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Platform Integration and Demand Spillovers in Complementary Markets: Evidence from Facebook's Integration of Instagram

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Abstract. Social media platform owners often choose to provide tighter integration with their own complementary applications (i.e., first-party applications) as compared to that with other complementary third-party applications. We study the impact of such integration on consumer demand for first-party applications and competing third-party applications by exploring Facebook's integration of Instagram, an application in its photo-sharing application ecosystem. We find that consumers obtain additional value from Instagram after its integration with Facebook, leading to a large increase in the use of Instagram for Facebook photo sharing. Further, we find that the growth of Instagram's user base has a positive spillover effect on big third-party applications and a negative spillover effect on small third-party applications in Facebook's photo-sharing ecosystem. As a result, while small third-party applications face reduced demand after integration, big third-party applications experience a small increase in demand. Thus, the overall demand for the entire photo-sharing application ecosystem actually increases, which suggests that Facebook's integration strategy benefits the complementary market overall. Our results highlight the role of platform integration for first-party applications and the application ecosystem overall, and they have implications for strategic management of first-party applications in the presence of third-party applications.

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1. Introduction

Social media platforms provide users with the ability to connect and exchange information with other users. In addition, these platforms often seek complementary innovations from third-party providers to meet the needs of heterogeneous users. For example, Facebook launched its platform in May 2007, providing a set of programming interfaces and tools for third-party software developers to create applications that interact with Facebook's core features (e.g., user profile and friendship network). As of February 2012, the Facebook platform supported more than nine million applications in a variety of categories such as games, photo sharing, music sharing, news, entertainment, sports, travel, and lifestyle (Darwell 2012), which in total attract more than 235 million users (Lunden 2012). As users use these applications, they can also share the consumption information or application related content with other users on these platforms.

While continuing to expand their ecosystem through third-party applications, social media platform owners may also provide their own applications to consumers (i.e., first-party applications), either by in-house development or by acquisition from third-party developers. These first-party applications tend to compete with third-party applications. To promote their own applications, social media platforms may choose to make a tighter integration of first-party applications relative to the integration of other third-party applications. Such integration grants first-party applications easy access to platform data and enhanced sharing capabilities such as automated content sharing with the platform users. For example, Facebook provided tighter integration with several applications acquired from third-party developers (e.g., Instagram and Karma; see MacMillan 2012). Although such platform integration may benefit the platform owner, third-party developers may resist such moves and hesitate to contribute to the ecosystem as it reveals the platform owner's ability to squeeze them ex post (Gawer and Henderson 2007). For example, Facebook's vertical integration strategy has raised concerns about the viability of the platform for third-party developers, as voiced in the following quote from the CEO of a third-party developer, Wrapp: "The $100 billion question now is whether Facebook will remain an open platform that partners and supports companies like Wrapp" (MacMillan 2012). Managing such tension between first-party applications and third-party applications has been a critical part of major platforms' strategies (Gawer and Henderson

2007, Huang et al. 2013). Platform owners have to carefully evaluate the impact of the integration of a first-party application on its application ecosystem. Analysis of the resulting consumer preferences and the substitution or complementary effects between first-party applications and third-party applications can help platform owners determine the overall impact of their strategy.[1]

The consequences of platform integration are multifold and not obvious. One possibility is that the integration has little impact as it does not introduce new product features. Without the integration, users could still complete the same tasks using the first-party application or any third-party application. Additionally, users may not like the automated sharing capability enabled by tighter integration due to privacy concerns (Acohido 2011). However, past literature suggests that ease of use is positively associated with product adoption (Davis 1989, Dhebar 1995, Cooper 2000). Thus, users may derive additional utility from the tighter integration of the first-party application with the platform as it enhances the ease of use for the first-party application as compared to that for other third-party applications. This may result in higher demand for the first-party application and lower demand for third-party applications. However, as users share application contents or consumption activities on social media platforms, their use of any application serves as a promotion and informs other users about the application as well as the application ecosystem. Such sharing can increase adoption of these applications (Aral and Walker 2011). Further, automated sharing due to integration can increase the awareness of the first-party application and may further raise the demand for the application. Additionally, it may also create a positive spillover effect on competing applications. Researchers have observed such positive spillover effect of advertising in various industries such as consumer goods (Lewis and Nguyen 2015, Liu et al. 2015), drugs (Shapiro 2017), and restaurants (Sahni 2016) due to increased consumer awareness of the product category. In our context, the increase in the demand of the first-party application due to tighter integration may also increase consumer awareness about other apps due to the sharing of related consumption information and further stimulate consumer demand for competing third-party applications. As a consequence, third-party applications may also benefit from the market expansion effect of integration. Finally, there can be heterogeneity in the spillover effect across competition as different competitors are likely to be activated differently (Roehm and Tybout 2006, Janakiraman et al. 2009) through such promotions due to sharing of consumption information of the first-party application. More specifically, competitors that are typical or more representative of the category are more likely to be activated and experience a strong spillover. Because of this heterogeneity in spillover effect, there can be differential impact of the integration on different third-party applications. Thus, the impact of platform integration on consumer demand in the ecosystem is not known.

Despite its importance, empirical research on consumer demand for first-party applications and third-party applications has been limited.[2] Furthermore, the impact of platform integration remains unclear. Gawer and Henderson (2007) use a qualitative approach to explore why Intel entered its complementary markets and how Intel balances its own strong incentives to enter against the risk of discouraging complementors' innovations. However, they do not focus on the effect of platform's integration strategy on consumer demand in complementary markets. Huang et al. (2013) focus on the role of intellectual property rights on third-party developers' incentives to join SAP's enterprise software platform, but they do not study the impact of first-party application on consumer demand for third-party applications. Lee (2013) investigates the role of exclusive titles on platform competition in the U.S. videogame industry. However, he evaluates the impact of exclusive titles on the demand for competing videogame platforms rather than competing titles. Furthermore, related theoretical papers have focused on how price competition influences market demand, leaving out consumer preferences for empirical studies. Thus, the effect of nonpricing strategies like platform integration in influencing consumer preferences and market demand is not known.

We fill the gap in the literature by studying the impact of Facebook's integration of Instagram on Facebook's photo-sharing applications market. Facebook acquired Instagram for $1 billion in April 2012. Instagram[3] and other Facebook photo-sharing applications offer social networking features for Facebook users to discover, like, comment on, or vote for photos from their friend network or even the entire Facebook network (the total number of active users of these applications was over 113 million in December 2012). After the acquisition, a partial integration[4] was made by Facebook in June 2012 to facilitate photo-sharing between Instagram and Facebook. This integration provided Instagram users an easy-to-use interface to access Facebook data (e.g., user profiles and friendship network) and share photos on Facebook through Instagram automatically. However, users of third-party applications needed several extra steps to complete the same tasks (Android Community 2012). The unique data set from this integration event allows us to evaluate the changes in consumer preferences and market demand after Instagram became a tightly integrated first-party application. We aim to address the following questions:

(1) What is the impact of the platform owner's integration strategy on consumer demand for the first-party application and third-party applications?

(2) How does the integration strategy impact the overall demand in the complementary market?

We build a model of consumer choices and estimate demand for the first-party application, third-party applications, and the overall photo-sharing application market before and after the integration event. We account for the possibility of spillover effects across applications. We also account for the unobserved consumer heterogeneity and control for network effects and switching costs arising from the social characteristics of photo-sharing applications. We estimate the model using a unique data set that consists of daily usage of different applications on the Facebook platform.

The main findings are as follows. First, we find that consumers obtain additional utility from Instagram after its tighter integration with Facebook, leading to a dramatic increase in the demand for Instagram. This is possibly due to the increase in the ease of use because of integration and the increased awareness because of automated sharing of Instagram's consumption by users. Second, we show that the growth of Instagram on the Facebook platform creates a positive spillover effect on third-party apps on Facebook. This can be attributed to the increase in consumer awareness about the app ecosystem created by the increasing usage of the first-party app and the sharing of related consumption information. Interestingly, there is heterogeneity in the spillover effect: the spillover effect is positive for the large third-party apps and negative for the small third-party apps. As a result, the Facebook–Instagram integration actually benefits competing third-party applications with a large user base whereas it hurts competing third-party applications with a small user base. Finally, the total demand in the entire ecosystem increases, which suggests that Facebook's integration strategy benefits the complementary market overall.

Our research makes several contributions. Our study contributes to the literature on platform strategies in complementary markets. Previous research has mostly relied on theoretical models to study strategic interactions between the platform owner and third-party developers (supply side behavior), given various assumptions on consumer behavior (Farrell and Katz 2000, Hagiu and Spulber 2013). Additionally, they do not focus on the platform owner's decision to have integration with first-party application and its implication for consumer demand. Our paper is the first study that empirically evaluates consumer preferences for first-party applications vis-à-vis third-party applications (demand-side behavior) and its implication for the platform owner's integration strategy in the context of social media platforms.

To the best of our knowledge, our paper is the first one to empirically demonstrate the value of integration of an application by a platform owner. Previous research has assumed that cross-product integration is valuable and demonstrated how initial technology architecture/design enables future cross-product integration (Baldwin and Clark 2000, Nambisan 2002). In these studies, platform owners do not own first-party applications that compete with third-party applications. Our paper demonstrates the effect of platform integration on consumer valuations and demand for applications in the context of a social media platform ecosystem with first-party applications and competing third-party applications.

Our research also contributes to the literature on the effects of social features on social media platforms. Previous research has demonstrated how the sharing ability of social media platforms can be used for product advertising and promotion. Our research adds to this stream of literature by illustrating how sharing consumption information on social media platforms creates positive spillover effects on competing products. Further, we show how it interplays with platform integration and leads to an overall positive effect on social media platforms.

From the platform owner's perspective, our findings shed light on the efficacy of the integration strategy for social media platforms. On one hand, such a strategy may be beneficial as the platform owner may gain new users due to the appeal of the tightly integrated first-party application while not hurting third-party applications too much. On the other hand, our research informs small third-party applications, platform owners, and policy makers about the potential dark side of platform integration. As small third-party applications are more vulnerable to the negative shock from vertical integration, such strategies may cause small third-party developers to exit the market, which reduces the variety of products/services available in the complementary market. Platform owners and policy makers should evaluate the trade-off between the demand increase in the short run and the potential losses in product variety in the long run.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. In Section 3, we describe Facebook's partial integration of Instagram, the data set we collected, and exploratory results. In Section 4, we present the empirical model and estimation procedure. We present the main empirical results in Section 5. Robustness checks with different instrumental variables and additional analyses are reported in Section 6. Finally, in Section 7, we discuss the implications of our study and conclude the paper.

2. Literature Review

Our research is related to the literature on platform-based ecosystems with a focus on complementary markets and network effects, literature on the promotional capabilities of social media platforms, and literature on the effect of promotions on competing products. We discuss these streams of research below.

2.1. Platform Ecosystems and Complementary Markets

Existing studies have mostly relied on analytical modeling to study the strategic interactions between the platform owner and third-party developers (i.e., supply side behaviors). For example, Eisenmann et al. (2011) study platform entry strategies when new entrants face entry barriers driven by strong network effects and high switching costs. Farrell and Katz (2000) evaluate how a platform owner's entry into its complementary market allows it to extract higher rents. Hagiu and Spulber (2013) investigate the strategic use of first-party applications and show that the level of investment in these applications is driven by the relationship between first-party applications and third-party applications and the market conditions. All these theoretical papers focus on the supply side behavior and firm strategies, given various assumptions on consumer behavior. Our paper is the first study that empirically evaluates consumer preferences for first-party applications vis-à-vis third-party applications (i.e., demand-side behavior) in the context of social media platforms. Furthermore, theoretical papers have focused on how price competition influences market demand. Our study of the Facebook platform highlights the role of a nonpricing strategy like platform integration in influencing market demand.

Empirical research on platform-based ecosystems, with a focus on complementary markets, is limited. Chipty (2001) examines the consequences of vertical integration between programming and distribution in the cable television industry. She assesses the role of ownership structure in program offerings and finds that integrated operators tend to exclude rival program services from their distribution networks. In our study, the platform owner did not exclude rival applications and instead adopted an approach of tighter integration with its own application. Gawer and Henderson (2007) use a deductive, qualitative approach to explore why Intel entered its complementary markets and how Intel balanced its own strong incentives to enter against the risk of discouraging complementors' innovations. Our paper provides concrete empirical evidence on the effects of a platform owner's vertical integration strategy in shaping consumer demand in the complementary market.

Using firm-level financial data, Huang et al. (2013) highlight the role of intellectual property rights in third-party developers' incentives to join SAP's enterprise software platform. Third-party developers that hold patents and copyrights, which protect developers from being squeezed by the platform owner, are more likely to join the platform. The focus of their paper is on third-party developers' entry behavior, whereas our paper controls for entry behavior and focuses on understanding consumer choices of first-party and third-party applications before and after platform integration. Lee (2013) investigates the role of exclusive titles on platform competition in the U.S. videogame industry. However, he evaluates the impact of exclusive titles on consumer demand for competing videogame consoles rather than competing third-party applications. Furthermore, in our study of Facebook photo-sharing applications, consumers may prefer the tightly integrated first-party application for its ease of use, a characteristic that is absent in the videogame setting.

2.2. Network Effects

Several studies have focused on the role of network effects on product adoption. Brynjolfsson and Kemerer (1996) show a positive impact of installed base and compatibility on the price of packaged software. Similarly, Gallaugher and Wang (2002) show a positive effect of network size on the price of web server software. They attribute network effects to three sources: exchange value, staying power, and extrinsic benefits. Using electronic banking as a context, Kauffman et al. (2000) provide empirical evidence on network externality as a determinant of product adoption and diffusion. Similarly, Xue et al. (2011) show that customers who reside in areas with a larger number of online banking adopters are faster to adopt online banking as well. Zhu et al. (2006) develop a conceptual model that captures network effects, expected benefits, and adoption costs as drivers in the adoption of Internet-based interorganizational systems. They highlight that the extent to which a firm's trading partners are willing to support the same systems as a key driver of the focal firm's adoption decisions. Fuentelsaz et al. (2012) show that higher switching costs and stronger network effects lead to lower levels of rivalry in the telecommunications market. Thus previous works have primarily focused on the role of network effects on product adoption and price competition. Our paper extends this stream of literature by evaluating the role of network effects in influencing consumer responses to a platform owner's integration of a first-party application. Further, we focus on social media platforms where the network effects are due to consumer networks.

2.3. Promotional Capabilities of Social Media Platforms

An important driver of the consumer preferences for different applications on social media platforms is the social network embedded in these applications. Users can influence others in their network to consume certain content or adopt a particular product. Previous studies have demonstrated how the promotional capabilities of social media platforms help grow membership (Trusov et al. 2009), increase product adoptions

(Aral and Walker 2011), and generate sales (Chen et al. 2011, Li and Wu 2014). However, these studies have primarily focused on the effect of social media promotions on consumer demand for the focal products and have not investigated the impact of such promotions on demand for competing products. Our paper extends this stream of literature by evaluating the role of app promotions on demand for competing apps and how it influences the outcomes of platform integration.

2.4. Effect of Promotions on Competing Products

Intuitively one can expect that advertising a product will negatively affect consumer demand for competing products. Promotion of a product creates interference effects, which may prevent consumers' from recalling a competing brand (Keller 1987, Burke and Srull 1988, Keller 1991). Such recall is important for a brand's product to be considered and included in the choice set (Nedungadi 1990). Further, exposure to advertising can lead to switching behavior (Deighton et al. 1994), a mechanism that explains the negative effect of advertising on competing products on existing users.

However, a few marketing studies have shown that advertising can also create a positive spillover effect. Shapiro (2017) shows that advertising for a new drug creates a positive spillover for other drugs in the same category. Similarly, Liu et al. (2015) show a positive spillover effect of advertising on competing brands in the refrigerated yogurt market. These studies attribute the positive spillover to category expansion as advertising creates awareness about the category. Such positive spillover effects have been explained using the accessibility-diagnosticity framework (Feldman and Lynch 1988). According to this perspective, a product can help infer the quality of another product provided both the products can be retrieved from the memory. Promotion of a brand or a product activates the brand or category need, which in turn activates the competing brand need. The same mechanism may apply to promotions through social media platforms. As users share product consumption information in their network, their friends/followers may be influenced to consider the app category as well. This may stimulate demand for the entire category.

There can be heterogeneity in the spillover effects of promotion on competing products. Activation of competing brands due to promotion depends on the accessibility of competing brand or product in the memory and which in turn depends on the linkages between brands (Collins and Loftus 1975). A competing product or brand is more accessible if it is similar to the advertised product or brand. Thus, proximity of the competing brand to the advertised brand can also lead to heterogeneity in the spillover effect. Janakiraman et al. (2009) find positive perception spillovers only for similar competing products. Similarly, Sahni (2016) finds that the advertising of a restaurant leads to positive spillover on similar competing restaurants. A competing brand is also more accessible if it is typical of the category (Roehm and Tybout 2006, Janakiraman et al. 2009). In an applications market with network effects, applications with a large user base are more representative of the category as compared to small apps. As a result, there might be differential spillover across competing big and small apps. We evaluate the existence of such spillover effects from the first-party app on the demand for big and small third-party apps.

3. Data Description and Exploratory Results

In this paper we focus on photo-sharing applications that enable Facebook users to discover, edit, and share photos on Facebook. Photo-sharing applications provide tools to create personalized photo collages, import pictures from an existing Facebook album, retouch, add filters or text, and share photos with friends on Facebook. When a user posts a photo on Facebook, the post is shown along with the app logo/name and thus the user's friends are aware of the application used for that post (see Figure 1). These applications also offer social networking features for users to discover, like, comment on, or vote for photos from their friendship network on Facebook or even the entire Facebook network. Instagram has been one of the most popular photo-sharing applications on the Facebook platform.

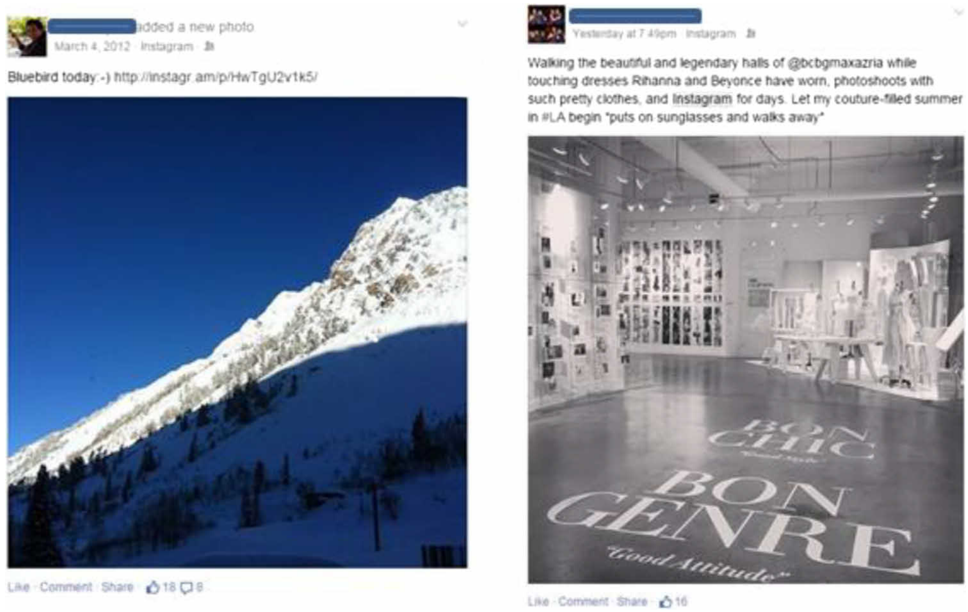
3.1. Integration Event

On April 12, 2012, Facebook acquired Instagram for approximately \$1 billion. After the acquisition, Facebook continued to run Instagram as an independent application, instead of fully integrating it into Facebook.com (Facebook 2012). There were no significant changes to Instagram and Facebook.com after the acquisition deal, except that, on June 26, 2012, a partial integration was made to facilitate photo sharing between Instagram and Facebook. After the tighter integration, if an Instagram user likes or comments on a photo on Instagram, the photo along with the "like" or comment may automatically appear as the user's news feed on Facebook; if a Facebook user likes or comments the photo, the "like" or comment may appear in the original post on Instagram as well. Note that the use of automated sharing capability was optional. The update also offers Instagram users enhanced capacity to find and connect to their Facebook friends and explore Facebook's network using this application (Android Community 2012). Users of third-party applications have to take several extra steps to complete these tasks.

3.2. Data Description

We obtained a unique data set from a business analytics company, AppData.com, that tracks usage of applications on Facebook. Our data set consists of the number of daily active users for the top 20 photo-sharing

Figure 1. (Color online) Sample Instagram Posts on Facebook



applications on the Facebook platform from April 27, 2012, to December 15, 2012.[5] Note that users may use these photo-sharing apps for other purposes,[6] but they are counted as active users on Facebook only if they post or share information on Facebook. Our data set does not consist of information about app usage outside the Facebook platform.

All the top 20 applications are free applications and cumulatively account for over 88% of the market share among all Facebook photo-sharing applications. Except Instagram, all other applications were owned by third-party developers. Besides the time-variant demand data, we also observe time-invariant product attributes such as release dates and distribution channels (Facebook canvas, iOS/Android applications). The data set also consists of an app's average user star ratings on Facebook's application center. The star ratings remained constant during the panel period, suggesting there were no visible quality improvements to the photo-sharing applications during the panel period.

We consider a balanced sample for estimation, which covers the first 124 days (two months before and two months after the integration event). We also validate our results, using an extended sample, which covers all the available data. Table 1 summarizes some descriptive statistics of the sample used for estimation. We compute market shares by dividing the number of application users by the total number of Facebook users (see, e.g., Berry et al. 1995, Nevo 2001). The statistics show that a large fraction of Facebook users did not use any photo-sharing application regularly for sharing on Facebook.

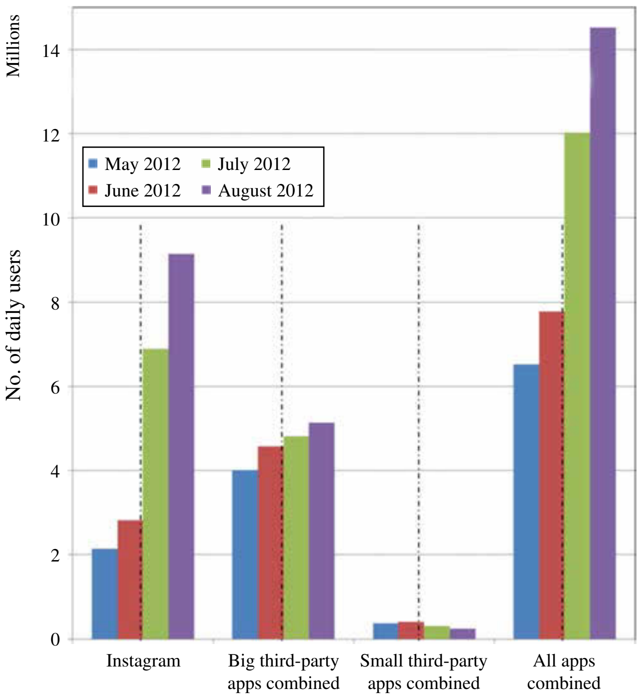
Figure 2 illustrates the demand changes for different applications before and after the integration event. Since its tighter integration with Facebook, Instagram has experienced significant growth in its user base. Moreover, the combined demand of the top third-party applications remains relatively stable. However, there is negative impact on third-party applications with a small network size. Finally, the total demand

Table 1. Daily Users of Instagram and Other Photo-Sharing Applications on the Facebook Platform

Variable	Mean	Std. dev.	Min	Max
Market Size (daily users of Facebook)	5.52×10^{8}	1.07×10^{7}	5.35×10^{8}	5.72×10^{8}
Natural Log of Market Size	20.12	16.19	20.10	20.16
Daily Users of Instagram	5.04×10^{6}	2.91×10^{6}	1.90×10^{6}	1.05×10^{7}
Natural Log of Daily Users of Instagram	15.43	14.88	14.46	16.17
Daily Users of Third-Party Apps	2.58×10^{5}	3.34×10^{5}	4.00×10^{2}	1.60×10^{6}
Natural Log of Daily Users of Third-Party Apps	12.46	12.72	5.99	14.29
Market Share of Instagram (%)	0.90	0.51	0.35	1.83
Market Share of Third-Party Apps (%)	0.047	0.060	7.07×10^{-5}	0.29

Notes. The total number of applications in the sample is 20 and the length of the panel period is 124 days (two months before and two months after the integration event). Thus, the total number of observations in this balanced panel is 2,480.

Figure 2. (Color online) Market Demand of Instagram, Third-Party Applications, and the Overall Market Before and After Facebook's Tighter Integration with Instagram



Notes. A tighter integration between Facebook and Instagram was made on June 26, 2012 (dashed line). We call the top 9 third-party applications (according to user base) big third-party applications and the remaining 10 applications small third-party applications. Instagram's user base (in millions) increased dramatically after the integration. However, the growth rate of big third-party applications became smaller and the user base of small third-party applications decreased. The total number of users for the photo-sharing category increased after integration.

for Instagram and third-party applications is growing. By the end of August, 2012, the total demand in the photo-sharing category almost tripled. These results imply that a large fraction of users joining Instagram are new users, rather than incumbent users of third-party applications. We conduct additional exploratory analysis to establish the effect of integration on different applications.

3.3. Exploratory Analysis

To determine the impact of Facebook's integration of Instagram on the number of active users on Facebook for different photo-sharing applications, we use the following regression model:

$$y_{jt} = \beta y_{j(t-1)} + \sum_{g} \gamma_g I_{g_j t} + \alpha_j + \tau(t) + \varepsilon_{jt}, \qquad (1)$$

where y_{jt} is the application user base (log) for application j in each period t and $y_{j(t-1)}$ is the lagged application user base. We create a dummy variable *SmallThirdPartyApp*, where *SmallThirdPartyApp* equals one if an app's user base ranks below 10th and zero otherwise.

Table 2. Parameter Estimates for the Exploratory Analysis

	Coefficients (standard errors)	
Variable	(1)	(2)
LaggedAppUserBase (log)	0.7111***	0.7065***
	(0.0102)	(0.0102)
Integration × *Instagram*	0.3686***	0.3703***
	(0.0404)	(0.0430)
Integration × *BigThirdPartyApp*	0.0568***	0.0539***
	(0.0124)	(0.0195)
Integration × *SmallThirdPartyApp*	−0.1045***	−0.1104***
	(0.0135)	(0.0202)
Control of Potential Time Trend	No	Yes
Sum of squared errors	140.0811	138.8396

Notes. Standard errors in parentheses and $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. This note also applies to Tables 3–7.

Similarly, we create a dummy variable *BigThirdPartyApp* for the top nine third-party applications. We categorize the applications into three groups: $g \in$ {first-party application (Instagram), big third-party applications, small third-party applications}; and $I_{g_j t}$ represents a vector of interaction terms *Integration* × *AppGroup* {*Integration* × *Instagram*, *Integration* × *BigThirdPartyApp*, *Integration* × *SmallThirdPartyApp*}, whose value is one if application j belongs to group g and $t \geq t_I$ (t_I is the integration time) and zero otherwise. These two interaction terms capture the impact of integration on consumer valuation of Instagram and third-party applications. The model also includes application dummies α_j to control for time-invariant fixed effects. Application dummies also account for observed and unobserved product characteristics that do not vary during the panel period. To control for potential time trends $\tau(t)$ that shift consumer usage of Facebook photo-sharing applications, we include two terms t and t^2 (we also try alternative specifications using week dummies, the results remain very similar). In the equation above, ε_{jt} is the app-specific shock that is not observed by our econometrician. Note that the applications are free and as a result, price is not relevant for our setup.

Results in Table 2 show that the number of users for Instagram and big third-party applications increases after Facebook tightly integrated Instagram. However, usage of small third-party apps decreases. In the remainder of the paper, we build and estimate a random-coefficient discrete choice model that captures consumer choices and also accounts for any possible spillover effects across applications.

4. The Model

Our objective is to estimate demand for different photo-sharing applications on the Facebook platform. We have aggregate data for the number of active users of each app in each period. When users use these apps for photo sharing on Facebook, they also reveal information about their app usage to other Facebook users (e.g., "posted via Instagram," "posted via Pixable," etc.). This can lead to spillover effects across applications. To account for these characteristics, we build a logit model that captures flexible substitution as suggested by Liu et al. (2015). This specification allows us to overcome the invariant property of substitution for random utility models and accommodate the possibility of spillover effects (Liu et al. 2015). Further, there can be consumer heterogeneity for different applications (Ghose and Han 2014). To capture this, we consider a random coefficient specification based on the literature of demand estimation using aggregate data (Berry et al. 1995, Nevo 2001). This approach allows us to derive market shares of each application as a function of product characteristics while accounting for unobserved consumer heterogeneity and demand shocks. Similar models have been used to study consumer choices in electronic markets and mobile applications markets (see, e.g., Ghose et al. 2012, Danaher et al. 2014, Ghose and Han 2014).

4.1. Model Setup

We observe period t, $t = 1, \ldots, T$, with M_t consumers. Previous research on app markets (e.g., Ghose and Han 2014) shows that users are not very likely to use more than one application on a daily basis. Further, a user can share photographs with all her Facebook friends just by using a single application as each photo-sharing application can reach all of user's Facebook friends. In that case, even if a user has multiple photo-sharing apps, she would at most use one app to share photographs with her Facebook friends.[7] So we assume that each consumer chooses at most one application j, $j = 1, \ldots, J$, in each period. In our setup of Facebook photo-sharing applications, $J = 20$. As mentioned earlier, all these photo-sharing applications are free and thus price is not relevant to consumer choices. We categorize the third-party applications into two groups: $g \in \{$Big Third-Party, Small Third-Party Applications$\}$. Denote $j = 0$ the option of outside good, i.e., the option of not using any of these J applications. Consumer i's utility of using application j in period t is specified as

$$\begin{aligned} u_{ijt} = {} & \beta_1^i y_{j(t-1)} + \beta_2^i I_{Instagram,\,t} \\ & + \sum_{g \in \{BigThirdParty,\, SmallThirdParty\}} \varphi_g y_{Instagram,\,(t-1)} \\ & + \gamma\left(\sum_{k \neq j \text{ or } Instagram} y_{k(t-1)}\right) \\ & + \alpha_j + \tau(t) + \varepsilon_{jt} + \epsilon_{ijt}, \end{aligned} \tag{2}$$

where $y_{j(t-1)}$ is the lagged application user base that determines the direct network effect (see, e.g., Fuentelsaz et al. 2012). Network externalities are known to play a role in consumers' adoption of technology products (Katz and Shapiro 1986). Products and services with a larger user base may provide higher exchange value to users. Such installed base effects may also come from behavioral factors such as social preferences, observational learning, and word of mouth, which influence product diffusion (Bass 1969, Mahajan et al. 1990). This is applicable in our setup as users share photographs with others. Further, as users share photos with their Facebook friends using a photo-sharing app, they also end up promoting the app as the app logo/name (Figure 1) is displayed along with the shared photograph. In that case, the active user base of the application in the previous period also serves as a proxy for the promotional effect from such sharing of consumption information. Note that consumers may also derive utility from the overall user base of Facebook (i.e., indirect network effect). This common network effect, however, is not identified, as it enters the utility function for each application and will be cancelled out.

Consumer valuation of the first-party application may increase after its tighter integration with the platform due to better ease of use (Davis 1989, Cooper 2000, Dhebar 1995). For example, reciprocal sharing between Instagram and Facebook allows Instagram users to manage photos across Instagram and Facebook in a seamless fashion. This effect is captured by $I_{Instagram,\,t}$, which represents the interaction terms *Integration* × *Instagram*, whose value is one if application j is Instagram and $t \geq t_I$ (t_I is the integration time) and zero otherwise.

Previous studies (Liu et al. 2015, Shapiro 2017) represent the spillover effect as a response to marketing instruments such as promotions. We use the active user base of the application in the previous period as a proxy for the promotional effect of sharing the consumption information and use it to capture the spillover effect. In our main model, we only consider the spillover effect from Instagram on the third-party apps. In our additional analysis in Section 6, we also consider the spillover effect from third-party applications on Instagram. Further, the literature suggests that the spillover effect on competing apps can be heterogeneous. For example, spillover may be more for competitors that are typical of the category and are more likely to be activated by promotions (Roehm and Tybout 2006, Janakiraman et al. 2009). Big applications, i.e., applications with a large user base, are more typical of the photo-sharing category. To account for the potential heterogeneity in the spillover effect across different apps, we allow such effects to be different for big and small third-party applications (the third term $\sum_{g \in \{BigThirdParty,\, SmallThirdParty\}} \varphi_g y_{Instagram,\,(t-1)}$ captures the spillover effect from Instagram on these two groups on third-party apps). The fourth term in Equation (2) captures the spillover effect from other applications, excluding Instagram. A similar approach has been used by Liu et al. (2015) to model spillover effects.

Our model controls for various unobserved shocks. In Equation (2), ε_{jt} is the app-specific shock that enters a consumer's utility in period t but is not observed by our econometrician, and ϵ_{ijt} is the idiosyncratic shock that is assumed to be drawn from the Type 1 extreme value distribution independently across consumers, applications, and time periods (Berry et al. 1995, Nevo 2001). The model also includes application dummies α_j and time trend variable $\tau(t)$ to control for time-invariant fixed effects and potential time trends that shift consumers' utility. Application dummies also account for observed and unobserved product characteristics that do not vary during the panel period. As noted by Nevo (2001), the rich specifications of fixed effects and time effects capture various components of unobservables such as unobserved promotional activities, unquantifiable product characteristics (e.g., brand equity), or systematic shocks to demand, which are common across all photo-sharing applications. Such rich specifications provide a semiparametric control that assuages potential misspecification concerns.

Following Berry et al. (1995), we model the distribution of consumers' taste parameters as multivariate normal, i.e.,

$$\beta_i = \bar{\beta} + \beta_\nu \nu_i, \quad \nu_i \sim \mathrm{N}(0, \Sigma_K), \tag{3}$$

where K is the dimension of product characteristics, $\bar{\beta}$ is a vector of the means of taste parameters, ν_i is a vector of unobserved individual tastes drawn from the multivariate normal distribution with mean 0 and variance-covariance matrix Σ_K, and β_ν is a scaling diagonal matrix that represents the standard deviations of the taste distributions. In the base model, we assume $\Sigma_K = I_K$, i.e., the off-diagonal elements of the variance-covariance matrix are fixed to zero (we relax this assumption as an extension and find that model estimates remain similar). In our setup, product attributes except application user bases do not change during the panel period and are already captured by the application dummy. In our robustness analysis, we also verify our results by controlling for actual product attributes. We assume random coefficient for the key variables, i.e., the network effect and the integration event $\{y_{j(t-1)}, I_{Instagram,t}\}$, to account for the possibility that consumers may be heterogeneous in their valuation of the size of an application's user base and the benefit from integration (thus we set $K = 2$). The random coefficients of the term $y_{j(t-1)}$ also capture the variation in consumer preferences due to the variation in their local networks (unobserved by us). For example, if a consumer has a larger local network, the coefficient of the installed base in her utility function is also larger.

Identification of random coefficients for dummy regressors is difficult as these variables have very limited cross-sectional or temporal variations, which hinders the identification of β_ν. As a result, we do not assume random coefficients for dummy regressors and interaction terms to avoid the explosion of parameters.[8] Finally, we normalize the mean utility from the outside option to zero, i.e., $U_{i0t} = \epsilon_{i0t}$.

Combining Equations (2) and (3), we have

$$u_{ijt} = \delta_{jt} + y_{j(t-1)}\beta_{\nu 1}\nu_{i1} + I_{Instagram,t}\beta_{\nu 2}\nu_{i2} + \epsilon_{ijt}, \tag{4}$$

where

$$\begin{aligned}\delta_{jt} = {} & \bar{\beta}_1 y_{j(t-1)} + \bar{\beta}_2 I_{Instagram,t} \\ & + \sum_{g \in \{BigThirdParty,\, SmallThirdParty\}} \varphi_g y_{Instagram,(t-1)} \\ & + \gamma\left(\sum_{k \neq j \text{ or } Instagram} y_{k(t-1)}\right) + \alpha_j + \tau(t) + \varepsilon_{jt}\end{aligned} \tag{5}$$

represents the mean utility and

$$y_{j(t-1)}\beta_{\nu 1}\nu_{i1} + I_{Instagram,t}\beta_{\nu 2}\nu_{i2} + \epsilon_{ijt}$$

corresponds to consumer i's individual-specific utility from using application j in time t.

4.2. Switching Costs

In our data set we observe the daily usage of each photo-sharing application. As a consumer uses these applications repeatedly, her choice in the current period may depend on her previous choices, i.e., consumers may reveal state-dependent preferences. Such dynamic consumer behavior may be driven by switching costs, which reduces a consumer's utility for other alternatives, or by variety-seeking behavior, which reduces a consumer's utility from using the same application. For Facebook photo-sharing applications, state-dependent preferences may be attributed to the social features (e.g., social network) in these applications. Switching to a new application means leaving the current network and joining a different community, which can be infeasible to some consumers with high switching costs but attractive to others with strong variety-seeking preferences.

The consumer utility function in Equation (2) can be modified to capture the effect of previous choices. Given that consumer i chose application $d_{i(t-1)}$ in period $t-1$, her utility from choosing application j in period t is

$$U_{ijt}(d_{i(t-1)}) = u_{ijt} - c_s^i \mathbf{1}\{d_{i(t-1)} \notin \{0, j\}\}, \tag{6}$$

where u_{ijt} is specified in Equation (2), and c_s^i is consumer i' cost (or benefit if negative) of switching from application j to another application. We allow such switching costs to be different for big applications and small applications, i.e., $s \in$ {big applications (i.e., Instagram and big third-party applications), small applications (i.e., small third-party applications)}. The term $\mathbf{1}\{d_{i(t-1)} \notin \{0, j\}\}$ is an indicator function defined as

$$\mathbf{1}\{d_{i(t-1)} \notin \{0, j\}\} = \begin{cases} 1 & \text{if } d_{i(t-1)} \neq 0 \text{ and } d_{i(t-1)} \neq j, \\ 0 & \text{otherwise.} \end{cases}$$

Specifically, we assume that a consumer i incurs a cost for switching to a different application. However, switching to/from the outside option does not incur such cost.

We assume c_s^i is drawn from a normal distribution $c_s^i \sim \mathrm{N}(\bar{c}_s \sigma_c^2)$, with mean $\bar{c}_s$ and variance σ_c^2. We fix $\sigma_c^2 = 1$ as it is difficult to identify both the mean and variance. Therefore, $c_s^i = \bar{c}_s + \varphi_i$, where φ_i follows the standard normal distribution. Again, we normalize the mean utility from the outside option to zero, i.e., $U_{i0t} = \epsilon_{i0t}$.

4.3. Identification and Estimation

Our focus in this paper is consumer choices before and after platform integration. To reduce the interference from supply side behaviors such as entry and exit following the integration, we restrict our analysis to a relative short horizon, two months before and two months after integration, such that application developers possibly have not yet responded to the integration event. We have separately verified that the set of top 20 applications remains the same, and further, the apps do not have any other design changes apart from the tighter integration of Instagram. This allows us to estimate the demand equation in (2) without the need to consider competition response to the integration event in terms of the design changes and entry and exit decisions. We also account for unobservable time varying shocks for each application under consideration.

The panel structure of the data set allows us to use the fixed-effects approach to control for potential unobserved/omitted time-invariant product characteristics and promotion efforts. The fixed-effects approach provides a semiparametric control that assuages many misspecification concerns (Wooldridge 2010). However, fixed-effects estimators are inconsistent when the model includes predetermined explanatory variables such as lagged user base (Nickell 1981, Anderson and Hsiao 1982). The intuition for the inconsistency is that future adoptions are a function of current adoptions, implying that current unobservables are correlated with the size of application user base in all future periods. This violates the strict exogeneity condition required for the consistency of fixed-effects estimators. However, this inconsistency becomes insignificant when the number of time periods T is relatively large (Hahn and Kuersteiner 2002), as it is the case in our model. Hahn and Kuersteiner (2002) find that the magnitude of biases is close to $2/T$, which is about 0.01, a negligible number in our setting (parameter estimate of network effect is about 0.7 in our model). As a robustness check, we also validate our results with various instruments for the lagged user base in Section 6.

It is possible that Facebook may coordinate the timing of integration based on some market trends for photo sharing. For example, an increased interest in photo sharing among consumers may influence the consumer response to integration. We account for such time trends using the time trend variable. It is also possible that Facebook may coordinate the timing of Integration with higher levels of external promotions for the Instagram application. We conducted a comprehensive review of Instagram's Internet activities during the same panel period. We went through historical news feeds and articles on major search engines (Google, Yahoo!, and Bing), mobile applications marketplaces (iTunes and Google Play), tech media websites (CNET and TechCrunch), and Instagram's company page on Facebook. We did not find any evidence that Instagram was executing unusual advertising or other promotional campaigns that may explain the demand patterns observed in Figure 2. However, it is possible that there are external unobserved market dynamics that influence consumer valuation and are correlated with the integration terms. As a robustness check, we validate our results with a suitable instrument for the integration variable in Section 6.

Details of the estimation algorithm are provided in Appendices A and B in the online appendix. Here we present the intuition of the estimation procedure. The model is of individual behavior, yet only aggregate data are observed. Our goal is to estimate the mean and variance of the vector of model parameters while accounting for consumer heterogeneity. We apply iterative methods similar to the contraction mapping algorithm used by Berry et al. (1995) and Nevo (2001). With an initial value of β_ν^0, we can predict individual utility and aggregate individual choices to obtain predicted market shares. We solve for the mean utility δ, such that the model-predicted market shares are equal to the observed market shares. We then form a minimal distance objective function based on the sum of squared errors (if instrument variables are used, we replace the minimal distance by a generalized method of moments (GMM) objective function based on a set of moment conditions.) We then update the parameter value and use it as the starting point for the next iteration. This procedure is repeated until the algorithm finds the optimal value of β_ν that minimizes the objective function. We tried different starting points and they routinely lead to the same estimates.

Identification of switching costs is methodologically challenging when only aggregate-level demand data are available. In the data set, we do not observe an individual consumer's historical choices. Our identification strategy relies on the observed demand patterns. We observe the volume of incumbent application users as well as the number of new users joining the ecosystem. Incumbent application users face switching costs, whereas new users do not. Given an initial set of parameter values, our iterative estimation procedure computes both existing and new users' probability of choosing an application based on product characteristics, users' previous choices, and switching costs. We equate the model-predicted market shares and the actual market shares in each period to solve for the mean utility and estimate the next set of parameter values. The algorithm iterates until the parameter estimates converges. Appendix C in the online appendix provides the details of the estimation procedure.

5. Empirical Analysis and Results

In this section, we explain the empirical results. At the end of this section, we conduct counterfactual simulations and estimate market demand for a hypothetical scenario in which Facebook did not seek tighter integration with Instagram. By contrasting demand estimates from this counterfactual "without integration" scenario with those from the real "with integration" scenario, we are able to estimate the impact of platform integration on different types of applications.

5.1. Parameter Estimates

Estimation results are in Table 3. Estimates in the first column are from the model without consumer heterogeneity (fixing β_v to zero). The second column provides the results from the enhanced model with consumer heterogeneity. The last two columns present estimates from the same models, but with control for switching costs. The sum of squared errors in Table 3 reveals that model fit increases as controls of consumer heterogeneity and switching costs are included in the model (smaller errors imply better fit).

The coefficient of lagged application user base is positive and significant. This suggests that consumers derive a higher utility from using an application with a larger user base. The strong network effect may be attributed to the unique features of photo-sharing applications: social and sharing. Further, the lagged application user base also represents the promotional effect of past consumption on the current consumption. Also note that the small but significant parameter of consumer heterogeneity indicates that users differ in their valuations of the network size. Some users value a large network size more than others. Ignoring this heterogeneity leads to overestimation of network effects.

The coefficient of *Integration* × *Instagram* is positive and significant, which suggests the more users are sharing Instagram content on Facebook after the integration event. Increased sharing can be driven by enhanced nonsharing capabilities that improve the quality of Instagram so that people are more willing use the app. Alternatively, it can be driven by the enhanced sharing capabilities or a combination of both. However, the prominent observed changes associated with the integration event were related to the improved sharing capabilities with the Facebook platform (Android Community 2012). More specifically, Instagram users had an easy-to-use interface to access Facebook data (e.g., user profiles and friendship network) and were

Table 3. Parameter Estimates of the Main Models

	Coefficients (standard errors)			
Variable	(1)	(2)	(3)	(4)
LaggedAppUserBase (log)	0.6971***	0.5930***	0.6741***	0.6741***
	(0.0105)	(0.0105)	(0.0104)	(0.0104)
Integration × *Instagram*	0.3956***	0.4338***	0.1485***	0.1487***
	(0.0473)	(0.0472)	(0.0470)	(0.0470)
UserBaseOthers (excluding Instagram)	−0.0385	−0.0209	−0.0356	−0.0356
	(0.0496)	(0.0495)	(0.0494)	(0.0494)
BigThirdPartyApp × *UserBaseInstagram*	0.0616***	0.0833***	0.0794***	0.0794***
	(0.0233)	(0.0237)	(0.0232)	(0.0232)
SmallThirdPartyApp × *UserBaseInstagram*	−0.0796***	−0.0745***	−0.0658***	−0.0658***
	(0.0239)	(0.0232)	(0.0238)	(0.0238)
Consumer Heterogeneity on AppUserBase (log)		0.1068***		0.0003
		(0.0056)		(0.0149)
Consumer Heterogeneity on Integration × *Instagram*		0.5906***		0.0016
		(0.0108)		(0.0710)
Switching Costs (*BigApp*)			4.6225***	4.6340***
			(0.1775)	(0.4149)
Switching Cost (*SmallApp*)			0.0122	0.0013
			(0.0845)	(0.0947)
Sum of squared errors	138.2350	137.6607	137.0267	137.0264

able to share photos on Facebook through Instagram automatically after integration. Thus, the positive effect can be attributed to the tighter integration, which facilitates data exchange with the Facebook platform in the form of searches and automated sharing. Further, the automated sharing is also likely to create more awareness about Instagram leading to increase in the adoption of Instagram.

The coefficient estimates show that the first-party application creates different spillover effects on big third-party applications and small third-party applications. Note that in the absence of spillover effects, the coefficients for $\sum_{g\in\{BigThirdParty,\,SmallThirdParty\}} \varphi_g \cdot y_{Instagram,(t-1)}$ should be insignificant. However, the coefficient for the big third-party applications is positive and significant, whereas that for the small third-party applications is negative and significant. A plausible explanation is that the sharing of Instagram photos increases consumer awareness about photo-sharing applications. This creates a positive spillover effect on competing third-party applications. Such spillover effects have been observed in other industries (Sahni 2016, Liu et al. 2015, Shapiro 2017). Further, typical competing products or services are more likely to be activated and receive a positive spillover (Roehm and Tybout 2006, Janakiraman et al. 2009). In our setup, big third-party apps with a large user base are more typical or representative of the category as compared to small third-party apps. As a consequence, they are more likely to be considered by users as compared to small third-party apps. In the absence of such activation, small third-party apps may face interference in consumer recall due to the promotional effect of content sharing using the first-party application (Keller 1987, 1991; Burke and Srull 1988). This may explain the negative spillover effects on small third-party applications. Note that the differential spillover effects can also be due to variation in switching costs (Anderson and Simester 2013) or attributes such as quality (Sahni 2016). However, as we explicitly control for switching costs and product attributes, these factors are not likely to drive the observed differential spillover effects.

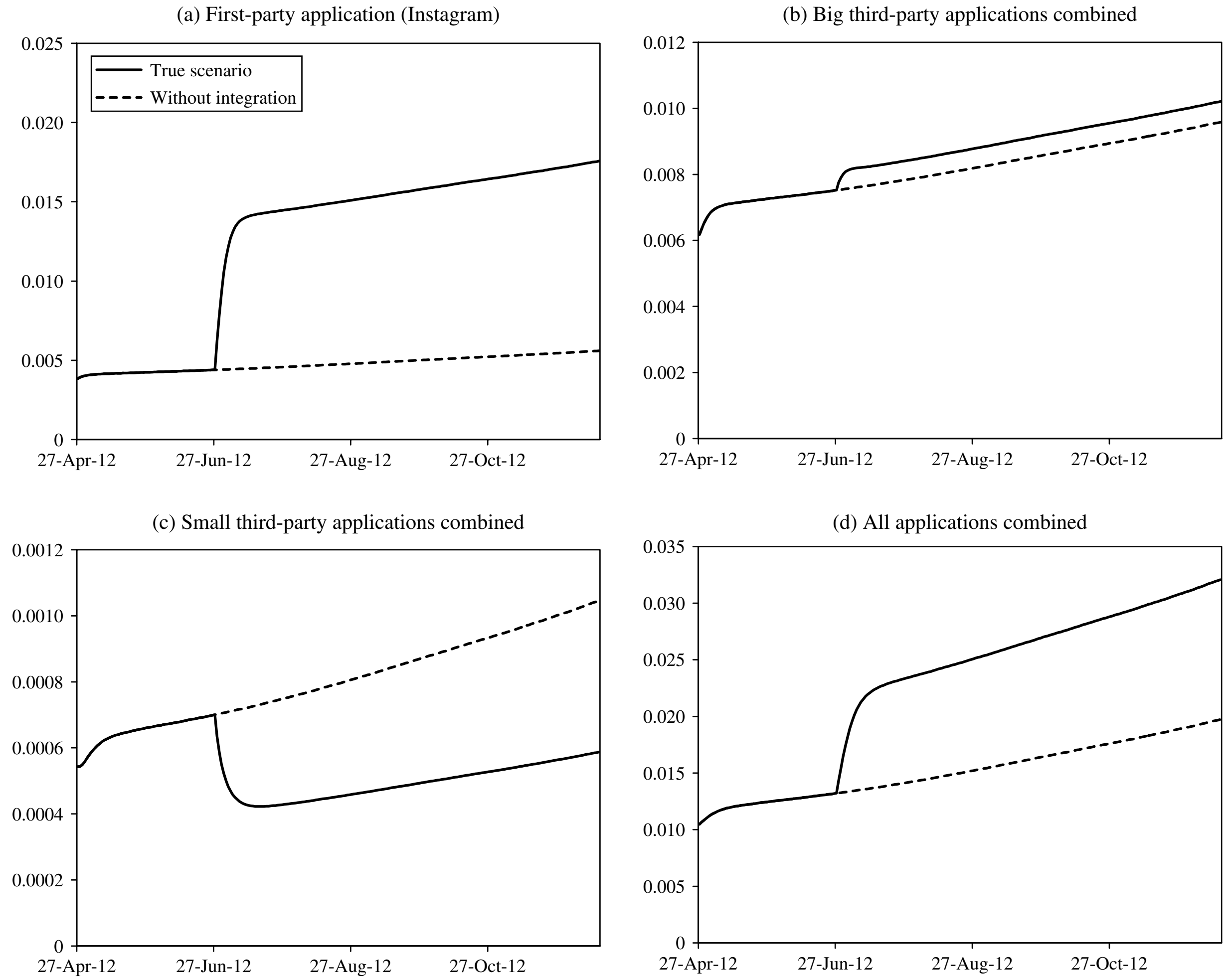
The coefficient of switching cost is positive and significant for big apps but insignificant for small applications (Table 3). Our results show that big third-party app users on average incur high switching costs, whereas small third-party app users incur very lower switching costs. Big photo-sharing applications provide a large network of users and nontransferable resources such as a large amount of free online photo storage, which significantly raise users' cost when switching to other applications. Small photo-sharing applications provide very limited resources and thus the switching cost is low.

Evaluating the overall impact of platform integration in the presence of network effects and spillover effects is nontrivial. The parameter estimate of integration in Table 3 captures the one-period effect (first-order effect). The one-period effect impacts consumer choices in current period t, but the resulting application user base will give rise to network effect in the next period through the lagged application user base and spillover effects, which enter a consumer's utility function in the next period (second-order effect). As a result, the overall effect of platform integration will be larger than the one-period effect. In other words, the second-order effect amplifies the one-period effect of platform integration. In our discrete choice models, it is impossible to derive a closed-form expression for the accumulated effect of platform integration. However, as demonstrated in Section 5.2, this accumulated effect can be easily computed by simulations using our model and parameter estimates.

5.2. The Impact of Integration on Market Demand

We first simulate consumer choices and compute market shares for each application under two alternative market scenarios: *with integration* (the true market scenario where integration occurred in late June 2012) and *without integration* (a counterfactual scenario where no integration was made). We then contrast the market shares under the counterfactual market scenario (s'_{jt}) to those under the true market scenario (s''_{jt}). Figure 3 shows the simulated market shares under the true market scenario (solid curve) and the counterfactual market scenario (dashed curve). The impact of platform integration can be identified by comparing the solid curve with the dashed curve. Figure 3(a) indicates that the first-party application experiences dramatic growth in market share due to its tighter integration with the platform. In addition, the integration event positively impacts consumer demand for big third-party applications (Figure 3(b)) and negatively impacts consumer demand for small third-party applications (Figure 3(c)). Note that in the absence of a spillover effect we should expect a negative effect of integration on the big third-party apps as integration increases the utility of the Instagram application relative to the competing applications. However, the resulting demand increase for Instagram creates a positive spillover effect on the demand for big third-party applications causing an overall increase in the demand for big third-party apps. Finally, as evidenced in Figure 3(d), the net impact of platform integration for the entire market is positive. Our results suggest that tighter integration of Instagram has an overall positive effect on the ecosystem for photo-sharing applications. To eliminate the effect of switching cost on the demand outcomes, we conduct additional counterfactual analysis with zero switching cost (see Figure 4). Our analysis suggests that our main results hold even without switching costs. Thus, our results for competing applications can be primarily attributed to the spillover effects.

Figure 3. Impact of Platform Integration on Market Shares of the First-Party Application, Big Third-Party Applications, Small Third-Party Applications, and the Overall Market



5.3. Integration of the Second-Biggest Application

To evaluate the impact of the size of the first-party application on the integration outcome, we compare our main results with the results from a counterfactual scenario where Facebook integrates the second-biggest application. Pixable was the second-biggest photo-sharing application on the Facebook platform when Facebook made tighter integration with Instagram (Pixable's user base was about one-third of Instagram's user base).[9] We assume that the Pixable is the first-party application while Instagram is a third-party application. We predict the demand for all apps under this scenario using our model estimates. The gain in demand for Pixable is much lower as compared to the gain in demand for Instagram under the true scenario (Figure 5(a)). Compared to the integration of Instagram, the integration of Pixable has smaller negative impact on small third-party applications, but the total gain in market demand is also smaller (Figure 5(d)). These results show that the impact of integration is proportional to the user base of the application being integrated. Clearly, the overall demand is lower as compared to the true scenario in which Facebook integrated Instagram. If the cost of integration is comparable, our result would suggest that Facebook is better off by integrating Instagram rather than a different third-party application.

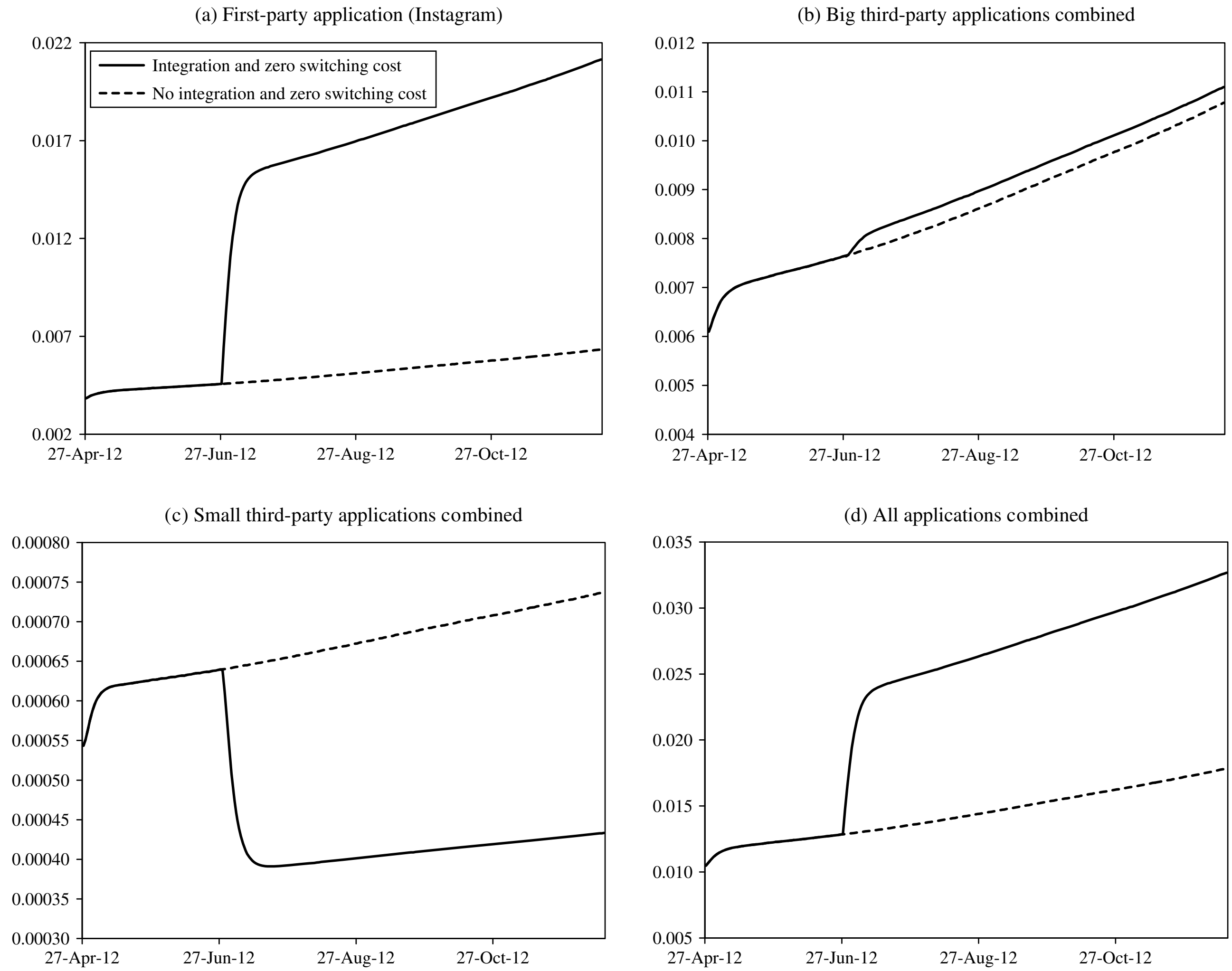
6. Additional Analysis

In this section we describe additional analysis to account for potential endogeneity issues, establish the drivers of the spillover effects, and conduct additional robustness checks.

6.1. Endogeneity Issues

6.1.1. Endogeneity of Lagged User Base. As explained earlier, our model estimates might be biased due to the use of a predetermined lagged user base that may be correlated with unobservables. To correct for this bias, we follow the approach of Arellano and Bover (1995) and use lagged differences of application user base as instruments for the mean utility function in Equation (5) and lagged application user base

Figure 4. The Impact of Integration with Zero Switching Costs

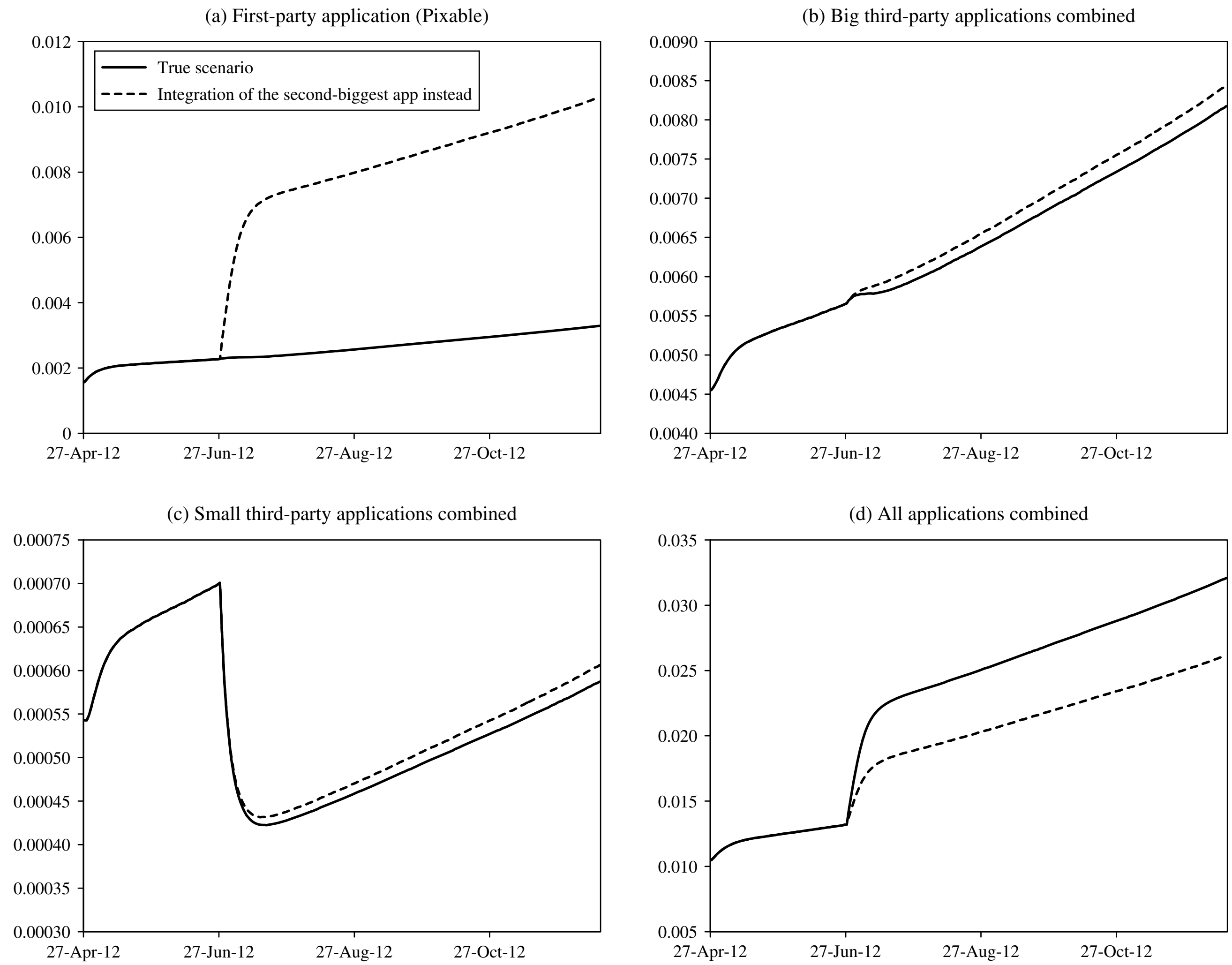


as instruments for the first-difference of this equation. The former equation is often referred to as "level equation," while the latter "first-differenced" equation. Blundell and Bond (1998) show that these instruments are correlated with explanatory variables and orthogonal to unobserved errors. These instruments have been successfully applied by researchers in a wide variety of fields within marketing and economics (see, e.g., Acemoglu and Robinson 2001, Durlauf et al. 2005, Clark et al. 2009, Yoganarasimhan 2012). To check the validity of these instruments in our context, we first perform weak identification tests on the instruments. The F statistic is greater than the recommended threshold of 10, suggesting the instruments are correlated with the suspected endogenous variable (i.e., our instruments are not weak). We then perform the overidentification test (Hansen's J test) and cannot reject the null hypothesis of valid overidentifying restrictions. We apply these instruments using the GMM method. Our estimation approach is explained in Appendix B in the online appendix.

6.1.2. Endogeneity of Integration Timing. Facebook and Instagram might have chosen the integration timing such that the integration is more likely to lead to positive outcome. In other words, the integration event might be correlated with the unobserved shocks that enter a consumer's utility function but are unobservable to us. To control for this potential endogeneity, we use Facebook's stock price as an instrument for the integration timing.

Corporate investments are sensitive to stock prices (Baker et al. 2003, Chen et al. 2007). Additionally, firms are expected to increase their innovation activities and exploratory search after going public (Wu 2012). Facebook held its initial public offering (IPO) in May 2012, but following that the share price dropped and the stock was considered disappointing (Maris 2012). The company was under pressure from investors to improve its stock performance. Therefore, Facebook's subsequent investments were likely to be driven by its unsatisfactory stock price. Tighter integration of Instagram was one such innovation investment where

Figure 5. Integration of Instagram vs. Integration of the Second-Biggest Application



Note. In (b), to make valid comparisons across the two scenarios (integration of Instagram vs. integration of Pixable), the plots of market share combined do not include market share of Instagram and Pixable.

Facebook explored seamless data exchange between Instagram and Facebook. Thus, the decision on the timing of integration was likely to be influenced by Facebook's stock price. The suspected correlation between the integration timing and Facebook's stock market performance is evident from the high correlation between the integration dummy and Facebook's stock price (correlation coefficient is −0.68).

Meanwhile, we expect that Facebook's stock price is not likely to influence consumers' relative preferences for various photo-sharing applications. The stock price may influence a user's decision to join Facebook. However, conditional on the fact that a consumer already joined Facebook, the stock price is not very likely to be directly correlated with the consumer's utility of using Instagram vis-à-vis any other photo-sharing application on the Facebook platform. Further, the Facebook platform was supporting over nine million applications in different categories and only a small fraction (<1%) of Facebook users were using Instagram for photo sharing on Facebook during our panel period (Table 1). As a result, although the stock price may be correlated with platform-specific unobservables, it is less likely to be correlated with unobservables specific to an individual application (e.g., promotions by Instagram).

We test the validity of using Facebook's stock price alone as an instrument for the integration timing. The F statistic is far greater than the recommended threshold of 10, suggesting the instrument is correlated with the integration timing. Note that we use stock performance data from SecondMarket (Primack 2012) for the month of April 2012 as Facebook's IPO took place in May 2012. We also test the validity of using Facebook's stock price together with lagged differences of application user base as instruments for both of the suspected endogenous variables (i.e., integration timing and lagged application user base). The

Table 4. GMM Estimates of the Models

	Coefficients (standard errors)	
Variable	(5)	(6)
LaggedAppUserBase (log)	0.7020*** (0.0632)	0.6007*** (0.0105)
Integration × *Instagram*	0.3899*** (0.0891)	0.2140*** (0.0474)
UserBaseOthers	−0.0361 (0.0583)	−0.0690 (0.0498)
BigThirdPartyApp × *UserBaseInstagram*	0.0609** (0.0250)	0.0902*** (0.0234)
SmallThirdPartyApp × *UserBaseInstagram*	−0.0774** (0.0369)	−0.0966*** (0.0240)
Consumer Heterogeneity on AppUserBase (log)		0.0015 (0.0077)
Consumer Heterogeneity on Integration × *Instagram*		0.0250** (0.0122)
Switching Costs (*BigApp*)		4.8364*** (0.1775)
Switching Cost (*SmallApp*)		0.0390 (0.0743)
GMM objective function	0.7365	0.5312

F statistic is much larger than the recommended threshold of 10, suggesting the instruments are not weak. The Hansen's J test cannot reject the null hypothesis of valid overidentifying restrictions. These tests provide statistical evidence that the instruments are valid.

Estimates with these instruments, as reported in Table 4, remain qualitatively unchanged compared to estimates of the models without using any instruments. These additional analyses provide evidence that our results and main findings are robust. We also conduct additional analysis to further establish that the effect of integration is primarily due to integration features, and we report it in Appendix D in the online appendix.

6.2. Identification of Spillover Effects

6.2.1. Spillover Effect on Instagram. We also check whether the third-party apps have a spillover effect on Instagram. Previous research has shown that if the competitor is very salient then the spillover effect due to awareness is less likely (Sahni 2016). As Instagram is the top photo-sharing application in our setup, users are more likely to be already aware of Instagram. In that case, the spillover effects of third-party applications on Instagram are less likely. The estimates, as reported in Table 5, show that both big third-party and small third-party apps do not have a spillover effect on Instagram. Further, this also confirms that the correlation between the demand for big and small third-party apps and Instagram is not spurious or due to some common time trend but is more likely due to the spillover effect caused by photo sharing.

6.2.2. Driver of the Spillover Effect. It is possible that Instagram has a spillover effect on third-party applications because of the size of its install base, which results in high volume of promotions due to photo sharing. In that case, even the second largest application should have a spillover effect on other third-party applications. We also check whether there is spillover from the second-biggest application (the biggest third-party application). The estimates, as reported in Table 5, show that the spillover effect from the second-biggest application is not significant. This result suggests that the spillover effects from Instagram are not necessarily due to the size of its install base. In that case, it could be due to some unique unobservable characteristic of Instagram or the fact that Instagram is a first-party application. To validate this further, we determine if Instagram has a spillover effect even before its acquisition by Facebook. Before Instagram was acquired by Facebook on April 12, Instagram was a third-party application on the Facebook platform. Using the preacquisition data sample from January 1, 2012, to April 12, 2014, we reestimate our model. We do not find evidence of spillover effects from Instagram before Instagram was acquired (Table 5). This suggests that the spillover effect of Instagram is due to its first-party status. This shows that even though there is a promotional effect of photo sharing, it is more likely to be effective only when there is a first-party application. A plausible explanation is that users are more willing to consider photo-sharing apps in the presence of a first-party application as they expect that the platform is more likely to support such apps.

6.3. Additional Robustness Checks

6.3.1. Serial Correlation. It is likely that the error terms ε_{jt} in Equation (2) are correlated across periods (serial correlation). In this case, the ordinary least squares/GMM estimators are still consistent but inefficient. To account for the possible serial correlation, we allow the error terms to follow the AR(1) process and estimate the model using generalized least squares and method of moments (see Gowrisankaran and Rysman 2012). The first column in Table 6 shows that the estimates remain qualitatively similar to our main analysis.

6.3.2. Correlation Between Random Coefficients. We allow random coefficients for network effects and integration to the correlated. In the base model, we assume $\Sigma_K = I_K$, i.e., the off-diagonal elements of the variance-covariance matrix are fixed to zero. We relax this assumption and estimate both diagonal and off-diagonal elements of the matrix. The second column in Table 6 shows that model estimates remain similar to our main model.

Table 5. Additional Models for Spillover Effects

Variable	Spillover effect from third-party apps on Instagram	Spillover effect from second-biggest app	Spillover effects in preacquisition sample
LaggedAppUserBase (log)	0.6741*** (0.0105)	0.6728*** (0.0105)	0.8658*** (0.0105)
Integration × *Instagram*	0.1594*** (0.0561)	0.1842*** (0.0539)	
UserBaseOthers	−0.0331 (0.0499)	−0.0322 (0.0328)	−0.2391** (0.1052)
BigThirdPartyApp × *UserBaseInstagram*	0.0783*** (0.0237)	0.0946*** (0.0253)	−0.0481 (0.0389)
SmallThirdPartyApp × *UserBaseInstagram*	−0.0669*** (0.0242)	−0.0532*** (0.0288)	−0.0377 (0.0399)
BigThirdPartyApp × *UserBase2App*		0.0810 (0.0715)	
SmallThirdPartyApp × *UserBase2App*		0.0846 (0.0724)	
Instagram × *UserBaseBigThirdPartyApp*	−0.0496 (0.1353)		
Instagram × *UserBaseSmallThirdPartyApp*	−0.0093 (0.0783)		
Consumer Heterogeneity on AppUserBase (log)	0.0001 (0.0350)	0.0003 (0.0148)	0.0005 (0.0067)
Consumer Heterogeneity on Integration × *Instagram*	0.0490 (0.2417)	0.0217*** (0.0030)	
Switching Costs (*BigApp*)	4.6411*** (0.1990)	4.6691*** (0.2149)	1.8354*** (0.1775)
Switching Cost (*SmallApp*)	0.0120 (0.1060)	0.0012 (0.0547)	0.00490 (0.0743)
Sum of squared errors	137.0196	136.9193	134.9894

6.3.3. Model with Product Features. We also estimate a model where we use product features instead of app-specific dummies. These characteristics include the age of the application, whether the application offers in-app purchase, and the languages supported by the app. Results remain qualitatively similar to our main model. However, the model fit is poorer (sum of squared error is 174) as compared to the main model (sum of squared error around 137). This confirms the argument made by Nevo (2001) that application or product dummies are more appropriate when there are unobservable/unquantifiable product characteristics (e.g., brand equity).

6.3.4. Alternate Definition of the Big Third-Party Apps Category. We also validate our results using an alternative categorization of big third-party applications. We reestimate our model using the top five applications as the big third-party applications and remaining third-party applications as the small third-party

Table 6. Alternate Models

Variable	Model with serial correlation	Model with correlation across random coefficients	Model with product characteristics	Model with alternate definition of big third-party app category
LaggedAppUserBase (log)	0.6297*** (0.0115)	0.6748*** (0.0104)	0.9458*** (0.0051)	0.7196*** (0.0098)
Integration × *Instagram*	0.4764*** (0.0539)	0.1487*** (0.0470)	0.0480 (0.0440)	0.1456*** (0.0476)
UserBaseOthers	−0.0495 (0.0549)	−0.0355 (0.0494)	−0.0016 (0.0494)	−0.0277 (0.0502)
BigThirdPartyApp × *UserBaseInstagram*	0.0726*** (0.0264)	0.0794*** (0.0232)	0.0110*** (0.0022)	0.0548** (0.0254)
SmallThirdPartyApp × *UserBaseInstagram*	−0.1047*** (0.0271)	−0.0659*** (0.0238)	−0.0289*** (0.0031)	−0.0011 (0.0231)
Sum of squared errors	139.1091	137.0263	174.3778	141.43

Table 7. Intensity of Usage

Variable	Coefficients (standard errors)
Integration × *Instagram*	0.88 (0.09)***
Integration × *BigThirdPartyApp*	0.08 (0.02)***
Integration × *SmallThirdPartyApp*	0.29 (0.03)***

applications. Our results remain qualitatively similar and are reported in Table 6.

6.3.5. Intensity of Usage. It is possible that the resulting demand increase for Instagram and the big third-party apps may not result in an actual increase in usage but just in downloads. We conduct additional analysis to evaluate how app usage intensity changes after the integration event. A common measure of app usage frequency is the ratio of daily active users to monthly active users (DAU/MAU). A large ratio indicates that a large number of users are repeated users. To see how usage pattern changes following the integration event, we run the following regression:

$$\begin{aligned}\mathrm{Log}\left(\frac{DAU}{MAU}\right)_{jt} &= \beta_0 + \beta_1 I_{Instagram} \times Integration\\ &\quad + \beta_2 I_{BigThirdParty} \times Integration\\ &\quad + \beta_3 I_{SmallThirdParty} \times Integration\\ &\quad + \alpha_j + \tau(t) + \varepsilon_{jt},\end{aligned}$$

where the interaction terms represent the interaction between each application group and the integration event. Parameter estimates are shown in Table 7. The ratio increases after integration, which suggests that incumbent consumers use the applications more frequently after integration. This also suggests that while the integration event increases the number of users for only Instagram and big third-party applications, it increases the intensity of use for all applications. A plausible explanation is that automated sharing of Instagram photos after integration also encourages existing users of the photo-sharing applications to increase their use of the application.

7. Discussion and Conclusion

In this paper, we investigate the impact of the tighter integration of a first-party application with the social media platform on consumer demand for the first-party application and competing third-party applications. We find that consumers obtain additional value from Instagram after its tighter integration with Facebook, leading to dramatic growth in demand for Instagram. However, the integration has different impact on big third-party applications and small third-party applications. This can be attributed to the differential spillover effects from Instagram on these applications. More specifically, Instagram has a positive spillover effect on big third-party applications and a negative effect on small third-party applications. As a result, consumer valuations of small third-party applications are reduced by a larger amount, whereas valuations of big third-party applications are resistant to the integration shock and the demand for big third-party applications also increases. As a result, the overall demand for Instagram and third-party applications actually increases, which suggest that Facebook's integration strategy benefits the complementary market.

Table 8. Examples of First-Party and Third-Party Applications

Platform	First-party application	Competing third-party applications
Facebook	Instagram	Pixable, Pixer, Pizap
Facebook	Riff	Vyclone, CollabraCam, JumpCam
Twitter	Vine	Taut
Twitter	Periscope	Meerkat

Our study makes several contributions and has implications for social media platforms. Managing the tension between first-party content and third-party content has been a critical part of major platforms' strategies. Social media platforms increasingly face this challenge while building their application ecosystems. For example, Table 8 shows the popular first-party and competing third-party applications for Facebook and Twitter. Previous research has mostly relied on theoretical models to study strategic interactions between the platform owner and third-party developers (i.e., supply side behaviors). This paper is the first study that empirically evaluates consumer preferences for first-party applications vis-à-vis third-party applications (i.e., demand-side behaviors) in the context of social media platforms. This paper is also the first to empirically demonstrate the impact of integration of an application by a platform on the application ecosystem. Our model and findings provide important implications for managing platform-based businesses. Analysis of the substitution and complementary effects between first-party applications and third-party applications may help social media platforms determine the overall impact of their platform strategies. Our analysis can also help social media platforms evaluate whether it is beneficial to tightly integrate certain third-party applications. Third-party developers may also benefit from a better understanding of consumer preferences for first-party applications and third-party applications. Our models and results may help developers decide whether it is profitable to participate in a social media platform in the presence of first-party applications.

Our findings shed light on the effectiveness of the platform's strategy to provide tighter integration with the first-party application. Our results suggest that platforms can reduce the negative effect of introducing the first-party applications by creating awareness and positive spillover effects for at least the top competing third-party apps. In that sense, this study has implications for a number of other platforms that routinely provide first-party applications and have to devise their vertical integration strategy. For example, Apple has also introduced its own applications (e.g., Apple Maps, Facetime, and iMovie) for its iOS platform, while Google has launched a variety of first-party applications for its Android platform. Our research also informs platform owners and policy makers about the potential dark side of platform integration. As small third-party applications are more vulnerable to the negative shock from vertical integration, such integration strategies may cause small third-party developers to exit the market, which may reduce the variety of products/services available in the complementary market. For platform owners and policy makers, our research informs the trade-off between the gains in accumulated demand in the short run and losses in product variety in the long run due to platform integration. As small third-party applications are more vulnerable to platform integration, platform owners may come up with certain subsidy schemes to incentivize small developers to stay in their ecosystems.

For third-party developers, our research has implications for their product design. Social applications like Facebook apps exhibit network effects and switching costs. Third-party developers may incorporate social features into their products/services to create a large user base that mitigates the negative impact of platform integration. Building a large user base not only creates high exchange value for users, but also helps maintain users' perceived staying power of the products (Gallaugher and Wang 2002). For small third-party applications facing the threat of first-party applications, the priority of their business strategies may be given to continuously growing the user base, instead of rushing to monetize the existing customers.

Our study is not without limitations. The focus of this paper is short-run demand-side consumer behaviors, i.e., how consumers respond to platform integration and the resulting demand patterns for different types of applications in the complementary market. We do not model third-party developers' strategic decisions such as entry and exit, which require different models and assumptions. Future research can use a longer panel data set to investigate these strategic responses and see how they impact the long-term viability of the ecosystem. We use an aggregate measure of daily active users to determine the demand for different applications. Future research can determine how integration influences the demand by considering the actual usage of applications by each user. Such analysis may provide insights into the heterogeneity in consumer preferences and usage patterns and allow platform owners to micro target users with the sharing information to achieve optimal results. Future research can also look into the role of product characteristics and product differentiation in influencing demand for first-party and third-party applications. For example, product differentiation may influence spillover and substitution effects. Understanding the role of product differentiation may provide third-party developers important insights into optimal product design to overcome the negative effect of integration. As our study is restricted to one application ecosystem, future studies should evaluate the robustness of the results in other application ecosystems and other platforms. Finally, we restrict our analysis of the impact of platform integration on the photo-sharing ecosystem. However, such integration may impact complementary applications in other categories such as travel and shopping. Future research can investigate the impact of platform integration of first-party application on other complementary applications.

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Endnotes

[1] We focus on the impact of the platform strategy on the focal photo-sharing ecosystem. It is possible that such a strategy may influence complementary applications in other categories, which is beyond the scope of this study.

[2] Platform owners conventionally do not release demand data about their tightly integrated first-party applications. For example, Facebook stops releasing application usage data once an application gets acquired by Facebook. The Instagram case we study is an exception—Facebook continued to provide publicly available data on consumers' use of Instagram for Facebook photo sharing until December 2012.

[3] Instagram can also be used independently and not just on Facebook. Instagram users can use the application to interact with other social networking services, such as Twitter, Tumblr, and Flickr. Our focus in this paper is Instagram's features that enable users to share photos on Facebook.

[4] A complete integration would imply that the application becomes an inherent component of Facebook and the default option for photo sharing on Facebook. The application no longer exists after being fully integrated into the platform.

[5] After December 2012, Facebook stopped providing accurate application usage data (it only reports the range of application users, e.g., 10,000–50,000).

[6] Apps can also be used independently and not just on Facebook. Instagram users can use the application to interact with other social networking services, such as Twitter, Tumblr, and Flickr.

[7] Consumers may use other apps to share photographs with non-Facebook friends. However, our data do not capture such usage and such usage is outside the scope of our study. In our data, the probability that a consumer uses an app on a certain day is very low (less than 0.05). Moreover, the ratio of DAU/MAU (daily active unique users over monthly active unique users) is around 0.08, which suggests that most of the users do not use these apps on a daily basis.

[8] Other studies using similar methodologies, such as Song (2011) and Gowrisankaran and Rysman (2012), assume only one random coefficient on the key explanatory variable.

[9] Pixable was acquired by SingTel in September 2012 for $26.5 million (http://techcrunch.com/2012/09/19/singtel-acquires-intelligent-social-photo-aggregator-pixable-for-26-5-million/, posted September 19, 2012).

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