crowd out innovation, which theoretical mechanisms underlie the positive effect of entry on complementors' innovation behavior? We motivated racing and attention spillover effects as two potential explanations. Econometrically, racing and attention spillover represent mediation effects. To estimate racing and attention spillover we follow the procedure of Baron and Kenny (1986). We first estimate the effects of entry on *AVERAGE RATING* and *NUMBER OF REVIEWS*.

Figure 2: Marginal Predicted Probability of a Major Update for Treatment and Control Apps over Time.

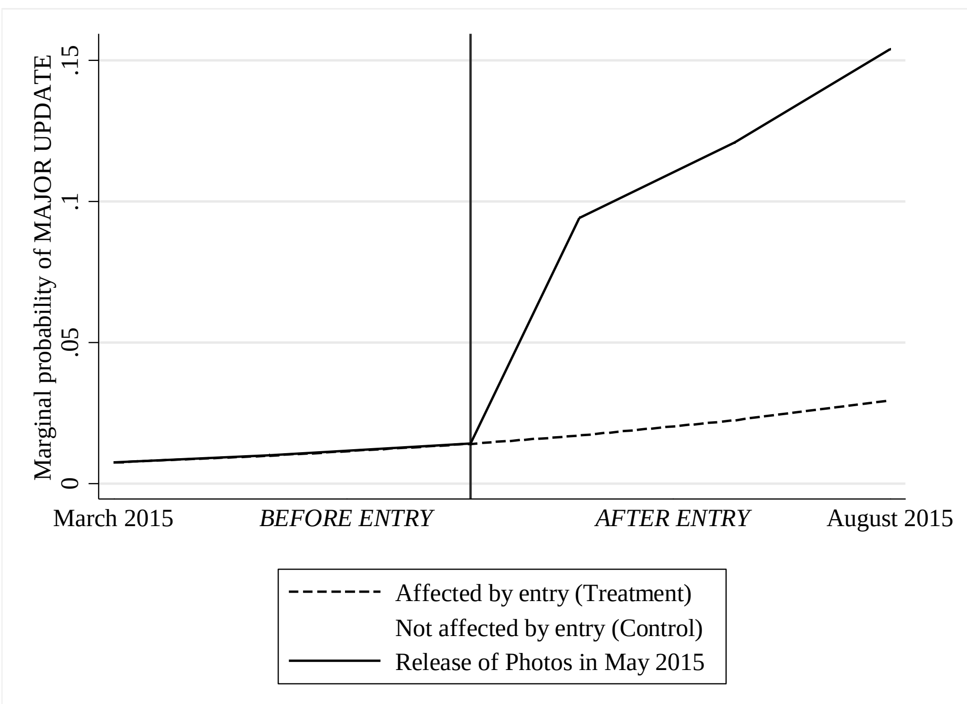


Table 3 shows the DID estimations. In Model 3, we observe that apps affected by entry do, on average, not differ in their ratings. Model 3 thus indicates that, on average, no racing effects are triggered by entry. In Model 4, the statistically significant positive DID coefficient indicates that apps affected by entry receive more reviews by customers compared to their control counterparts. This finding lends support to our hypothesis that entry significantly increases consumer attention to same-category apps and provides evidence for the first step in assessing the mediating effects of *NUMBER OF REVIEWS*.

Table 3: Effect of Google's Entry on the Number of Reviews, Price, and Rating of Apps

	Average rating	**Number of reviews**
	Model 3	**Model 4**
Predictor		
Photos x After entry	.006 (.003)	.015*** (.002)
Controls		
App fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Constant	3.615*** (.001)	.673*** (.000)
Specification	Linear	Linear
Adj. R-squared	.949	.99
N	41,616	41,616

* p < .05, ** p < .01, *** p < .001
Note: OLS coefficients presented. Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

Although we find no support for the racing effect as a mediator in the first stage, we proceed with the mediation analysis to further test the effects of *DIFFERENCE IN RATING* after entry. We first turn toward investigating a potential racing effect. Table 4 shows the results. As *DIFFERENCE IN RATING* is naturally only observed in the post-entry period, we follow prior work (Kovács and Sharkey 2014) and split the sample along the AFTER ENTRY variable into a pre-entry (Model 5) and post-entry (Model 6) estimation. Because app fixed effects would now perfectly predict the DID estimator, we introduce complementor fixed effects to account for unobservable time-invariant heterogeneity[6]. As Model 6 demonstrates, before entry, apps in control and treatment groups show a similar likelihood of update, thereby increasing our confidence in the choice of our control group. Model 6 gives then the baseline. If the racing effect exists, then we should observe that, by introducing *DIFFERENCE IN RATING* as a covariate in our model, the coefficient of *PHOTOS* should loose in significance and effect, and *DIFFERENCE IN RATING* should be significant. In other words, if the racing effect exists, *DIFFERENCE IN RATING* would mediate the effect of *PHOTOS*. In Model 7, the insignificant coefficient of *DIFFERENCE IN RATING* indicates that apps suffering I n ratings are not more likely to be updated, neither does this effect explain the treatment effect. Thus, there is no indication that racing is more likely for apps affected by entry compared to apps not affected by entry.

Next, we turn toward the attention spillover effect, which suggests entry to increase complementor innovation via the spillover of customer attention and feedback, which implies better access to new ideas and opportunities. As we have explored earlier, we find that entry increases both the likelihood of *MAJOR UPDATE* and the *NUMBER OF REVIEWS*, which supports the first two steps of Baron and Kenny (1986). If the attention spillover effect exists, then we should observe that, when introducing *DIFFERENCE IN REVIEWS* as a covariate in our

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[6] As our intent is to show the existence of different mechanisms that explain our main finding, we are less concerned with the magnitude of the effect due to a lack of app fixed effects. However, the effects and standard errors of our baseline estimation using complementor fixed effects are similar to our specifications using app fixed effects.

model, the coefficient of *PHOTOS* should loose in significance and effect, and *DIFFERENCE IN REVIEWS* should be significant.

Table 4: Racing Effect: Mediation Analyses of Difference in Rating on Major Update

	Major update		
	Model 5	**Model 6**	**Model 7**
	Before entry	**After entry**	**After entry**
Predictors			
Photos	.008 (.007)	.071** (.027)	.071** (.027)
Difference in rating			.007 (.014)
Controls			
Complementor fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Constant	.004* (.002)	.028*** (.005)	.028*** (.005)
Specification	LPM	LPM	LPM
Adj. R-squared	.04	.32	.32
N	20,898	20,718	20,718

* p < .05, ** p < .01, *** p < .001
Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

We show the results in Table 5. Models 8 and 9 show the split along the entry variable. Model 10 includes *DIFFERENCE IN REVIEWS* to the specification. We observe a significant positive effect of the coefficient of *DIFFERENCE IN REVIEWS*. Thus, *DIFFERENCE IN REVIEWS* positively affects the probability of *MAJOR UPDATE*. Moreover, we observe that the coefficient of *PHOTOS* loses in magnitude and statistical significance. The mediation effect was significant when assessed with the Sobel test (p<.001), Aroian test (p<.001), and Goodman test (p<.001) tests. The presence of the direct effect of *PHOTOS* suggests partial mediation. Thus, the positive effect of consumer feedback on the likelihood of *MAJOR UPDATE*, combined with the finding that entry increases consumer feedback, results in the partial mediation of the effect of entry on the likelihood of *MAJOR UPDATE*.

Table 5: Attention Spillover Effect: Mediation Analyses of Increase in Reviews on Major Update

	Major update		
	Model 8	**Model 9**	**Model 10**
	Before entry	**After entry**	**After entry**
Predictors			
Photos	.008 (.007)	.071** (.027)	.045* (.017)
Difference in reviews			.552*** (.043)
Controls			
Complementor fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Constant	.004* (.002)	.028*** (.005)	.056*** (.004)
Specification	LPM	LPM	LPM
Adj. R-squared	.04	.32	.41
N	20,898	20,718	20,718

* p < .05, ** p < .01, *** p < .001
Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

ROBUSTNESS

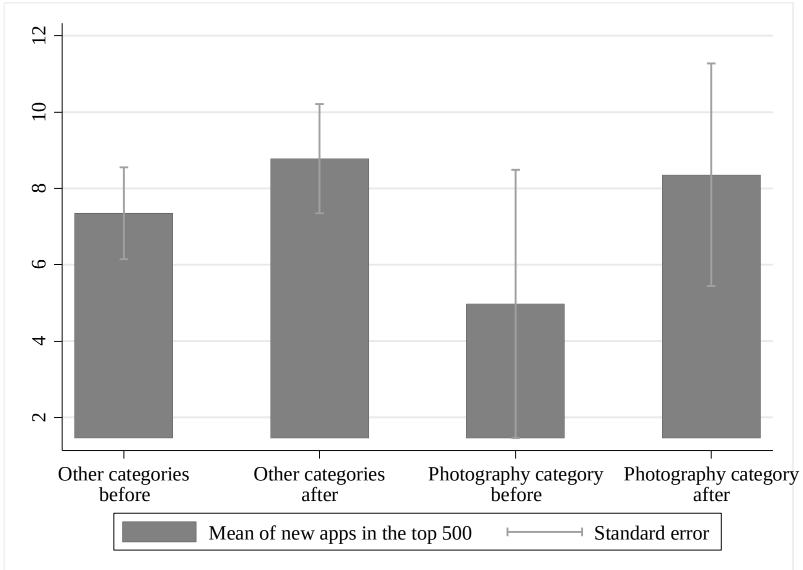
We conducted four main robustness checks: (1) We use new app releases as an alternative measure of innovation, (2) we compare pre-entry heterogeneity in treatment and control groups, (3) we conduct a falsification test, and (4) we construct a continuous treatment measure using the approach of Hoberg and Phillips (2010). In the following we report robustness checks (1) and (2), the remaining ones are listed in the Appendix.

Alternative measure of innovation

Whereas our main results have been stable across different specifications, consistently pointing to the finding that entry did not crowd out innovation, several alternative explanations exist. Concern may exist regarding our measure of innovation, i.e., app updates. To strengthen our findings, we used new app releases as an alternative measure of innovation. New product releases are a measure that is widely used in prior work to assess the innovation outcome of firms. Although our data on new app releases do not allow inferring racing or attention spillover effects, observing that entry leads to a significant increase in new app releases compared to the treatment category would further increase confidence in our findings.

We constructed an additional dataset to examine new app releases before and after Google's market entry. For each category, Google maintains a ranked list of 500 paid and free apps respectively that were either newly released or updated within the last 30 days. Although Google does not specify further conditions for membership in the ranking, analyzing fluctuations in the lists allows drawing inferences on the number of new apps released to the photography category compared to other categories. We collected monthly snapshots of the ranking for each category in Google Play over the pre-entry and post-entry periods. We then calculated the ratio of apps that were included in a ranking compared to the preceding month. We plot the mean new entrant ratios in Figure 2, which compares the ratios for the photography category with all other categories in Google Play before and after entry. We observe a substantial increase in entrants in the photography category compared to all other categories. When estimating the results using OLS regressions and category-fixed effects, we observe a positive and significant DID estimator, which we do not list specifically for the sake of brevity. The results support the validity of our major finding that complementors increase their innovation efforts in the market space affected by entry.

Figure 2: Descriptive Evidence: Plot of the Mean of New Apps in Treatment Category Compared to All Other Categories in Google Play, Before and After Entry.



Pre-entry heterogeneity in treatment and control groups

The critical assumption underlying a DID approach is that sorting into the matched or treatment group is based on pre-entry covariates and that residual variation between the groups is random (Bertrand et al. 2004; Shadish et al. 2002). In other words, we assume that, but for their exposure to the treatment, the treated sample would behave like the control set, and vice versa. To investigate potential differences in pre-entry observational characteristics, we run a set of regression models predicting major update, price, ratings, and reviews in the pre-entry period. We observe in Table 6 that prior to entry, treatment and control apps show similar characteristics: They have the same likelihood of major update, have the same average price, receive a similar amount of reviews, and have the same average rating.

Table 6: Robustness: Pre-Entry Observational Differences in Treatment and Control Groups

	Major update	Price	Number of reviews	Average rating
	Model 11	**Model 12**	**Model 13**	**Model 14**
	Before entry	**Before entry**	**Before entry**	**Before entry**
Predictor				
Photos	.008 (.007)	.009 (.017)	.069 (.058)	.029 (.034)
Controls				
Complementor fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Constant	$.004^{*}$ (.002)	$.113^{***}$ (.004)	$.681^{***}$ (.011)	3.612^{***} (.007)
Specification	LPM	Linear	Linear	Linear
Adj. R-squared	.04	.90	.78	.72
N	20,898	20,898	20,898	20,898

* $p < .05$, ** $p < .01$, *** $p < .001$
Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

Despite observational equivalence, it is still possible that there is unobserved heterogeneity in the time trends between treated and untreated apps that our previous analyses did not reveal. Although we have safeguarded our estimations by including time fixed effects, there is the possibility that treatment and control apps were on different pre-treatment time trends. To assess differences in pre-entry time trends, we follow the procedure proposed by Bertrand et al. (2004) and estimate models were we interact a continuous time indicator (time trend) with the treatment indicator *PHOTOS* for the pre-entry periods. Table 7 shows estimations of pre-entry time trends regarding major update, reviews, price, and rating.

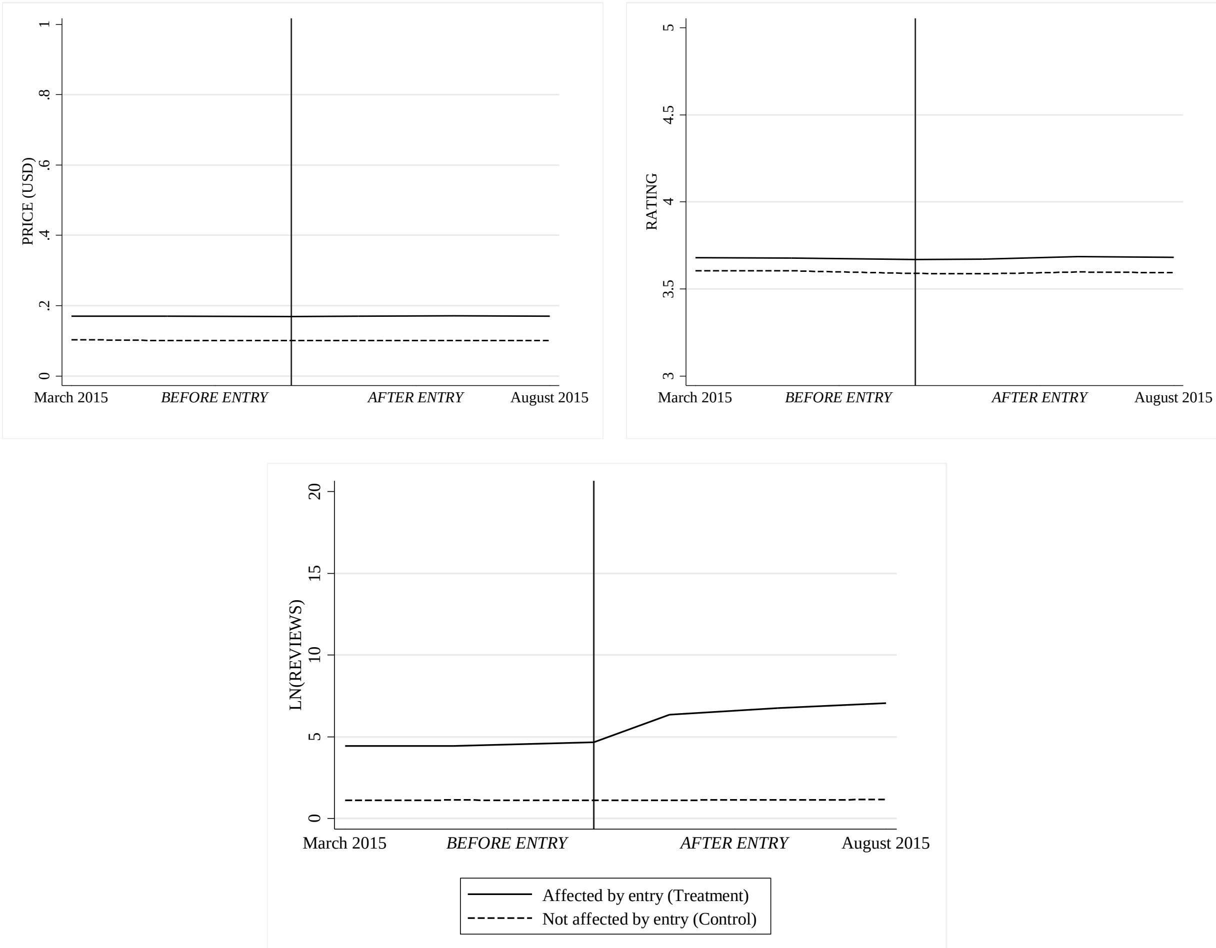
Table 7: Robustness: Treatment-Control Time Trends Before Entry

	Major update	**Price**	**Number of reviews**	**Average rating**
	Model 15	**Model 16**	**Model 17**	**Model 18**
	Before entry	**Before entry**	**Before entry**	**Before entry**
Predictors				
Photos	.001 (.008)	.008 (.018)	.350 (.200)	.024 (.034)
Time trend	.006*** (.001)	-.001 (.001)	.073*** (.001)	-.007*** (.001)
Photos x Time trend	.003 (.003)	.001 (.002)	-.005 (.003)	.003 (.002)
Controls				
Complementor fixed effects	Yes	Yes	Yes	Yes
Specification	LPM	Linear	Linear	Linear
N	20,898	20,898	20,898	20,898

* $p < .05$, ** $p < .01$, *** $p < .001$
Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

The estimates suggest that there is a time trend in the outcomes used, but this trend is identical for apps affected by treatment and control apps. The estimated coefficient of *PHOTOS* is not statistically different from zero, further supporting our choice of the control group. To the extent that this analysis allows addressing differences in time trends, the results reinforce the claim that our extant fixed effects strategy has effectively controlled for ex ante heterogeneity in the groups. Figure 3 depicts these trends.

Figure 3: Price (top left), Rating (top right), and Reviews (bottom) over time.



DISCUSSION

We investigated the impact of firms' decision to enter markets complementary to their platform. In particular, we sought to understand the consequences of entry for complementary innovation. Although complementary innovation is a key outcome for platform managers and policy makers, studies that address this outcome are scarce. To document robust empirical evidence, we analyzed 7,000 randomly selected apps of Google Play over a timeframe of six months in a quasi-experimental design. Such as setup is novel in the literature on two-sided markets and technology platforms, which has largely relied on analytical modeling (e.g., Choi and Stefanadis 2001; Farrell and Katz 2000; Rochet and Tirole 2003) or deductive, qualitative approaches (Eaton et al. 2015; Gawer and Henderson 2007; Wareham et al. 2014). We are, to the best of our knowledge, the first to investigate platform owner's decisions in such a setup and to quantify the effects of a platform management decision on complementary innovation.

The key contribution of this paper lies in the identification of entry effects. While some studies suggest entry to crowd out complementary innovation (Boudreau 2010; Choi and Stefanadis 2001; Farrell and Katz 2000), our study of the Android platform indicates no such penalty. Instead, we observe Google's entry to foster complementary innovation. On average, we determine the likelihood of complementary innovation to increase by 9.4% following entry, compared to complementors not affected by entry. This effect is strongly significant and accounts for app-level heterogeneity and temporal confounders.

In contrast to prior discussions (Gawer and Cusumano 2002; Gawer and Henderson 2007; Shapiro and Varian 1999), our results suggest relatively positive consequences of entry for complementors, at least on average: Their apps do not decrease in price or rating. Most importantly, demand for their apps increases strongly, which suggest that Google's entry strategy benefits the complementary market. Of course, we cannot rule out that entry erodes, in first place, complementors' appropriability concerns. What we can show in detail, however, is that the spillover of consumer demand triggered by entry represents a new and strong incentive to innovate, ultimately outweighing complementors' concerns. The finding challenges a number of existing studies that suggest entry to curb complementary innovation (Choi and Stefanadis 2001; Farrell and Katz 2000; Huang et al. 2013).

This finding is also surprising when seen in the light of work that has argued for entry to increase complementary innovation. Gawer and Henderson (2007), for example, document that

Intel entered complementary markets to stimulate complementary innovation. In particular, Intel assumed entry to trigger racing mechanisms, which ultimately increase complementors' innovation outputs. We do not find evidence for such racing effects in our setting using various model specifications. A possible explanation for the absence of racing effects is that complementors deliberately avoid getting involved in active competition with the platform owner. In platform settings such as ours, complementors find themselves in a power imbalance to platform owners in terms of size and resources. It seems likely that complementors refrain from retaliation when they suffer performance decreases. Building on our results, we would expect to encounter racing effects in platforms where power is more equally distributed between platform owners and complementors.

Our findings provide one answer to the enduring question in organizational research of whether competition spurs or stifles innovation. Prior work in economics suggests that there is a tension, some arguing for positive effects (Porter 1990), others for negative ones (Blundell et al. 1999). While economists often look at competition between platform owners (e.g., Eisenmann et al. 2011; Rochet and Tirole 2003), we particularly focus on competition between platform owners and complementors. With such an intraplatform perspective, we do not find evidence that competition would explain differences in complementary innovation.

This paper relates to an extensive literature examining whether and when platform owners' decisions are successful. Several models predicted consequences of platform owners' actions but either focused a pricing perspective (e.g., Choi and Stefanadis 2001; Farrell and Katz 2000) or did not investigate consequences for complementary innovation (e.g., Anderson et al. 2014; Boudreau 2010; Huang et al. 2013). Our study is the first take an in-depth perspective on one popular decision of platform owners, entry, and examine its consequences for complementary innovation.

In particular, we are able to theoretically and empirically untangle the effects of entry on complementary innovation. The observation that two fundamentally different economic mechanisms were set in motion by entry documents the complexity characteristic to platforms, and two-sided markets in general. Whereas platform owners' actions might erode the incentives of one market side to commit to the platform in the first place, platform owners' actions might compensate or even outweigh such erosions by excessively stimulating commitment by the other market side.

In this stream of literature, some studies have argued that platform owners, if excessively intervening their complementary markets, might hurt complementary innovation in the end (Tiwana et al. 2010; Wareham et al. 2014). We document a situation where a platform owner, by excessively intervening in its complementary market, creates a win-win-win situation for themselves, complementors, and consumers.

Our final contribution is methodological and we are the first to use the unique platform setting for a quasi-experimental design. Platform products represent complex micro economies that confront researchers with unique opportunities to design research but also issues concerning collecting and analyzing data. We offer an interesting avenue on how to exploit platform owners' management decisions as policy changes for identifying causal inferences. In addition, we emphasize the role of software updates as a proxy of innovation (Kemerer and Slaughter 1999), and our analyses relied on computational linguistics, which offers rich insights in textual data. Innovation in software markets largely takes place in the form of updates, and we encourage future research to build on this notion.

Whereas our setup allows insights in how complementors altered innovation of their apps affected by entry, we can only speculate how complementors altered their app portfolios following the release of Photos. From our data we can conclude that, on average, complementors have a portfolio of 1.2 apps. While complementors could publish apps in any category, we observe them to focus their innovation efforts in one or few categories. In our dataset, for example, 85% of complementors are active in one category, 91% in two or fewer categories, and 98% in three or fewer categories.

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APPENDIX

Coding of Minor and Major Updates

Table A1: Exemplary Data on the Coding of Minor and Major Updates

Release note	Code
With springtime comes bugs, and we've squashed quite a few! In particular, we've improved all-day events and the appearance of the splash screen as well as added some fun capabilities to the app bar.	Minor
Sorry to rush this new version out so quickly, but it fixes several crashes that were occurring after the release of version 8.1. Version 8.1 contains a redesign of [B]. It also allows you to login with your twitter account now. Enjoy and make sure you let us know if there are anything you want to see on the app.	Minor
The new horizons mission is reaching Pluto! Celebrate this historic occasion with your own space voyage—a brand new episode based on our corner of the universe—the solar system! 15 new levels: visit planets, comet, satellites and more. Watch unique videos directly from NASA experts. Learn about the solar system with fascinating trivia tidbits. Harness the power of s.p.a.r.k., literally a smart bomb, drops knowledge and destruction. Keep tapping for Pluto!	Major
New features! Native quizzes supporting 6 questions types. Bookmarks allow you to navigate somewhere with as little as one click. Inbox has been redesigned and makes communication so much easier. Colors now sync between your android device and canvas.	Major

Robustness A: Falsification Test

The identifying assumption of our research design is that the release of Photos affects photography apps only. We observed that entry did not affect our control group of entertainment apps, which gives confidence that the reaction to the treatment is as expected, in terms of affecting photography apps. If we observe, in addition, that entry did not alter complementors' decision to update their apps in all categories of the Android ecosystem besides photography, then this should provide substantial evidence for the identifying assumption of our research design.

To investigate this possibility we reestimated our core regression predicting the likelihood of *MAJOR UPDATE*, Model 1, for each app category in our sample. Table A1 summarizes these reestimations using the apps within each category as a subsample. The coefficient of *AFTER ENTRY* captures the difference in the likelihood of *MAJOR UPDATE* before and after the entry. If the identifying assumption holds, we should observe the coefficient of *AFTER ENTRY* to be insignificant for all other categories in our sample besides "Photography". Table A2 shows that the coefficient of *AFTER ENTRY* is statistically insignificant for all other categories in our sample, providing strong support for our identification strategy[7].

[7] Note that the coefficient for *AFTER ENTRY* in the category "Travel and Local" is significant but the model itself is not.

Table A2

Robustness: Effect of Entry on Non-Photography Apps*

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
	Major update	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**
Panel A									
Category / Subsample	Business	Comm-unication	Education	Finance	Health and Fitness	Lifestyle	Media and Video	Medical	Music and Audio
After entry	.013 (.009)	.010 (.008)	.002 (.004)	.011 (.008)	.000 (.007)	.006 (.005)	.015 (.008)	.011 (.010)	.010 (.006)
Constant	-.002 (.006)	.001 (.005)	.003 (.002)	.002 (.005)	-.003 (.004)	.002 (.003)	.006 (.005)	-.002 (.006)	$.012^{***}$ (.004)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
N	9,750	9,510	28,086	11,532	10,824	22,290	6,630	4,620	13,638
Panel B									
	(10)	**(11)**	**(12)**	**(13)**	**(14)**	**(15)**	**(16)**	**(17)**	**(18)**
	Major update	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**	**Major update**
Category / Subsample	Personal-ization	Productivity	Shopping	Social	Sports	Tools	Transp-ortation	Travel and Local	Weather
After entry	-.003 (.005)	.003 (.007)	.000 (.013)	.013 (.008)	.004 (.006)	.004 (.003)	.008 (.010)	$.014^{*}$ (.007)	.005 (.017)
Constant	-.003 (.003)	.001 (.004)	-.005 (.008)	.001 (.006)	-.000 (.004)	$.005^{*}$ (.002)	-.000 (.006)	-.004 (.004)	.011 (.008)
App fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Specification	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM	LPM
N	24,486	13,224	6,222	6,828	11,598	35,220	7,104	15,984	2,436

* $p < .05$, ** $p < .01$, *** $p < .001$

Note: Heteroskedasticity-robust, clustered standard errors are in parentheses. N is given in app months.

Robustness B: Varying Treatment Intensity

Another empirical concern is the identification of treatment apps in our sample. In particular, even within the photography category some apps may be more similar to Photos than others. For example, even within the set of photography apps, some apps may offer functionality identical to Photos, whereas other apps may only share a subset of functionality with Photos. One may thus argue that our identification of the treatment requires further granularity, in that Google's entry may have affected photography apps with different intensity. To ensure the robustness of our findings toward within-category heterogeneity, we constructed a continuous treatment measure of app similarity.

An intuitive measure of app similarity is given by the similarity of product descriptions between the apps in our sample and Photos. More specifically, we measure app similarity by computing the cosine similarity of the descriptions of apps to the description of Photos (Hoberg and Phillips 2010). Cosine similarity is a measure of similarity between two vectors of an inner product space that measures the cosine of the angle between them. As a measure of text similarity, the cosine similarity has been widely applied outside the management and information systems disciplines (Hoberg et al. 2014; e.g., Hoberg and Phillips 2010).

To construct the similarity measure, we use computational linguistics to obtain a vector of unique words in the product descriptions of the apps in our sample. Our first step was to remove filler words, punctuation, and stop words from the app descriptions. We then lemmatize the descriptions and represent each app as a vector summarizing its usage of unique words. The vector is based on the "term frequency-inverse document frequency" measure, which represents the normalized (relative) frequency of a term in a document in order to avoid biased estimates due to varying description lengths (Hoberg and Phillips 2010).

The cosine similarity is calculated by viewing a document together with its contained terms as a so-called "word vector" with every term describing a different dimension of this vector. With the different vectors set up, the angle between them indicates their similarity. That is, if the angle between two vectors is 0°, the corresponding descriptions are identical; if it is 90°, they are completely different. The cosine similarity then takes the cosine of this angle to receive a numerical score. The cosine similarity of these vectors is bounded in the range [0,1], and apps having descriptions with more words in common have a higher similarity. Given two vectors of attributes, A and B, the cosine similarity, cos(θ), is represented as:

$$similarity = \cos(\theta) = \frac{A * B}{\|A\| \|B\|}$$

We calculate the cosine similarity for both control and treatment apps. We then reestimate our baseline model using the cosine similarity as a measure of treatment intensity. If our extant identification of treatment apps is biased we should see significant differences compared to our baseline estimates. In sum, the reestimated models confirm our findings. We observe comparable effect size and significance as in our prior analyses and we also observe a partial mediation.

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