Does Platform Owner's Entry Crowd Out Innovation? Evidence From Google Photos

Completed Research Paper

Jens Foerderer
University of Mannheim
68131 Mannheim, Germany
foerderer@uni-mannheim.de

Thomas Kude
ESSEC Business School
95021 Cergy Pontoise Cedex, France
kude@essec.edu

Sunil Mithas
Robert H. Smith School of Business,
University of Maryland
College Park, MD
smithas@rhsmith.umd.edu

Armin Heinzl
University of Mannheim
68131 Mannheim, Germany
heinzl@uni-mannheim.de

Abstract

We study platform owner's decision to enter the market complementary to its platform with its own complement, and the consequences of such an entry on complementors' decision to innovate in the affected market category. 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 complementary innovation. A racing mechanism, which prompts affected complementors to innovate due to competitive "Red Queen" dynamics, and an attention spillover mechanism, which suggests increased innovation to result from spillover consumer attention to same-category complements. We exploit a unique setting provided by Google's entry into the market for photography apps on its own Android platform in 2015 as a quasi-experiment. Whereas several models predict such an entry will erode complementors' incentives to innovate, our difference-in-differences analyses of time-series data on a random sample of 6,620 apps suggest the contrary. After entry, app developers were more likely to incrementally innovate their photography apps and to release new apps to the affected market category. Although we do not observe a racing effect, our analyses support the attention spillover effect. In other words, Google's entry created additional consumer attention and demand for photography apps, which spill over to complementors in the same category.

Keywords: Platform entry, Complementors, Innovation, Google Photos, Racing, Attention spillover
Introduction

Platform owner’s entry into complementary markets 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., Adner and Kapoor 2010; Gawer and Henderson 2007; Li and Agarwal 2016; Shapiro and Varian 1999; Tiwana 2014). 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. Prior research documents Intel's activities on the market for complements to its computing platform (Gawer and Henderson 2007) and Facebook’s integration of Instagram (Li and Agarwal 2016). SAP, for example, publishes a 2-year road map that informs complementors about SAP’s activities in markets complementary to its platforms (Iansiti and Lakhani 2009). Similarly, entry continues to attract significant policy interest as the recent antitrust investigation against Google’s behavior toward its Android hardware complementors indicates (Reuters 2016). Researchers have framed the decision to enter complementary markets as a trade-off in platform governance. Platform owners have strong incentives to enter as they may benefit from appropriating complementors’ rents (Farrell and Katz 2000; Huang et al. 2013), increasing customer experience through integration (Adner and Kapoor 2010; Eisenmann et al. 2011; Li and Agarwal 2016), and retaining control over platform evolution (Eaton et al. 2015; Gawer and Henderson 2007). However, entry may hurt complementors’ revenues, eventually causing them to hesitate contributing to the platform in the future (Gawer and Henderson 2007). In particular, such entry may “crowd out” future innovations of complementors, thus limiting category innovations to platform owners’ own efforts (Farrell and Katz 2000). From a platform owner’s perspective, by deteriorating complementors’ incentives to innovate, entry may appear to run counter to the initial motivation of establishing a platform, namely profiting from third-party innovation (Gawer and Henderson 2007; Shapiro and Varian 1999). Thus, analyzing the consequences of entry on complementary innovation can help platform owners and policy makers determine the overall impact of this strategy.

Existing work on platform markets suggests different effects of entry on complements or 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 (Gawer and Henderson 2007). 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. Specifically, entry may trigger a racing effect in that complementors affected by the platform owner’s market entry may feel urged to innovate to not to lag behind (Barnett and Hansen 1996; Barnett and Pontikes 2008). Another potential explanation is attention spillover: Entry is a public event, which attracts consumers to the focal market category. Increased attention may spill over to same category complements (Li and Agarwal 2016; Liu et al. 2014), providing same-category complementors with new demand and feedback, from which they can draw to innovate.

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). Several studies model platform owners’ behavior toward complementors but focus on pricing strategies (Choi and Stefanadis 2001; Farrell and Katz 2000). Other work found appropriability concerns, in general, to deter platform adoption (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 study closes this gap. We empirically identify the effects of entry on complementary innovation. Our identification strategy is a quasi-experiment (Shadish et al. 2002). We exploit a unique setting: in May 2015, Google released *Google Photos*, an all-purpose app for organizing, editing, and sharing digital photographs, to users of its smartphone platform Android (Google 2015). This event is intriguing because thousands of photography-related apps existed before Google’s entry. Because Google did not announce Photos prior to its release, this context offers two empirical benefits. First, the release of Photos is exogenous to complementors and their innovation outcomes. Second, this context allows to isolate the effects of entry on the innovation outcomes of producers of photography-related apps, and to compare innovation outcomes to a control group of complementors not affected by entry. We avoid selection bias by using time-series panel data on a representative sample of more than six thousand apps from Google Play, the largest store for Android apps worldwide. We observe the apps monthly, beginning three months prior and ending three months after the release of Photos. We then 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 or functionalities. This operationalization of innovation is appropriate because a growing portion of innovation in software industries takes place in the form of updates. 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 (Ramsey 2015). We identify major updates by text-analyzing the release notes published by complementors. Our DID analyses of apps affected by Google’s entry compared to apps not affected by entry suggest strong and positive effects of entry on complementary innovation. Subsequent tests consistently point toward an attention spillover effect as explanation for the increase in complementary innovation: 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**

In organizing the commercialization and development of products (Teece 1986), platforms have gained significant popularity (e.g., Evans et al. 2008; Gawer and Cusumano 2002; Parker et al. 2016; Rochet and Tirole 2003). Platform owners’ activities go beyond designing, developing, and distributing predefined products, but require the purposeful orchestration of an ecosystem of complementary innovation (Adner and Kapoor 2010; Boudreau 2010; Boudreau and Hagiu 2009; Cennamo and Santalo 2013; Tiwana 2014). Scholars have called for research to understand the impact of orchestrating activities (Grover and Kohli 2012; Kallinikos et al. 2013; Tiwana et al. 2010; Yoo et al. 2010) and recent work substantially advanced this area (e.g., Eaton et al. 2015; El Sawy et al. 2016; Ghazawneh and Henfridsson 2013; Tiwana 2015). Yet, few studies provide insight into the consequences and mechanisms of entry.

Several studies relied on analytical models to study the interactions between platform owners and complementors, largely based on pricing mechanisms (Anderson et al. 2014; 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 complementary innovation suggest entry to erode complementors’ incentives to innovate, given various assumptions of complete information and complementor behavior (Choi and Stefanadis 2001; Farrell and Katz 2000; Miller 2008; Niedermayer 2013).

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 owners’ inability to commit to not squeezing complementors and show that prospective complementors respond to appropriability concerns by safeguarding returns from their innovations through patents, copyrights, and downstream capabilities. Gawer and Henderson (2007) use a 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. Zhu and Liu (2015) find that Amazon enters product spaces of third-party sellers when these markets are well-rated and popular. After Amazon’s entry, affected third-party sellers reduce the prices of their products and their engagement on Amazon’s marketplace (Zhu and Liu 2015).

Most closely related to our work is Li and Agarwal’s (2016) study of Facebook’s acquisition of Instagram, an existing, popular complement for sharing photos. Li and Agarwal (2016) find Facebook’s acquisition to increase consumer demand not only for Instagram but also for other photography-sharing complements. Whereas Li and Agarwal (2016) study consumer reactions to entry, we study how entry affects complementary innovation in a setting where we can address endogeneity issues to answer substantive policy-relevant questions.¹

**Mechanisms to Explain the Effect of Entry on Complementary 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 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 (2016) 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 (2016) observe, for example, that Facebook’s integration

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). In particular, we look at both consumers’ and complementors’ reactions to entry.
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.

**Method**

**Empirical Context**

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).

The "Photos" entry by Google was somewhat unexpected and 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 described Photos as being “best of breed”, highlighting its superiority compared to leading rival products (Mossberg 2015). The New York Times featured Photos as “simple”, “clean”, and “impressive” (Swanson 2015). In sum, Photos was perceived as a product that should be taken seriously by same-category complementors (Mossberg 2015). 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 exploits 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

\(^2\) Unlike its major competitor in the app market (Apple), Google had largely refrained from entering the market for apps.
in general. Software is technologically flexible, meaning that producers can redefine and shape software products after their market release (Kemerer and Slaughter 1999; MacCormack et al. 2001). These changes 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 tracked app-specific information, including an app’s average rating by customers, the number of reviews, updates, and prices over time. 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 made use of the categorization system in Google Play. Categories isolate the effects of entry because they represent the basic structure for discovering apps in Google Play (Ghose and Han 2011; Salz 2014). Categories group apps by their functional purpose. 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). Thus, as categories blend in and out rival apps to the user, they represent a key determinant of competition and consumer attention in our empirical context (Li and Agarwal 2016). In addition, the use of categories to isolate the effects of entry helps 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

---

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”.

---
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. Our final sample includes 39,720 app-month observations.

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. Therefore, 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, thus providing detailed insights into the extent and novelty of changes made (Kemerer and Slaughter 1999). Release notes are highly 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.

Our approach to text analysis follows prior work that has used word lists (i.e., dictionaries) to systematically and objectively identify specified characteristics within text in order to 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”. 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.

After the computer-assisted text analysis procedure had concluded, we ensured the validity of the algorithm by backward-coding a subset of the release notes. We drew a random sample of 100 release notes from our dataset and let two independent research assistants code the release notes into minor and major updates based on our agreed upon definitions. The results of this procedure increased our confidence that the employed algorithms were accurately identifying major updates as the research assistants agreed in 96 of the 100 cases with the algorithm-based coding.
Independent Variables

Focal predictors (PHOTOS and AFTER). 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 in our models, which is 1 for the periods after the release of Photos. The DID estimator is then given by interacting AFTER with PHOTOS.

Racing and 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 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.

Attention spillover and NUMBER OF 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 logged NUMBER OF REVIEWS.

Controls. We estimate our models with app-level fixed effects and time (i.e. month) fixed effects. Table 1 reports summary statistics and correlations.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>S.D.</th>
<th>Min.</th>
<th>Max.</th>
<th>1</th>
<th>2</th>
<th>3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major update</td>
<td>0.01</td>
<td>0.07</td>
<td>0</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log(Number of reviews (in thousands))</td>
<td>0.66</td>
<td>0.45</td>
<td>0.26</td>
<td>7.16</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rating</td>
<td>3.61</td>
<td>0.41</td>
<td>1.20</td>
<td>4.40</td>
<td>0.04*</td>
<td>0.16*</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>0.12</td>
<td>0.79</td>
<td>0</td>
<td>42.60</td>
<td>-0.01</td>
<td>-0.05*</td>
<td>-0.08*</td>
</tr>
</tbody>
</table>

Model

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

\[
MAJOR \ UPDATE_{i,t} = \beta_0 + \beta_1 AFTER_{i,t} \times PHOTOS_i + V_i + \tau_t + \epsilon_{i,t}
\]

We are aware of the method proposed by Garg and Telang (2013) for inferring app demand from publicly available data on these apps. This method is not applicable in our case because it requires data on app ranks, in terms of the rank of an app in the top charts (e.g., top paid, top free, or top grossing). Ranks are not given in our case as we are looking at a representative sample of apps from Google Play, and most apps in our sample are not ranked.

App and time fixed effects absorb the main effects of AFTER and PHOTOS.
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_{t} equals 1 if the current month is after the release of Photos, V_{i} are app fixed effects and T_{t} are time fixed effects.

**Results**

**Effects of Entry on Innovation**

To investigate whether entry crowds out complementary innovation, we examine the change in the likelihood of update between treatment and control apps after the release of Photos. Table 2 shows our estimations, specified as a linear probability model (LPM) in Model 1 and as logit in Model 2. In Model 1 we observe a statistically significant positive coefficient of AFTER x PHOTOS, which indicates that the probability of 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 assertion that Google’s entry positively influenced complementary innovation.

This finding is—as Model 2 in Table 2 shows—robust to a logit formulation, and consistent with Angrist and Pischke (2009) in terms of that there is typically little qualitative difference between LPM and logit specifications. The predicted probabilities are between zero and one. Thus, the potential bias of the LPM that is evident if predicted values lie outside the range of zero and one is not an issue for our estimation (Horrace and Oaxaca 2006). We focus on LPM specifications hereafter 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 may lead to inconsistent standard errors (Long and Freese 2006).

### Table 2: Regression Models of the Consequences of Entry on MAJOR UPDATE

<table>
<thead>
<tr>
<th>Specfication</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major update</td>
<td>LPM</td>
<td>Logit</td>
</tr>
<tr>
<td>Predictors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Photos</td>
<td></td>
<td>.259*** (.181)</td>
</tr>
<tr>
<td>After x Photos</td>
<td>.096*** (.009)</td>
<td>1.472*** (.193)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>App fixed effects</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>.005*** (.001)</td>
<td>-5.382*** (.187)</td>
</tr>
<tr>
<td>Adj. / Pseudo R-squared</td>
<td>.039</td>
<td>.121</td>
</tr>
<tr>
<td>F / Wald test</td>
<td>63.180***</td>
<td>658.51***</td>
</tr>
</tbody>
</table>

**Analyses of Mechanisms**

If entry does not crowd out innovation, which theoretical mechanisms underlie this effect? 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 three-step procedure of Baron and Kenny (1986). As the first step of the analysis is given by regressing MAJOR UPDATE on AFTER x PHOTOS, we proceed with the second step: estimating the effects of entry on RATING and NUMBER OF REVIEWS.

Table 3 shows the DID estimations. In Model 1, we observe that apps affected by entry do, on average, not differ in their rating. The coefficient of AFTER x PHOTOS remains near to zero and insignificant. Model 1 thus indicates no racing effects triggered by entry, in terms of that consumers do not evaluate affected apps differently after entry, and compared to their control counterparts. In Model 2, the statistically
significant positive coefficient of AFTER x PHOTOS indicates that apps affected by entry receive more reviews by consumers compared to their control counterparts. This finding lends support to our assertion that entry significantly increases consumer attention to same-category apps and provides evidence for the second step (Baron and Kenny 1986) 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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rating</td>
<td>Linear</td>
<td>Linear</td>
</tr>
<tr>
<td>Number of reviews</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Specification</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Predictor</td>
<td></td>
<td></td>
</tr>
<tr>
<td>After x Photos</td>
<td>-.002</td>
<td>.086***</td>
</tr>
<tr>
<td></td>
<td>(.003)</td>
<td>(.014)</td>
</tr>
<tr>
<td>Controls</td>
<td></td>
<td></td>
</tr>
<tr>
<td>App fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>-.000</td>
<td>.002</td>
</tr>
<tr>
<td></td>
<td>(.000)</td>
<td>(.002)</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>.008</td>
<td>.215</td>
</tr>
<tr>
<td>F-test</td>
<td>30.556***</td>
<td>1355.367***</td>
</tr>
</tbody>
</table>

We proceed with the mediation analysis to further test for explanations of the innovation-increasing effects of entry. Although we find no support for the racing effect as a mediator in the first stage, we want to explore potential explanatory effects. Table 4 shows the results. Model 1 gives the baseline. If the racing effect exists, then we should observe that, by introducing RATING as a covariate in our model, the coefficient of AFTER x PHOTOS should loose in significance and effect size, and RATING should be significant. In other words, if the racing effect exists, RATING would mediate the effect of PHOTOS. In Model 2, the insignificant coefficient of RATING indicates that it is not decreases in app ratings that explain the innovation-increasing effects of entry. Taken together with the observations in Model 1 in Table 3, there is no indication that racing is more likely for apps affected by entry compared to apps not affected by entry.

Next, we turn to the attention spillover effect, which suggests entry to increase complementary innovation via the spillover of consumer attention. As we have explored earlier, we find that entry increases 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 NUMBER OF REVIEWS as a covariate in our model, the coefficient of AFTER x PHOTOS should decrease in significance and effect, and NUMBER OF REVIEWS should be significant.

We show the results in Table 4. Model 3 includes NUMBER OF REVIEWS as a predictor. We observe a significant positive effect of the coefficient of NUMBER OF REVIEWS. Thus, NUMBER OF REVIEWS positively affects the likelihood of MAJOR UPDATE. Moreover, we observe that the coefficient of AFTER x PHOTOS loses in magnitude and statistical significance. Sobel (p<.001), Aroian (p<.001), and Goodman (p<.001) tests further confirm the significance of the mediation effect. The presence of the direct effect of AFTER x PHOTOS suggests partial mediation. Thus, the positive effect of consumer attention on the likelihood of MAJOR UPDATE, combined with the finding that entry increases consumer attention, results in the partial mediation of the effect of entry on the likelihood of MAJOR UPDATE. In Model 4, we include both RATING and NUMBER OF REVIEWS to further test our explanations. We find that NUMBER OF REVIEWS stays significant alongside RATING, thus further confirming our conclusion.
Table 4: Mediation Analyses

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Specification</td>
<td>Major update</td>
<td>Major update</td>
<td>Major update</td>
<td>Major update</td>
</tr>
<tr>
<td>Predictors</td>
<td>LPM</td>
<td>LPM</td>
<td>LPM</td>
<td>LPM</td>
</tr>
<tr>
<td>After x Photos</td>
<td>.096***</td>
<td>.094***</td>
<td>.037***</td>
<td>.036***</td>
</tr>
<tr>
<td></td>
<td>(.009)</td>
<td>(.009)</td>
<td>(.005)</td>
<td>(.005)</td>
</tr>
<tr>
<td>Rating</td>
<td></td>
<td>.004**</td>
<td></td>
<td>.010</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(.008)</td>
<td></td>
<td>(.008)</td>
</tr>
<tr>
<td>Number of reviews</td>
<td></td>
<td></td>
<td>.482***</td>
<td>.474***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.032)</td>
<td>(.032)</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>App fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Time fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Constant</td>
<td>.005***</td>
<td>.004**</td>
<td>.005***</td>
<td>.004***</td>
</tr>
<tr>
<td></td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
<td>(.001)</td>
</tr>
<tr>
<td>Adj. R-squared</td>
<td>.039</td>
<td>.033</td>
<td>.177</td>
<td>.156</td>
</tr>
<tr>
<td>F</td>
<td>63.180***</td>
<td>58.952***</td>
<td>92.750***</td>
<td>86.689***</td>
</tr>
</tbody>
</table>

**Robustness**

We conducted three 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, and (3) we compare pre-entry heterogeneity in time trends in treatment and control groups; (4) we use an alternative identification strategy using the similarity of two apps, (5) we used different specifications of the control group (e.g., replacing entertainment apps with any other category in Google Play, synthetic control group design), (6) we conducted placebo tests in other app categories to validate whether entry triggered significant reactions outside the photography app category, and (7) we used an alternative measure of racing effects. For the sake of brevity, we report (1), (2), and (3) here. In sum, all of the conducted robustness checks strongly confirm our findings.

**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. The results support the validity of our major finding that complementors increase their innovation efforts in the market space affected by entry.
Does Platform Owner’s Entry Crowd Out Innovation?

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 find 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.

Pre-entry heterogeneity in time trends in treatment and control groups. 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 where we interact a continuous time indicator (time trend) with the treatment indicator PHOTOS for the pre-entry periods. We find that there is a time trend in the outcomes used, but this trend is identical for apps affected by treatment and control apps. 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.

The above robustness checks strongly confirm our findings.

Discussion

We investigated the impact of a firm’ decision to enter markets complementary to its platform to understand the consequences of entry for complementary innovation. To document robust empirical evidence, we analyzed a sample of 6,620 apps of Google Play over a timeframe of six months in a quasi-experimental design. By exploiting Google’s entry in the market category of photography apps as an exogeneous shock to app-level innovation, we are able to provide a number of novel contributions to literature. The key contribution of this paper lies in the identification of entry effects. Whereas 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 9.6% following entry, compared to complementors not affected by entry. This effect is robust to a number of specifications and accounts for app-level heterogeneity and temporal confounders.
Prior literature showed that platform owners have incentives to use their dominant market position to appropriate rents from complementors (Farrell and Katz 2000), thus facing the tension between appropriating rents and fostering complementary innovation (Gawer and Henderson 2007; Parker and Van Alstyne 2005; Rochet and Tirole 2003). Although scholars have extensively studied the interactions between platform owners and complementors using diverse methodological approaches (e.g., Boudreau 2010; Farrell and Katz 2000; Wareham et al. 2014), empirical evidence on the consequences of entry is rare partly because effects of entry are difficult to isolate in practice.

Our study provides new insights regarding effects of entry. For example, while some studies investigating complementary innovation suggested crowding-out effects of entry (Boudreau 2010; Choi and Stefanadis 2001; Farrell and Katz 2000), our study of the Android platform documents no such penalty. Instead, we observe Google’s entry to foster complementary innovation. Our interpretation of this finding is that greater caution may be warranted in assuming that entry per se harms complementor innovation. Our findings suggest that Google’s entry caused a secondary mechanism that eventually stimulated complementary innovation.

Our findings also challenge the widely held belief that tightening control over a platform reduces complementor innovation (Boudreau 2010; Shapiro and Varian 1999). In particular, entering complementary markets is often interpreted as a control mechanism. Much of this understanding builds on the assumption that control mechanisms are opposed to opening a platform (Boudreau 2010; Katz and Shapiro 1986; Shapiro and Varian 1999). Our findings show that this conceptualization may be too limited and that focusing on control mechanisms and the assumption of direct consequences may be too simple.

Our analyses of racing versus attention spillover is also new to the literature. For example, Gawer and Cusumano (2002) suggest that platform owners may use entry to stimulate complementary innovation, and they give example of Intel's entry to stimulate racing effects to induce complementary innovation. We fail to find evidence for such racing effects in our setting using a variety of model specifications. A possible explanation for the absence of a racing 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.

In this vein, 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 (Aghion et al. 2005; Blundell et al. 1999), some arguing for positive effects, others for negative, or nonlinear effects. We also complement research on competition between platform owners (e.g., Eisenmann et al. 2011; Rochet and Tirole 2003) and among complementors (Tiwana 2015) with a perspective on how platform owners compete with complementors. With such an intraplatform perspective, we do not find evidence that competition would explain differences in innovation.

The finding that a consumer-side mechanism is responsible for the increase in complementary innovation adds to existing work on attention spillover by accounting for the consequences of such a spillover (Li and Agarwal 2016; Liu et al. 2014; Sahni 2016). Prior studies supported the idea that marketing instruments (Liu et al. 2014; Sahni 2016) and acquisitions (Li and Agarwal 2016) may have spillover effects of consumer attention on same-category products. Moreover, entry may trigger spillover effects of consumer feedback. Our study elucidates that complementors exploit increases in consumer attention and consumer feedback to innovate.

This paper relates to an extensive literature examining whether and when platform owners’ decisions are successful. Several models predict consequences of platform owners from a pricing perspective (e.g., Choi and Stefanadis 2001; Farrell and Katz 2000) or outcomes other than complementary innovation (e.g., Anderson et al. 2014; Huang et al. 2013). Our study takes an in-depth perspective on one important decision of platform owners, entry, and examines its consequences for complementary innovation. The observation that two fundamentally different economic mechanisms were set in motion by entry documents the complexity of platforms (Antonopoulos et al. 2016; Kallinikos et al. 2013; Sandberg et al. 2013; Yoo et al. 2010), and two-sided markets in general. We believe that substantial contributions can be
made when investigating the phenomenon of entry on other types of platforms, especially by comparing and understanding the consequences.

Our final contribution is methodological and we are among the first to integrate text analysis (Bao and Datta 2014; Hoberg et al. 2014; Hoberg and Phillips 2010) and quasi-experimental designs. 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.

References


