Private Regulation by Platform Operators
– Implications for Usage Intensity

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Abstract: Platforms operators act as private regulators to increase usage and maximize profits. Their goals depend on the development of the platform: overcoming the chicken-egg problem early on requires attracting platform participants while quality becomes more important later on. Private regulators influence third-party business models, entry barriers, and usage intensity. We analyze how drivers of usage intensity on Facebook's application platform were affected by a policy change that increased quality incentives for applications. This change led to the number of installations of each application becoming less important, applications in more concentrated sub-markets achieving higher usage, and applications staying attractive for longer.

Keywords: private regulation, multi-sided platforms, usage intensity

JEL Classification: L1, L50, O33

1. Introduction

A platform sponsor has to manage multiple sides of a platform (or multi-sided market) simultaneously. Consumers will only use the platform if there are sufficient complementary goods available, while producers of complementary goods will only provide them if the number of potential users is sufficiently large. In other words, platform markets frequently display indirect network effects (Farrell and Klemperer 2007). To ensure a sufficient variety of complementary goods, platform providers often open up their platform to third-party developers who supply additional modules and functionality (Wheelwright and Clark 1992). Opening one side of the market poses challenges to the platform owner as its ability to generate revenues and profits depends on the quality and quantity of both market sides, none of which the owner controls directly.

Managing incentives for both sides is comparable to the problem of a regulator maximizing overall welfare – the sum of utilities of consumers and platform developers. Observers of platform markets therefore frequently denote the management of a platform "private platform regulation" (Boudreau 2008, Boudreau and Hagiu 2009, Hagiu 2009). As many platforms monetize platform usage by way of advertising or transaction-based charges, effectively managing usage intensity or frequency is often at the core of platform regulation. This is often done through non-price instruments imposing rules and constraints, creating inducements and shaping demand and supply behavior (Boudreau and Hagiu 2009).

Multi-sided platforms face a chicken-egg-problem (Caillaud and Jullien 2003, Evans 2003) as each side of the platform only becomes attractive for potential participants if there are enough participants on the other side. The key goal of a platform operator in the early stages therefore is to attract a sufficient number of participants. Once a critical mass of users has been reached on both sides of the platform however, goals change as retaining existing adopters becomes more important than attracting new ones. If existing adopters value quality on the other platform side, increasing quality becomes the key goal. Therefore, the quality/quantity tradeoff introduced by Hagiu (2009) changes along the lifecycle of multi-sided platforms: quantity matters more in the startup phase while quality matters more for established platforms.

In this paper, we examine the policies used by the social networking site Facebook, one of the most successful recent platforms, and its effects on usage intensity, which is a useful indicator for the commercial potential of a platform. In a significant shift in incentives for application developers (i.e. participants on one market side), Facebook attempted to increase the average quality of applications and thereby maintain high user involvement and activity.

We study applications developed for Facebook and observe their usage between September 2007 and June 2008.[1] This captures both the startup and mature phases of the platform. On Facebook, the amount of information an application can send out to users critically influences usage intensity and thus monetization opportunities. In February 2008, Facebook implemented a radical policy change regarding the amount of notifications applications could send out: before February 2008, all applications could send out the same amount of messages, while thereafter, the amount of notifications permitted was determined by how frequently the notifications were clicked on, which proxies for application quality. Facebook thus increased incentives for producing high-quality applications and punished applications that send out information considered useless by users.

We use this policy change (assumed to be endogenous to the platform operator but exogenous for application developers) to analyze how drivers of usage intensity changed following the policy change. We analyze a set of economic determinants that may drive usage intensity. First, we consider network effects from the installed base of an application's users and from portfolio effects from sister applications by the same developer. Second, we analyze if and how application age influences usage intensity. Finally, we study if the degree of concentration in an application's submarket affects usage. In addition to estimating the time-invariant effects, we allow these drivers to have different effects over different stages of the diffusion process.

We use a rich, longitudinal data set on 18,552 applications on the social networking site Facebook. The empirical setting is favorable for several reasons. First, we have data on applications soon after the launch of the platform, which lets us examine the dynamics of a nascent and dynamic market. Second, we have a complete listing of applications on the platform, avoiding selection and survivor biases. Third, Facebook's platform is one of the largest and most successful platforms for applications. Its approach to managing a platform is widely considered and copied in the industry.

We estimate fixed-effect OLS models and analyze the overall effects on an application's usage intensity before disentangling how they are affected by the policy change and diffusion stage. We find that the policy change led to quantity (as expressed by the number of installations of each application) becoming less important, in line with expectations. Further, we find that applications in more concentrated sub-markets generate higher usage after the policy change, suggesting a move towards winner-takes-all outcomes in such submarkets. Finally, although usage intensity always declines as applications become older, the decline becomes less severe after the policy change, which suggests that the policy change was successful in keeping adopters more active over time.

[1] The application platform was opened in May 2007.

The paper proceeds as follows. In section 2, we introduce the role of Facebook as a private regulator. Section 3 describes a set of economic conditions that are likely to determine usage intensity. The data source, variables as well as illustrative examples are presented in section 4. In section 5, we specify our empirical model and discuss the results. Section 6 concludes.

2. Facebook as a private regulator

In the following, we discuss the ongoing interventions by Facebook, operator of the world's biggest online social network. Access restrictions, rules and dynamics of the platform and particularly the market for applications are managed by Facebook with the aim of optimizing its benefit. Facebook's interventions, however, differ from the more common price-setting regulations set by platform operators (Parker and Van Alstyne 2005, Rochet and Tirole 2006). Only recently, research has begun to consider regulatory tactics beyond price-setting such as imposing rules and constraints, creating incentives and otherwise shaping behavior (Boudreau and Hagiu 2009). Facebook has a set of regulative instruments with which it directly and indirectly influences the number and quality of available applications. On the one hand, Facebook can make decisions on the technology of the programming platform or the design of the user interface. On the other hand, it requires developers and users to comply with legal terms and conditions that regulate the extent to which developers can use the technological platform and how they can market their application.

Facebook is a major player in social networking websites (other examples are Orkut, LinkedIn, or MySpace). Consumers use social networking services to interact with friends, family members, and increasingly business partners. Core components include personal mini-homepages with which a user creates a digital representation of him-/herself (Boyd and Ellison 2007), different means to communicate (personal messages, boards, chats) and to exchange different media.[2] Facebook is the largest and fastest-growing social network with over 400 million active users of which 70% are outside the U.S. (as of February 2010).[3]

Facebook has been actively managing their platform from the start. In May 2007, Facebook launched a platform consisting of a set of programming tools and standards as well as the opportunity for third-party developers to extract revenue from usage of their applications. In May 2008, one year after the platform launched, more than 30,000 applications had been developed. Those applications attracted more than 900 million installations in total (90% of all users had installed at least one application). This large variety of applications has important consequences for consumers' product search and adoption. On Facebook, adoption and usage takes place in a strongly embedded social

[2] Facebook is the largest online photo sharing utility.
[3] Source: http://www.facebook.com/press/info.php?statistics.

context. The functionality provided by the platform operator lets developers build applications which are designed to intensify social interactions (Boudreau and Hagiu 2009). Thus, application discovery and adoption is highly influenced by a user's social context. Users are passively influenced through the visibility of usage patterns in the network through reviews, ratings or matching mechanisms (Oestreicher-Singer and Sundararajan 2006, Hervas-Drane 2010). Active forms of social influence take the form of recommendations which are directly conveyed via predominantly digital or online word-of-mouth processes (Katz and Lazarsfeld 1955). Marketing scholars have examined the conditions under which consumers are likely to rely on others' opinions in their purchase decisions, the motives for people to spread the word about a product, and the variation in strength of influence people have on their peers in word-of-mouth communications (Dellarocas 2003, Phelps et al. 2005). It is widely acknowledged that in such contexts bandwagon processes – positive feedback loops where adoption decisions by some increase the incentive or pressure to adopt for others – are common (Katz and Shapiro 1985, Katz and Shapiro 1986, Abrahamson and Rosenkopf 1993).[4]

We now discuss three dimensions of regulation important for platform operators: monetization, application entry, and usage.

2.1. Regulating monetization opportunities

When Facebook launched its platform for third-parties in May 2007, developers may have been primarily intrigued by the opportunities to integrate their applications in Facebook's service. However, there was also a clear economic opportunity. Facebook announced that it would allow "mass distribution" and create "new opportunity … to build a business".[5]

Facebook's objectives are largely aligned with their third-party developers' and is based on capitalizing on its active user base. Revenues are realized via selling advertising space to brands, advertisers or Facebook applications who target specific users. Facebook has also experimented with "Engagement Ads" that not only display brand messages but allow users to interact with a brand through gift-giving, commenting and promotion. Next to each application's canvas page (the space allocated to an application), Facebook can place its own advertising. As a consequence, the more users engage with applications, the more page impressions or time Facebook is able to sell to advertisers. Another strategy is to keep a revenue share of transactions that take place on the

[4] Another feature relates to the costs that users incur in installing and using applications. Due to the dominant business model of indirect monetization, the vast majority of applications are free to use. Also, due to technical and design features, users can install and use multiple applications in parallel, thus "multi-home" (Rochet and Tirole 2003).

[5] See release: http://developers.facebook.com/news.php?blog=1&story=21

platform or by re-directing users to shopping sites (e.g. a music application may forward interested users to the iTunes service where copyrighted music can be purchased). In the future, Facebook will launch its own payment system "Facebook Credits" comparable to PayPal. This will allow Facebook to directly benefit from purchases that go through its system (with a revenue split of about 30%).

Consequently, the level of revenue that can be realized is directly determined by the number of active users of the platform and applications. Thus, growing the platform (applications) and keeping existing users active (and therefore generating transactions or looking at and clicking on ads) is among their most important objectives.

Facebook left it open to developers how to monetize their application pages through advertising or other transactions that they control themselves. Facebook deliberately did not impose restrictions on the form of advertising. The most common form are advertisements next to the website's content and core functionality. The placement is determined by the fit between the (micro-)site's content and the advertiser's message as well as competitive bidding between advertisers (Evans 2008). Similar to Facebook itself, applications can also keep a share of revenues generated by on-site transactions (e.g. online games can offer additional functionality for a premium fee) or by transactions referred to external sites. As an important strategic decision, Facebook decided not to take a share of transaction sales initially, leaving developers to capitalize on this revenue stream.[6]

2.2. Regulating application entry

As in most markets with indirect network effects, platform operators want to encourage a wide variety of applications and experimentation in parallel (Church and Gandal 2000, Boudreau et al. 2008). Consequently, they provide developers with a set of tools that decrease their development costs and thus entry barriers. Low barriers to entry lead to high rates of entry, both from new entrants as well as from developers with multiple applications. This affects both the users and the developers' incentives. On the one hand, a large variety of applications presents novel challenges for consumers to discover and adopt applications (Oestreicher-Singer and Sundararajan 2006, Hervas-Drane 2010). On the other hand, high rates of entry could result in particularly high levels of competition which again would diminish profits and incentives around the platform (Boudreau 2008).

Facebook wanted to facilitate entry of as many developers as possible. The company offered strategic subsidies to third-party developers (Shapiro and Varian 1998) by providing open and well-

[6] Due to the (open) installation process and the lack of a payment system, Facebook could not take a revenue cut from developers without further development. In contrast, Apple takes a 30% revenue share from all sales in its iTunes store.

documented application programming interfaces, multiple development languages, free test facilities, as well as support for developers through developer forums and conferences. Facebook also has minimal requirements for applications to be included in the official directory and it does not "police" developers imitating or producing "copy-cats" of existing applications.

2.3. Regulating application diffusion and usage

The primary objective of a social networking service is to grow and activate its user base. We therefore focus on the regulatory activities relating to Facebook's rules of how applications are visible within the social networking service and therefore affect its user base.

Users adopt applications through two main channels. First, users of an application can directly invite friends who are not currently users of the application (invites). Second, Facebook users get regular updates on friends' activities from the built-in "News Feed". To some extent, applications can send messages to this news feed and signal a friend's activity in this particular application (notifications).

Both channels are regulated heavily by Facebook. In the first phase, from launch in May to August 2007, invites and notifications could be sent almost without restrictions. Application developers used this to "spam" many of their users' friends. In September 2007, the start of our study period, Facebook imposed a set of restrictions (the number of invites and notifications by user was limited). In the following months the rules remained unchanged.[7]

However, after months of steady growth, Facebook made a series of announcements that changed significantly how developers could activate both channels. On January 1st, 2008, Facebook announced that there would be changes in the near future. On February 6th, 2008 a major announcement followed that specified that the rules would be changed such that notifications and invites would be allocated based on user feedback. Applications whose users react more heavily to notifications/invites that are sent out (a measure for relevance of the notifications/invites), would be able to send out more notifications/invites. One week later, feedback allocation was launched for notifications, requests, and invites. These changes implied that applications that send out more successful notifications and invites could utilize the two channels more actively, leading to a reinforcing loop that favors applications that are used more actively already.

What motivated Facebook to initiate these changes? And how did it affect developers? In the early phases of a platform such as Facebook's market for applications, the platform operator (or regulator) wants to attract entry by application developers. This is done by lowering the costs developers incur when learning the "language" of the new platform. Further, it relates to the costs

[7] To the best of our knowledge based on the official announcements of Facebook to its developers.

of marketing a novel application and ensuring its diffusion. Hence, Facebook was interested in providing developers with easy access to the option space and awareness of its user base. This was done by allowing developers to send out many notifications and invites. Highly publicized success stories created a gold rush among developers, e.g. the music application iLike grew to several million users within days. Within weeks, several thousand application developers had signed up for access credentials to the platform and had started to launch a wide variety of applications. Besides providing specific incentives for developers, Facebook also wanted to "educate" users about the option to install add-on applications to make the service fresh and exciting. Users learned quickly. Through invites and a flood of notifications in their news feed, the vast majority of users had installed at least one application within weeks. Also, many users installed dozens of applications at the same time (multi-homing is comparatively costless here), sometimes even several with largely identical functionality (e.g. within the first month there were several enhanced "Walls" that allowed posting and exchanging multi-media items).

After the initial enthusiasm, however, the sentiment among users towards applications changed. With the rapid increase of the installed base of applications and the increasing professionalization of developers in terms of exploiting the opportunities to use the "viral channels", the volume of notifications and invites grew exponentially. Users were increasingly annoyed by constant updates about their friend's activities and applications. For both Facebook as the platform operator and the developers this would eventually lead to adverse effects. Instead of inducing additional application adoption and usage, users would start ignoring and delete notifications and requests.

In response to this, Facebook introduced the regulatory changes described above. Its objective changed from trying to ensure rapid diffusion of applications towards emphasizing application quality and notifications that would induce usage intensity for established applications. While this objective may be aligned to the developers of mature and established applications, it may have adverse effects on the incentives of new entrants or developers of smaller applications.

We disentangle the impact of Facebook's private regulatory change on the usage intensity of applications. The following section identifies possible drivers of usage intensity.

3. Determinants of application usage intensity

Following the description of the main economic characteristics of Facebook's application platform, we now derive factors that may influence usage intensity of individual applications. We distinguish between effects caused by externalities such as an application's installed base as well as effects across applications within a developer's portfolio. We also consider application age, concentration of sub-markets, and update activity.

3.1. Within-application externalities: installed base effects

The installed base of users of an application can relate to usage intensity through network effects as well as through implications of different diffusion models.

If there are network effects at the application level, we expect a positive effect of installed base on usage intensity. However, if network effects only exist on a local level, i.e. an application becomes more attractive the more friends of a user have installed it, we do not expect to observe a positive effect of an application's (global) installed base on usage intensity.

The second mechanism that drives average usage intensity through the installed base can be derived from two of the most common diffusion theories (Grajek and Kretschmer 2009), namely the epidemic model of diffusion and the probit diffusion model (Geroski 2000). Both of these models have different predictions on how usage intensity changes along the diffusion process and a growing installed base (Cabral 2006). If diffusion takes place among heterogeneous adopters, late adopters have lower utility than early adopters under reasonable assumptions. Therefore, usage intensity is expected to decline with a growing installed base. Conversely, the epidemic model assumes identical preferences and users gain knowledge about a new technology at different points in time through an epidemic process. So, if an epidemic process drives diffusion, we do not expect to observe a positive effect of an application's installed base on usage intensity.

As network effects and the different diffusion models have conflicting implications regarding how the installed base of an application determines usage intensity, we cannot disentangle the two but can compare their relative strength by observing the net effect (Grajek and Kretschmer 2009).

3.2. Within-portfolio externalities: effects across applications

The next determinant we analyze is in how far the portfolio of a firm's applications affects an application's usage intensity. As entry barriers are low, one developer or one firm can easily offer multiple Facebook applications. We consider how the number of installations from sister applications as well as the number of sister applications itself could influence usage intensity.

Regarding the number of users that have installed sister applications, we can argue similarly as for the number of users of the focal application. One the one hand, the larger an application provider is in terms of installations, the higher the chances to attract resources that can be used for usage-increasing activities. Larger firms will find it easier to obtain external equity financing, which in turn can be used to improve applications and to increase advertising spending, both potentially leading to increased usage. Further, the firm can directly monetize their consumers with advertising revenues, which allows them spending money on the same usage-increasing activities as discussed above. Finally, firms can build direct cross-links between applications, leading to usage spillovers. On the other hand, large installation number can again proxy overall consumer heterogeneity, which would let us expect lower usage. Again, we can only observe the net effect.

The second way to proxy for a firm's resources is by the number of applications. Here, we expect more negative usage implications than from the sister applications' number of registered users. If a firm has a lower number of applications (controlling for the number of users of these applications), we expect the firm to be better able to focus on actively managing these few applications and therefore achieving higher usage intensity. Further, if a firm has a less applications, user awareness is divided over fewer applications, there is less self-cannibalization, and usage intensity increases.

3.3. Application age

Application age, i.e. the time since which the application has been launched, may also drive usage intensity. As applications become older, the developer can remove bugs from the application, react to user feedback, and implement new features. This suggests that older applications have higher quality and if users value this, usage intensity will go up. However, older applications may be used less intensively if usage follows a fad, i.e. users are only interested in the application for a short time.

3.4. Concentration of sub-markets

Applications on Facebook's application platform have no direct consumption costs (prices are zero). However, usage of an application comes at an opportunity cost as time could have also been spent on activities outside Facebook or on other applications.

Therefore, if several similarly sized applications are active in the relevant market segment of an application (i.e. concentration is low), users have more alternatives to choose from, incur higher opportunity costs of using this application and will therefore use each application less. They may even multi-home and spread their usage over several applications. Further, in less concentrated markets, a user's friends will probably be also distributed on different applications so that local network effects will be lower.

3.5. Update activity

Update activity can actively be influenced by the application developers. Facebook applications usually have quite a narrow scope of functionality. As argued, an application can become less attractive for each individual (who has already installed the application) over time. However, user interest can be retained if an application is regularly updated and improved. Updating an application could include adding new features, new content, or just changing the application's appearance. Applications that are actively managed and updated regularly should therefore be able to retain their customers more effectively and achieve higher usage intensity.

4. Data

This paper analyzes a unique dataset collected by the authors. Data comes from Facebook's public directory of applications which includes all applications available on the Facebook platform.[8] These applications have "About"-pages which were downloaded and relevant data extracted.

We utilize weekly data from the period of September 1, 2007 to June 30, 2008.[9] This period was characterized by strong growth in terms of users of Facebook's service and the number of applications and their users on the platform. Facebook's active user base grew from 15 million to just over 30 million in this period (see Figure 1). The number of applications on the platform grew immensely from around 2,000 in the beginning of September 2007 to over 18,000 in early 2008. The number of active users of these applications increased at a significantly lower but still substantial pace. From September to December the number doubled (15 to 35 million daily active users). The total of application users peaked shortly before Christmas 2007. During Christmas break, usage was lower and decreased further as Facebook's changes to the platform took effect. Despite further growth in the number of applications, the total usage of these stabilized at 30 million active users a day, below the previous peak (Figure 2).

INSERT FIGURE 1 HERE

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[8] Accessible at http://www.facebook.com/applications/. See Figure B. 1 for an example of an application page in the directory.

[9] Note that Facebook's platform for applications was launched on May 24, 2007. We exclude the first three months of data from our analysis because of one main reason. Facebook did not report usage statistics with regard to active users and percent active usage until August 28, 2007. Before that date, the success metric was the number of users measured by number of installations.

INSERT FIGURE 2 HERE

We obtained records for 18,552 applications. The records include data on an application's entry to the platform, its usage by Facebook members, its developer and finally an assignment to certain categories. Further, we computed a number of measures by observing changes made to the directory page as well as from clustering applications by developer name.

Our data is particularly suitable for the analysis of usage intensity for several reasons. First, we have precise measures for usage and usage intensity. Facebook reports continuously how many users have interacted with the application within the previous 24 hours. It also specifies the percentage of all users, i.e. the ratio of active users (last 24 hours) to all users who have installed the application in the same time period. Consequently, we observe both the (active) installed base of an application and the intensity with which it is used. Second, the measures of usage directly indicate the potential for economic success. Third, our data mitigates selection problems originating from deterred entry and observed survival. Developer entry to the platform is frequent due to low entry barriers. More importantly, however, costs of entry can be assumed to be homogeneous. Finally, the dataset includes applications that were successful and applications that did not reach a meaningful user *base. Since data is recorded from the first day an application appears in the directory, information is* available independent of the application's following success. This is rather unique particularly for studies on Internet-based industries. Here, determining entry accurately is usually difficult due to poor documentation of the early history of a category or firm. Published accounts on the entities often do not appear before they reach a "threshold scale" (Eisenmann 2006, p. 1193).

4.1. Variables

The variables are described in Table 1 and Table 2 reports summary statistics.

INSERT TABLE 1 HERE

INSERT TABLE 2 HERE

Dependent variable $(\boldsymbol{UsageIntensity_{it}})$**.** Our dependent variable $(\boldsymbol{UsageIntensity_{it}})$ is an application i's usage intensity in week t measured as the average percentage of daily active users. This means we observe the percentage of an application's installed base of users that uses the application on a given day and form the weekly average. All of the following time-dependent variables are also observed on a daily basis and then aggregated up to the weekly level. [10] For most regressions, we use the logarithm of $(\boldsymbol{UsageIntensity_{it}})$. [11]

Regulation $(\boldsymbol{PolicyChange_t})$**.** As discussed in section 2.3, Facebook changed the rules in how far applications can send out notifications in February 2008. We therefore construct a dummy variable $PolicyChange_t$ which takes a value of zero before the change (until the sixth week of 2008) and a value of one thereafter.

Number of users $(\boldsymbol{NumUsers_{it}})$**.** On an application level, we observe the number of Facebook users that have installed an application on their profile page ($NumInst_{it}$).

Firm resources $(\boldsymbol{NumSisterApps_{it}}, \boldsymbol{NumUsersSisterApps_{it}})$**.** As developers can release several applications, we measure a firm's resources in the form of sister applications. While $NumSisterApps_{it}$ is the number of an application i's sister applications at time t, $NumUsersSisterApps_{it}$ is the cumulated number of users that have installed sister applications.

Application age $(\boldsymbol{WeeksActive_{it}})$**.** We measure the age of the application ($WeeksActive_{it}$) by counting the weeks since the application has appeared in the application directory for the first time.

Market concentration $(\boldsymbol{HHIcat_{it}}, \boldsymbol{HHIccat_{it}})$**.** We construct two measures of market concentration to define the relevant market for the application broadly or narrowly. When application developers register their application in the Facebook application directory, they can assign their application to two categories from a choice of 22 possible categories. Therefore, a broad market definition is to define the competitive field as all active applications in one of the two registered categories, while a narrow definition includes only the applications registered for the same two categories. We measure concentration by the Herfindahl Hirshman Index (HHI).

Product updates $(\boldsymbol{UpdateFreq_{it}})$**.** We observe several variables that indicate an update of the underlying application: we check if the name or one of the descriptive elements of an application has changed, if the screenshot was updated, and if the category of the application has changed. For

[10] We aggregate data from a daily to a weekly level to average out weekday-dependent differences in usage intensity.

[11] We do this as the distribution of $UsageIntensity_{it}$ is skewed, as can be observed in Figure B. 2 and Figure B. 3.

each observed point in time, we calculate an application's update intensity $UpdateFreq_{it}$ as the cumulative number of updates divided by the age of the application ($WeeksActive_{it}$).

Diffusion stage $(\boldsymbol{DiffStage_{it}})$**.** We construct an indicator for the diffusion stage, which takes on a value of zero before an application reaches the inflection point of the diffusion process (discussed in section 4.3) and a value of one thereafter.

Season $(\boldsymbol{Christmas_t})$**.** Finally, we construct a dummy for the holiday season to account for changed usage behavior during this time of year. We set $Christmas_t$ to one for the last two weeks of 2007 and for the first week of 2008, and zero for the remainder of our observation period.

4.2. Examples

The following gives an illustration of two key measures for our analysis: the number of users of an application (Figure 3) and the percent of daily active usage (Figure 4). The first describes how many users have installed an application. The second is the percentage of the number of all users who have installed the application who have been active within the last 24 hours.

INSERT FIGURE 3 HERE

INSERT FIGURE 4 HERE

We chose the following three applications: *Are You Interested?* is a dating application that lets users rate others with regard to their perceived attractiveness. Users can also indicate if they want to get to know the other person. *Entourage* lets users display the profile pictures of selected friends on one's own profile page. This enables a quick overview of one's most important friends – useful for users who may have more than 1,000 "friends" on their list. *Super Wall*[12] is an application that uses some of the core functionality of Facebook's service (the "Wall", a virtual blackboard) and extends it by letting users post pictures and videos. It also has features for interactive communication.

Figure 3 plots the number of users for each application during the time of our analysis. One can clearly observe differences. *Super Wall* has been the most successful of the three applications in terms of overall installations, with a steadily increasing number of users. *Are you interested?* follows second with lower diffusion speed at around the half of the observation period. Finally, *Entourage*

[12] Now re-branded to "RockYou Live".

diffuses at the same speed as *Are you interested?* up to around half of the observation period and levels off thereafter and the application fells well behind *Are you interested?.* [13]

The second measure of interest in this study is the intensity to which applications are being used. Figure 4 plots that measure for the abovementioned applications. In all three graphs, usage intensity is rather low on average. *Entourage* is typical for many applications with modest network effects: the percentage of active users is steadily and rapidly decreasing. In the later stages of our study period, it approaches 1-2%. The picture is somewhat different for the other two, which are more likely to exhibit direct network effects. While *Are You Interested?* also declines rapidly at the beginning (from 28 to 6%), there is also a period in which daily active usage climbs again to over 10%, and it stabilizes at around 6-7%. *Super Wall*, after weeks of steady increase (from 8 to 12%) there is a spike just before Christmas, where active usage climbs to over 20%, and it later declines again, also consolidating at around 6-7%.

These examples show different patterns both in absolute and relative usage of applications. Anecdotally, we can also observe that applications more prone to exhibit direct network effects have different usage patterns than applications that do not: their growth path is steeper and their relative usage appears to be higher.

4.3. Diffusion of individual applications

As already observed in Figure 3, the diffusion of individual applications typically follows an S-shaped curve. As in Grajek and Kretschmer (2009) we fit a logistic diffusion model to capture the diffusion of individual applications:

$$NumUsers_{it} = \frac{NumUsers_i^*}{1 + \exp\left(-\beta(t - \tau)\right)}$$

$NumUsers_i^*$ denotes the market potential of application i, β the diffusion speed, and τ the inflection point of the diffusion process, i.e. the point at which half of potential adopters $NumUsers_i^*$ have installed the application. For our analysis, we focus especially on the inflection point τ, as this allows us to differentiate between the stages of the diffusion process: the growth rate of $NumUsers_{it}$ increases before τ and decreases thereafter. We estimate the logistic diffusion model with NLS and use τ to construct the dummy variable $DiffStage_{it}$.

[13] Note that all three applications can be classified as "success" since they were among the 50 most successful applications throughout the period of this study. The vast majority of applications do not attract nearly as many users.

Table 3 reports estimation results for the three example applications discussed above. Figure 3 also shows the fitted values for these three applications, which fit the actual values well.

INSERT TABLE 2 HERE

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5. Empirical specification and results

5.1. Usage regression

We estimate usage intensity of application i at time t with the following baseline specification.

$$\begin{aligned} UsageIntensity_{it} &= \beta_1 NumUsers_{it} + \beta_2 WeeksActive_{it} + \beta_3 HHIcat_{it} + \beta_4 HHIccat_{it} \\ &+ \beta_5 NumSisterApps + \beta_6 NumUsersSisterApp_{it} + \beta_7 UpdateFreq_{it} \\ &+ \beta_8 Christmas_t + a_i + u_{it} \end{aligned}$$

We use fixed-effect OLS with cluster-robust standard errors.

5.2. Results

In the following, we first analyze the overall effects on usage intensity before disentangling in how far these effects are influenced by the and by the policy change and by the diffusion stage. Finally, we report results of our robustness checks.

5.2.1 Overall results

Our baseline model is reported in Table 4. The results reported here cover the entire observation period from September 2007 to June 2008. For this section we assume coefficients for the entire observation period to be constant. We later relax this assumption and allow the coefficients to change with Facebook's policy change in February 2008 and the diffusion stage.

INSERT TABLE 4 HERE

First, we see that the number of application users ($NumUsers_{it}$) has a significantly negative impact on usage intensity. Following Cabral (2006) Grajek and Kretschmer (2009), this suggests that consumer heterogeneity dominates network effects as additional users imply a less keen user base.

Next, we observe usage-increasing effects of higher market concentration both at the category-level ($HHIcat_{it}$) and the cross-category-level ($HHIccat_{it}$). This is in line with our expectations that we find less multi-homing and higher local network effects in more concentrated markets, which leads to higher usage intensity. The fact that the coefficient of $HHIcat_{it}$ is larger than the coefficient of $HHIccat_{it}$ suggests that the appropriate market definition seems to be a single category.

Regarding the sister applications we observe a significantly negative effect from the number of sister applications ($NumSisterApps_{it}$) and from the aggregate number of users of all sister applications ($NumUsersSisterApps_{it}$). As a user's attention will be split across different applications for higher $NumSisterApps_{it}$, we can explain declining usage intensity for a growing number of sister applications. The negative influence of $NumUsersSisterApps_{it}$ indicates customer heterogeneity also at the portfolio level in addition to the already observed effect on application level.

Finally, we see that an actively managed application with a high update frequency ($UpdateFreq_{it}$) can maintain higher usage intensity and that we see a significant decrease of usage intensity during the Christmas season.

5.2.2 Influence of policy change and diffusion stage

We now analyze in how far the policy change conducted by the platform operator Facebook as well as the diffusion stage of an application have an impact on usage intensity of individual applications. We therefore interact our usage drivers with $PolicyChange_t$ and $DiffStage_{it}$ and report the results in Table 5. The first column reports the main effects while the second and third column report the interaction terms with $DiffStage_{it}$ and $PolicyChange_t$, respectively.

INSERT TABLE 5 HERE

Our first variable of interest is $NumInst_{it}$. First, we see there is no significant main effect, i.e. network effects and customer heterogeneity seem to balance in the early stages of diffusion. However, as an application reaches an advanced diffusion stage, it is better able to profit from network effects. In contrast, the policy change more than offsets this usage-increasing effect. The negative coefficient in the baseline model is therefore driven primarily by the usage-decreasing effect from the policy change.

We then analyze if the effect of market concentration as measured with $HHIcat_{it}$ and $HHIccat_{it}$ is affected by diffusion stage and policy change. We find that the positive effect in the baseline model is driven by the diffusion stage and the policy change, suggesting that post-intervention and in the advanced diffusion stages, usage in concentrated markets is especially high, possibly suggesting winner-take-all outcomes.

Next, we analyze effects from the portfolio of sister applications. Regarding the number of sister applications, $NumSisterApps_{it}$, we see a negative main effect, which is reduced slightly by the policy change. Regarding the number of users of sister applications, $NumUsersSisterApps_{it}$, there are no significant effects for the main effect or the interaction with the diffusion stage. The negative baseline effect is therefore driven by the negative coefficient with the policy change interaction.

We see that the positive effect from update activity is slightly increased for later stages of the diffusion process and slightly reduced after the policy change. Finally, applications that reached a later diffusion stage at Christmas 2007 suffer less from the usage-decreasing season effect. We have no interactions with the policy change, as the policy change happened after Christmas.

5.2.3 Robustness Checks

We check robustness of our results with a number of alternative regression models.

First, we analyze if the interaction term coefficients reported in Table 5 are robust. Therefore, in Table A. 1, we report interactions with $DiffStage_{it}$ and $PolicyChange_t$ in independent regressions. In Table A. 2, we also allow for three-way interactions with $DiffStage_{it}$ and $PolicyChange_t$. We see that our alternative regressions deliver the same consistent results.

In a second set of robustness checks we report alternative regressions to the baseline regression reported in Table 4. In Table A. 3, we first rerun the results of the baseline model and compare them with an identical model in which all observations without any active users are dropped. We then add two more models (one including observations with inactive applications and one excluding them) with a linear instead of a logarithmic dependent variable. Finally, we report results for a fixed-effect Poisson model. Our results are largely confirmed with these robustness checks. The only noteworthy difference is the significantly positive coefficient for $NumUsers_{it}$ in the Poisson regression.

6. Conclusion

We analyze drivers of usage intensity for Facebook applications, one of the most popular multi-sided platforms in today's Internet business. We study the effect of measures capturing network effects, market concentration, and application age. Our findings suggest that customer heterogeneity dominates network effects, usage intensity declines over time, and that more concentrated sub-markets have higher usage levels. We let the effects vary by the applications' stage of the diffusion process, and study if the usage drivers have changed significantly following a policy change undertaken by Facebook to increase the incentives to provide high-quality applications. Following the policy change, the effect of network size has decreased, while applications in advanced stages of their diffusion process have higher network effects, suggesting critical mass phenomena.

Active regulation is important for establishing a successful multi-sided platform. In the early stages of a platform, platform owners maximize growth by allowing fast spread of applications via viral channels. Once the variety of applications in the market is sufficiently high, the platform provider's goals change: instead of maximizing growth, policies are aimed at ensuring long-term customer retention. Facebook tried this by changing the way in which applications can use viral channels. This intervention led to applications staying attractive to customers for longer, but also fosters the emergence of concentrated market structures in the different application submarkets.

With the increasing proliferation of the digitization of word-of-mouth processes (Dellarocas 2003), research on the impact of such mechanisms on market structure has intensified. There are two opposing lines of argument (Dellarocas and Narayan 2007): On the one hand, the opportunity for users to easily discuss and recommend even largely unknown products will shift demand towards the "long tail" of less popular products (Anderson 2006). The underlying hypothesis is that such forms of communication reduce the informational inequality between hit and niche products and helps other consumers discover products otherwise consigned to the "long tail", resulting in less concentrated markets. On the other hand, it has been argued that other drivers, such as user-generated rankings and the prevalence of prominently displayed statistics about other consumers' actions (Duan et al. 2006, Tucker and Zhang 2007) will lead to bandwagon behavior, directing consumer attention to already popular products, a phenomenon referred to as the "superstar effect" (Rosen 1981). Indeed, Boudreau and Hagiu (2009) suggest that platform operators like Facebook regulate the market for applications such that winner-takes-all outcomes arise in niches to incentivize developers to contribute high quality applications.

This paper contributes to the growing empirical literature on platform markets and their dynamics. A number of extensions would seem particularly promising. First, we can only impute the motives for the policy changes Facebook undertook. If indeed they were initiated to increase usage intensity and consequently monetization opportunities, matching diffusion and usage information with financial information on the revenue flows could indicate if the changes actually worked. Second, some of the applications studied have "in-built" network or peer effects, while others carry significant utility independent of the number of other users. Analyzing the usage and diffusion patterns of these groups might help assess the strength of word-of-mouth (which exist for all applications) and network effects (which matter only to a subset of applications). Finally, our finding that users substitute applications by multi-application developers suggests that there may be limits to the size of a developer. Studying the size and growth dynamics of these developers could deliver insights into the role of "attention diseconomies" from the users' point of view in the growth of firms.

References

ABRAHAMSON, E. & ROSENKOPF, L. 1993. Institutional and competitive bandwagons: Using mathematical modeling as a tool to explore innovation diffusion. *Academy of Management Review,* 18**,** 487-517.

ANDERSON, C. 2006. *The long tail: How endless choice is creating unlimited demand,* London, Random House.

BOUDREAU, K. 2008. Too Many Complementors? Evidence on Software Firms. Available at SSRN: http://ssrn.com/abstract=943088.

BOUDREAU, K. & HAGIU, A. 2009. Platform Rules: Regulation of an Ecosystem by a Private Actor. *In:* GAWER, A. (ed.) *Platforms, Markets and Innovation.* Cheltenham, UK and Northampton, MA, US: Edward Elgar.

BOUDREAU, K., LACETERA, N. & LAKHANI, K. 2008. Parallel search, incentives and problem type: Revisiting the competition and innovation link. *Harvard Business School Technology & Operations Mgt. Unit Working Papers.*

BOYD, D. & ELLISON, N. 2007. Social network sites: Definition, history, and scholarship. *Journal of Computer-Mediated Communication,* 13**,** 210.

CABRAL, L. 2006. Equilibrium, epidemic and catastrophe: Diffusion of innovations with network effects. *New Frontiers in the Economics of Innovation and New Technology: Essays in Honor of Paul David, Edward Elgar, London***,** 427-437.

CAILLAUD, B. & JULLIEN, B. 2003. Chicken & egg: Competition among intermediation service providers. *RAND Journal of Economics,* 34**,** 309-328.

CHURCH, J. & GANDAL, N. 2000. Systems Competition, Vertical Merger, and Foreclosure. *Journal of Economics & Management Strategy,* 9**,** 25-51.

DELLAROCAS, C. 2003. The digitization of word of mouth: Promise and challenges of online feedback mechanisms. *Management Science,* 49**,** 1407-1424.

DELLAROCAS, C. & NARAYAN, R. 2007. Tall Heads vs. Long Tails: Do Consumer Reviews Increase the Informational Inequality Between Hit and Niche Products? *Robert H. Smith School of Business Research Paper.*

DUAN, W., GU, B. & WHINSTON, A. 2006. Herd Behavior and Software Adoption on the Internet: An Empirical Investigation. Available at SSRN: http://ssrn.com/abstract=872576.

EISENMANN, T. 2006. Internet companies growth strategies: Determinants of investment intensity and long-term performance. *Strategic Management Journal,* 27**,** 1183-1204.

EVANS, D. 2003. Some empirical aspects of multi-sided platform industries. *Review of Network Economics,* 2**,** 191-209.

EVANS, D. 2008. The economics of the online advertising industry. *Review of Network Economics,* 7**,** 359-391.

FARRELL, J. & KLEMPERER, P. 2007. Coordination and Lock-In: Competition with Switching Costs and Network Effects. *In:* ARMSTRONG, M. & PORTER, R. (eds.) *Handbook of Industrial Organization.* Elsevier.

GEROSKI, P. 2000. Models of technology diffusion. *Research Policy,* 29**,** 603-625.

GRAJEK, M. & KRETSCHMER, T. 2009. Usage and diffusion of cellular telephony, 1998–2004. *International Journal of Industrial Organization,* 27**,** 238-249.

HAGIU, A. 2009. Quantity vs. Quality and Exclusion by Two-Sided Platforms. *Harvard Business School Working Paper.*

HERVAS-DRANE, A. 2010. Word of mouth and taste matching: A theory of the long tail. Available at SSRN: http://ssrn.com/abstract=1025123.

KATZ, E. & LAZARSFELD, P. 1955. *Personal influence: The part played by people in the flow of mass communications,* Glencoe, IL, Free Press.

KATZ, M. & SHAPIRO, C. 1985. Network Externalities, Competition, and Compatibility. *American Economic Review,* 75**,** 424-440.

KATZ, M. & SHAPIRO, C. 1986. Product compatibility choice in a market with technological progress. *Oxford Economic Papers,* 38**,** 146–65.

OESTREICHER-SINGER, G. & SUNDARARAJAN, A. 2006. Network structure and the long tail of electronic commerce. *Proceedings of the Tenth INFORMS Conference on Information Systems and Technology (CIST 2006).*

PARKER, G. & VAN ALSTYNE, M. 2005. Two-Sided Network Effects: A Theory of Information Product Design. *Management Science,* 51**,** 1494-1504.

PHELPS, J., LEWIS, R., MOBILIO, L., PERRY, D. & RAMAN, N. 2005. Viral marketing or electronic word-of-mouth advertising: Examining consumer responses and motivations to pass along email. *Journal of Advertising Research,* 44**,** 333-348.

ROCHET, J. & TIROLE, J. 2003. Platform competition in two-sided markets. *Journal of the European Economic Association,* 1**,** 990-1029.

ROCHET, J. & TIROLE, J. 2006. Two-sided markets: A progress report. *RAND Journal of Economics,* 37**,** 645-667.

ROSEN, S. 1981. The economics of superstars. *American Economic Review,* 71**,** 845-858.

SHAPIRO, C. & VARIAN, H. 1998. *Information rules: a strategic guide to the network economy,* Boston, MA, Harvard Business School Press.

TUCKER, C. & ZHANG, J. 2007. Long Tail or Steep Tail? A Field Investigation into How Online Popularity Information Affects the Distribution of Customer Choices. *MIT Sloan School of Management Working Paper.*

WHEELWRIGHT, S. & CLARK, K. 1992. *Revolutionizing product development: quantum leaps in speed, efficiency, and quality,* New York, Free Press.

Figures and tables

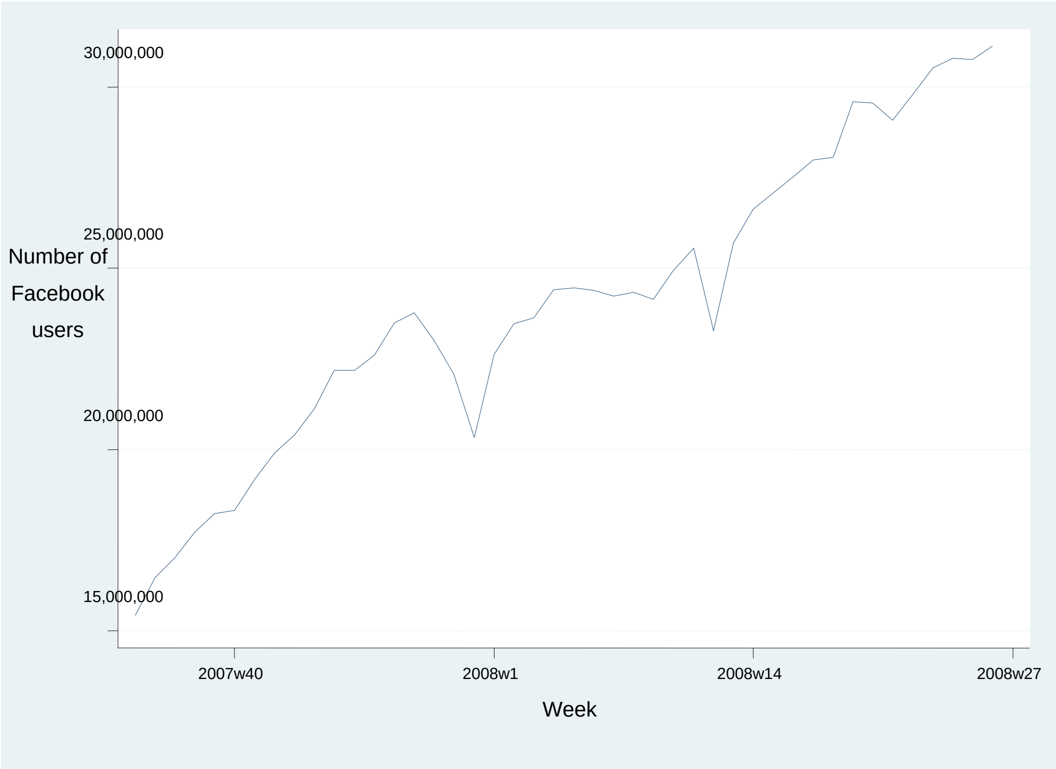

Figure 1: Active Facebook user

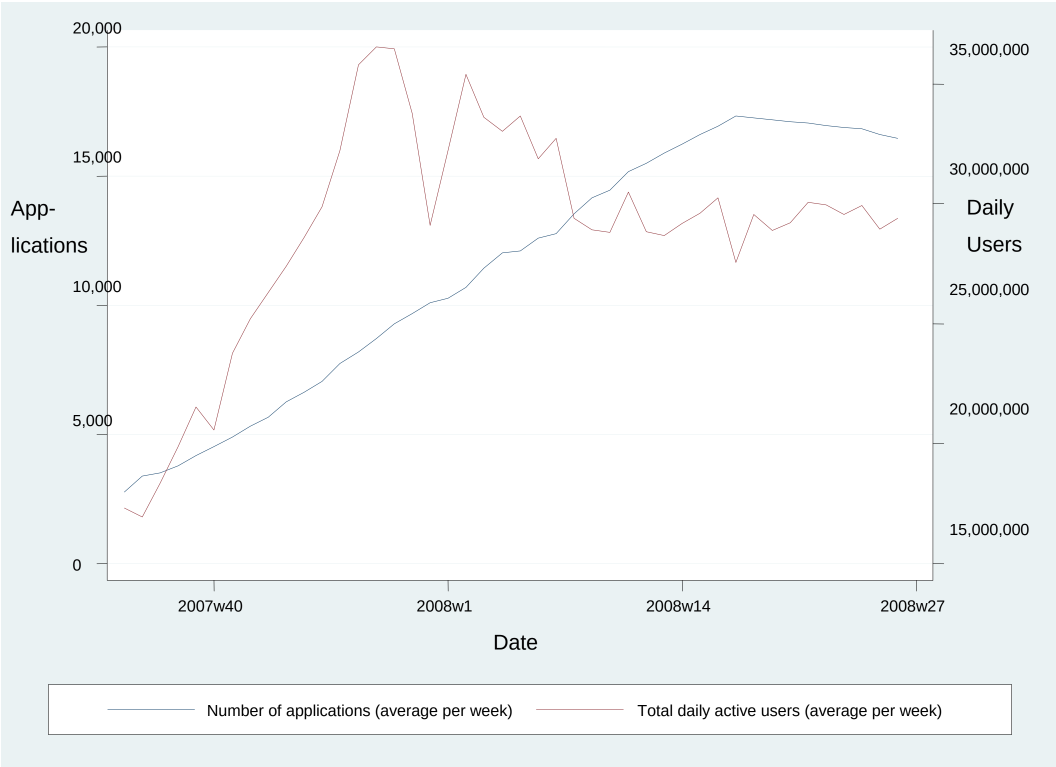

Figure 2: Overall number of Facebook application and their usage

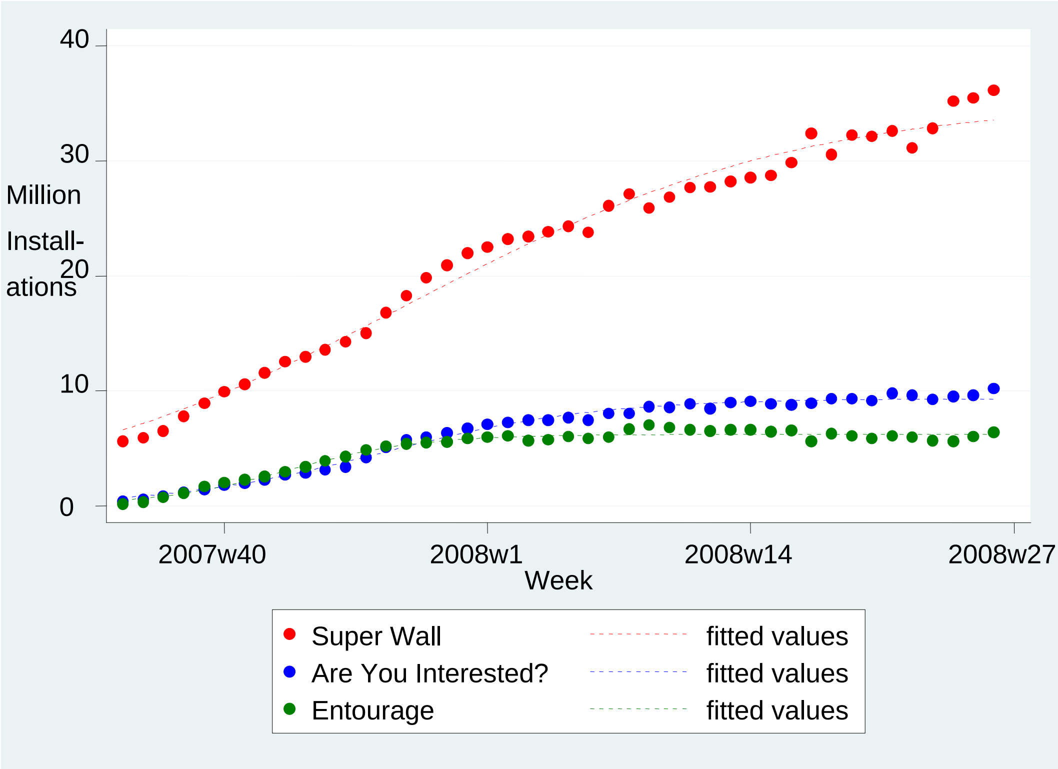

Figure 3: Number of installations for three selected applications

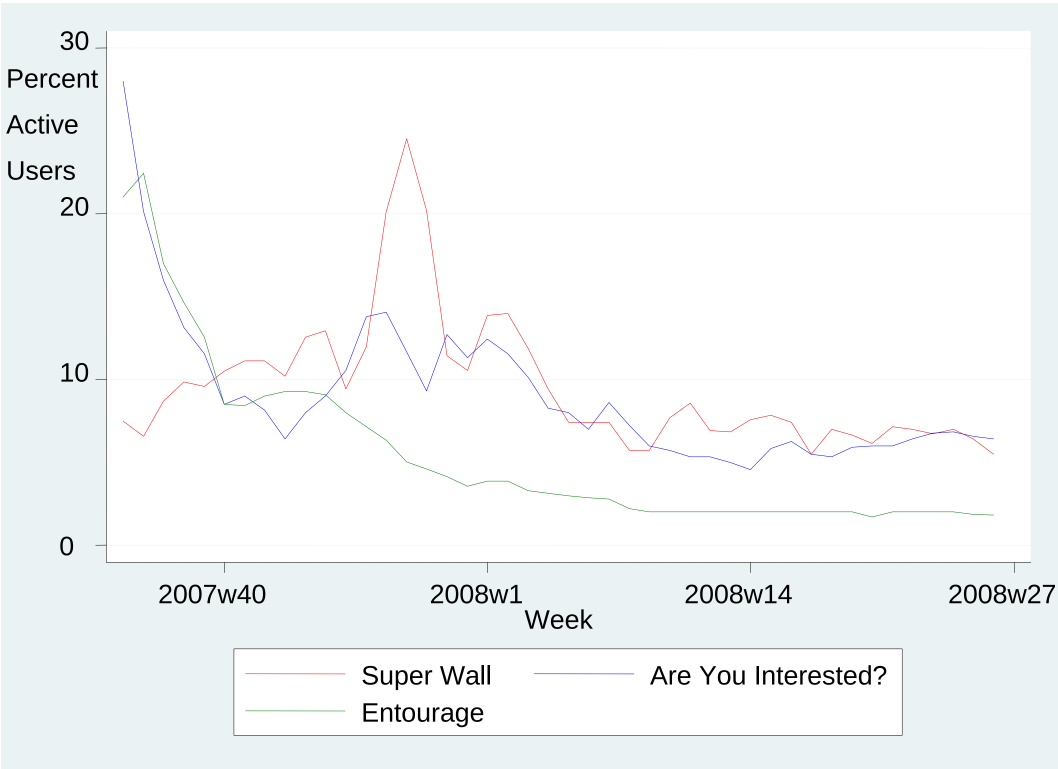

Figure 4: Percent of daily active users for three selected Facebook applications

Table 1: Variable definitions

Variable	Definition
$UsageIntensity_{it}$	Usage intensity of an application measured as percentage of daily active users of $NumUsers_{it}$
$NumUsers_{it}$ [mn]	Number of users that have installed an application
$WeeksActive_{it}$	Weeks since an application has first appeared in Facebook's application directory
$HHIcat_{it}$	Average Herfindahl-Hirshman-Index of the two categories an application is assigned to
$HHIccat_{it}$	Herfindahl-Hirshman-Index of the market defined by the intersection of the two categories assigned to an application
$NumSisterApps_{it}$	Number of sister applications offered by the same developer
$NumUsersSisterApps_{it}$ [mn]	Number of users that have installed a sister application by the same developer
$UpdateFreq_{it}$	Total number of updates of an application divided by $WeeksActive_{it}$
$Christmas_t$	Christmas dummy (last two weeks of 2007 and first week of 2008)
$DiffStage_{it}$	Dummy for the diffusion stage (zero before τ one thereafter)
$PolicyChange_t$	Dummy for the policy change (zero before sixth week of 2008 and one thereafter)

Table 2: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
$UsageIntensity_{it}$	498403	3.947474	8.130413	0	100
$NumUsers_{it}$ [mn]	498403	0.0695	0.780967	0	100.1983
$WeeksActive_{it}$	498403	16.9841	12.15892	0	58
$HHIcat_{it}$	498403	0.1595677	0.1280011	.0255039	.9118252
$HHIccat_{it}$	498403	0.2774588	0.24899	0	1
$NumSisterApps_{it}$	498403	19.48498	49.61799	0	287
$NumUsersSisterApps_{it}$	498403	0.4162556	1.34609	0	31.61227
$UpdateFreq_{it}$	498403	0.7405133	0.9204854	.0892857	5
$Christmas_{t}$	498403	0.0598612	0.2372297	0	1
$DiffStage_{it}$	498422	0.6753313	0.4682514	0	1
$PolicyChange_{t}$	498403	0.6399079	0.4800273	0	1

Table 3: Logistic diffusion coefficients for three selected applications

	γ	β	τ
Super Wall	35.29	0.10	2492 (2007w49)
Are You Interested	9.35	0.19	2490 (2007w47)
Entourage	6.23	0.30	2486 (2007w43)

Table 4: Baseline model for the usage intensity regression

DEPENDENT VARIABLE: $\ln(UsageIntensity_{it} + 1)$	
INDEPENDENT VARIABLES	(4)
$NumUsers_{it}$	-0.0137***
	(0.00489)
$WeeksActive_{it}$	-0.0285***
	(0.000187)
$HHIcat_{it}$	0.310***
	(0.0347)
$HHIccat_{it}$	0.0368**
	(0.0150)
$NumSisterApps_{it}$	-0.00265***
	(0.000117)
$NumUsersSisterApps_{it}$	-0.0282***
	(0.00362)
$UpdateFreq_{it}$	0.486***
	(0.00196)
$Christmas_{t}$	-0.103***
	(0.00347)
Constant	1.218***
	(0.00743)
Observations	498403
R^2	0.707
Number of Applications	18552

Fixed-effect OLS regression, cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Usage regression with $DiffStage$ and $PolicyChange$ as interaction effects. The first main effects are reported in the first column, while interactions with of the respective variables with $DiffStage$ and $PoiliyChange$ are reported in column two and three.

DEPENDENT VARIABLE: $\ln(UsageIntensity_{it} + 1)$			
INDEPENDENT VARIABLES	Base Coefficients	Interaction * $DiffStage$	Interaction * $PolicyChange$
$NumUsers_{it}$	0.00911	0.0149***	-0.0256***
	(0.00964)	(0.00574)	(0.00462)
$WeeksActive_{it}$	-0.0415***	0.00143***	0.0177***
	(0.000459)	(0.000388)	(0.000332)
$HHIcat_{it}$	-0.127***	0.132***	0.213***
	(0.0422)	(0.0350)	(0.0296)
$HHIccat_{it}$	-0.0127	0.00272	0.0689***
	(0.0195)	(0.0184)	(0.0154)
$NumSisterApps_{it}$	-0.00167***	6.16e-05	0.000131*
	(0.000177)	(9.17e-05)	(6.92e-05)
$NumUsersSisterApps_{it}$	-0.00665	0.00280	-0.0129***
	(0.00520)	(0.00400)	(0.00309)
$UpdateFreq_{it}$	0.441***	0.0410***	-0.0684***
	(0.00244)	(0.00465)	(0.00401)
$Christmas_t$	-0.135***	0.0468***	
	(0.00536)	(0.00657)	
Constant	1.601***	-0.221***	-0.331***
	(0.0107)	(0.0101)	(0.00880)
Observations		498403	
R^2		0.724	
Number of Applications		18552	

Fixed-effect OLS regression, cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix A

Table A. 1: Usage intensity regressions with $DiffStage$ or $PolicyChange$ as moderating effects

DEPENDENT VARIABLE: $\ln(UsageIntensity_{it} + 1)$				
	(A.3-1)		(A.3-2)	
INDEPENDENT VARIABLES	Base Coefficients	Interaction $* DiffStage$	Base Coefficients	Interaction $* PolicyChange$
$NumUsers_{it}$	-0.0155**	0.0113*	0.00946	-0.0226***
	(0.00737)	(0.00611)	(0.00731)	(0.00471)
$WeeksActive_{it}$	-0.0287***	0.00286***	-0.0436***	0.0197***
	(0.000390)	(0.000420)	(0.000350)	(0.000323)
$HHIcat_{it}$	0.143***	0.261***	-0.0680*	0.238***
	(0.0432)	(0.0359)	(0.0365)	(0.0290)
$HHIccat_{it}$	0.0270	0.0243	-0.0154	0.0734***
	(0.0200)	(0.0186)	(0.0161)	(0.0150)
$NumSisterApps_{it}$	-0.00234***	-9.83e-05	-0.00166***	0.000124*
	(0.000164)	(9.98e-05)	(0.000153)	(7.12e-05)
$NumUsersSisterApps_{it}$	-0.0219***	-0.00171	-0.00938**	-0.0108***
	(0.00503)	(0.00426)	(0.00424)	(0.00306)
$UpdateFreq_{it}$	0.449***	0.0374***	0.463***	-0.0550***
	(0.00238)	(0.00479)	(0.00224)	(0.00390)
$Christmas_t$	-0.127***	0.0399***	-0.107***	
	(0.00568)	(0.00681)	(0.00316)	
Constant	1.386***	-0.293***	1.510***	-0.380***
	(0.0102)	(0.0101)	(0.00918)	(0.00844)
Observations	498403		498403	
R^2	0.711		0.722	
Number of Applications	18552		18552	

Fixed-effect OLS regression, cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A. 2: Usage regression with $DiffStage$ and $PolicyChange$ as moderating effects and three-way interactions

DEPENDENT VARIABLE: $\ln(UsageIntensity_{it}+1)$				
INDEPENDENT VARIABLES	Base Coefficients	Interaction $* DiffStage$	Interaction $* PolicyChange$	Interaction $* DiffStage$ $* PolicyChange$
$NumUsers_{it}$	0.0127	0.00394	-0.0293***	0.00878
	(0.0158)	(0.00955)	(0.0113)	(0.0104)
$WeeksActive_{it}$	-0.0454***	0.00770***	0.0185***	-0.00254***
	(0.000562)	(0.000648)	(0.000511)	(0.000618)
$HHIcat_{it}$	-0.131***	0.180***	0.324***	-0.166***
	(0.0444)	(0.0420)	(0.0493)	(0.0551)
$HHIccat_{it}$	-0.0109	-0.00334	0.0625**	0.0131
	(0.0206)	(0.0214)	(0.0275)	(0.0302)
$NumSisterApps_{it}$	-0.00153***	-0.000208*	-0.000332**	0.000667***
	(0.000189)	(0.000120)	(0.000136)	(0.000142)
$NumUsersSisterApps_{it}$	-0.00500	-0.00110	-0.0133*	0.00166
	(0.00645)	(0.00528)	(0.00698)	(0.00712)
$UpdateFreq_{it}$	0.437***	0.0585***	-0.0839***	-0.00639
	(0.00257)	(0.00633)	(0.00483)	(0.00895)
$Christmas_{t}$	-0.109***	-0.00144		
	(0.00537)	(0.00649)		
Constant	1.606***	-0.235***	-0.246***	-0.0919***
	(0.0117)	(0.0136)	(0.0143)	(0.0173)
Observations	498403			
R^2	0.725			
Number of Applications	18552			

Fixed-effect OLS regression, cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table A. 3: Robustness checks for usage intensity regressions. (A.5-1) repeats the results from the base-line model (4). In (A.5-2) all observations with zero usage intensity are taken out. (A.5-3) and (A.5-4) repeat (A.5-1) and (A.5-2) with an untransformed (linear) dependent variable. Finally (A.5-5) reports results for a Poisson model.

	DEPENDENT VARIABLE: $UsageIntensity_{it}$				
INDEPENDENT VARIABLES	(A.5-1) OLS DV: log with 0s	(A.5-2) OLS DV: log w/o 0s	(A.5-3) OLS DV: lin with 0s	(A.5-4) OLS DV: lin w/o 0s	(A.5-5) Poisson DV: lin with 0s
$NumUsers_{it}$	-0.0137***	-0.0370**	-0.376**	-1.250***	0.0418***
	(0.00489)	(0.0151)	(0.187)	(0.271)	(0.0137)
$WeeksActive_{it}$	-0.0285***	-0.0267***	-0.00314**	0.00242	-0.0647***
	(0.000187)	(0.000186)	(0.00153)	(0.00174)	(0.000624)
$HHIcat_{it}$	0.310***	0.293***	2.949***	3.056***	0.421***
	(0.0347)	(0.0319)	(0.326)	(0.352)	(0.0798)
$HHIccat_{it}$	0.0368**	0.0367***	0.406***	0.402***	0.101***
	(0.0150)	(0.0140)	(0.143)	(0.156)	(0.0356)
$NumSisterApps_{it}$	-0.00265***	-0.00296***	-0.0225***	-0.0244***	-0.00208***
	(0.000117)	(0.000100)	(0.00184)	(0.00190)	(0.000240)
$NumUsersSisterApps_{it}$	-0.0282***	-0.0344***	-0.325***	-0.351***	-0.0401***
	(0.00362)	(0.00442)	(0.0333)	(0.0398)	(0.00918)
$UpdateFreq_{it}$	0.486***	0.484***	7.032***	7.223***	0.433***
	(0.00196)	(0.00176)	(0.0377)	(0.0380)	(0.00208)
$Christmas_{t}$	-0.103***	-0.120***	-0.795***	-0.855***	-0.119***
	(0.00347)	(0.00335)	(0.0414)	(0.0428)	(0.00873)
Constant	1.218***	1.311***	-1.143***	-1.059***	
	(0.00743)	(0.00706)	(0.0820)	(0.0902)	
Observations	498403	429698	498403	429698	498332
R^2	0.707	0.737	0.650	0.664	
Number of Applications	18552	18552	18552	18552	18481

Fixed-effect OLS/Poisson regression, cluster-robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Appendix B (not intended for publication)

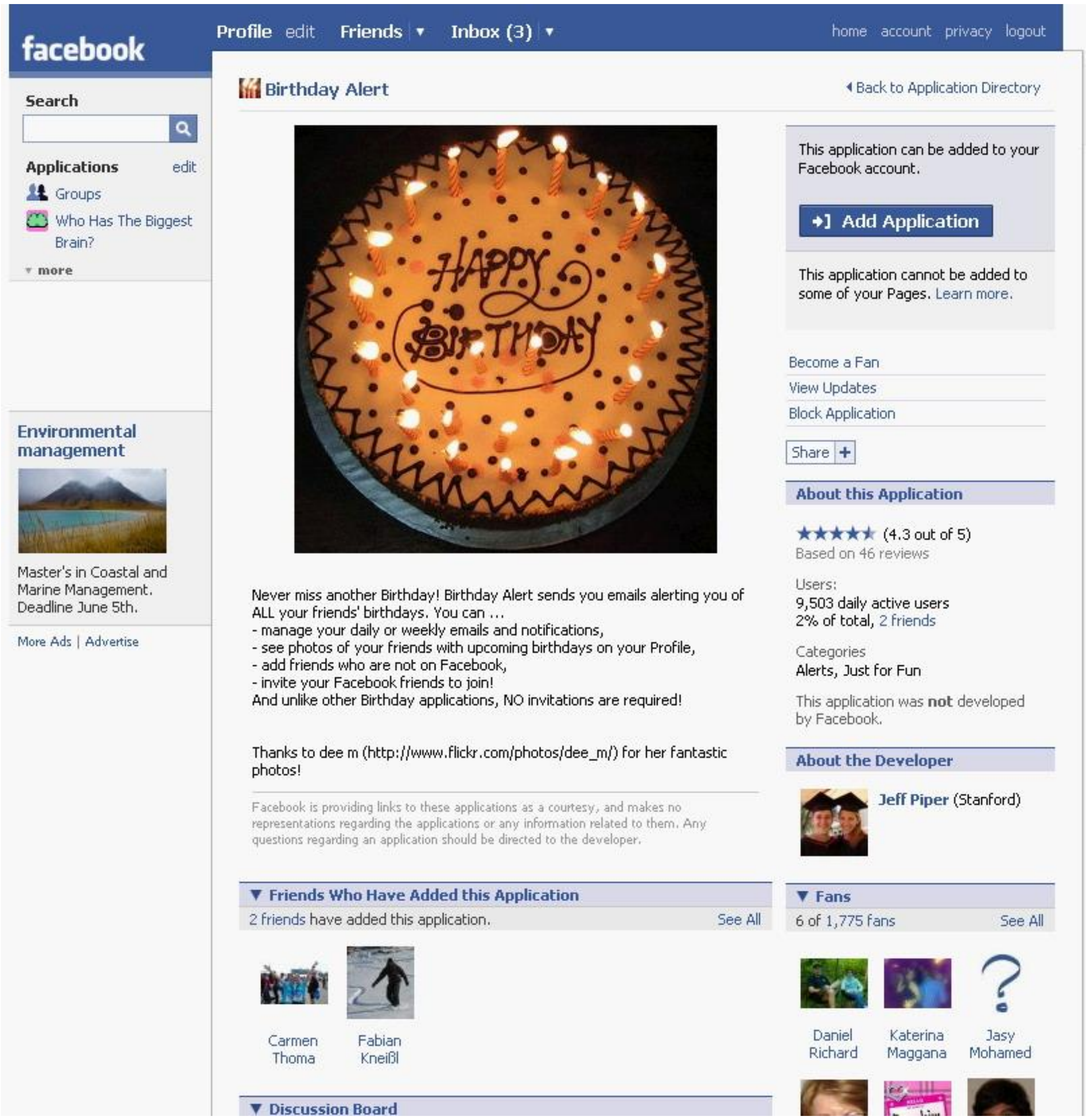

Figure B. 1: Example for an application entry in the Facebook application directory

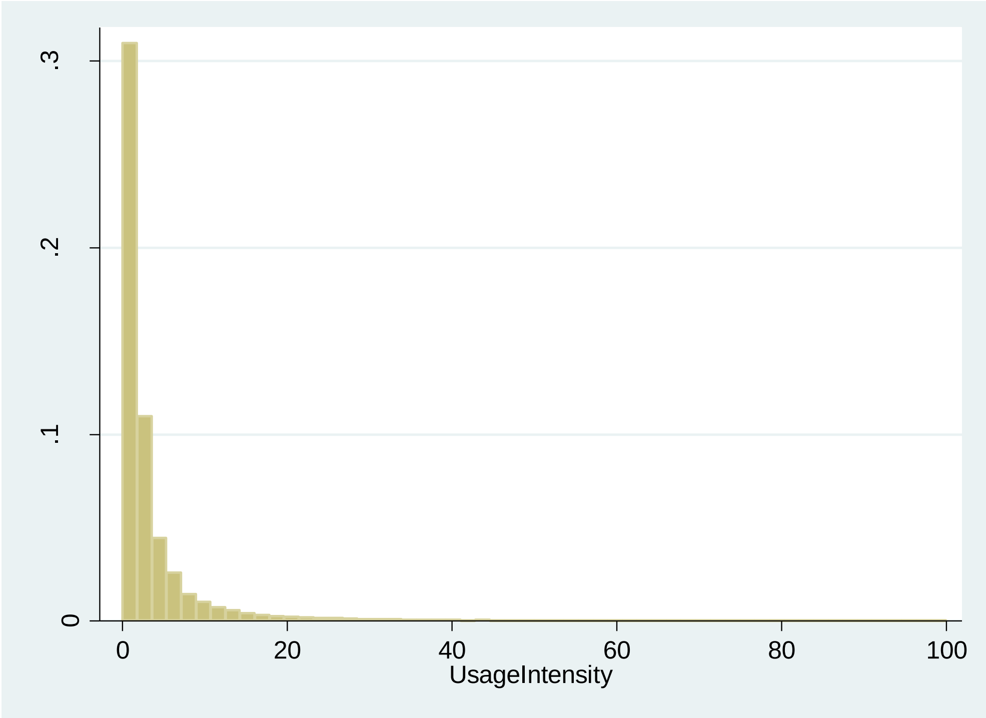

Figure B. 2: Histogram of the dependent variable $UsageIntensity_{it}$

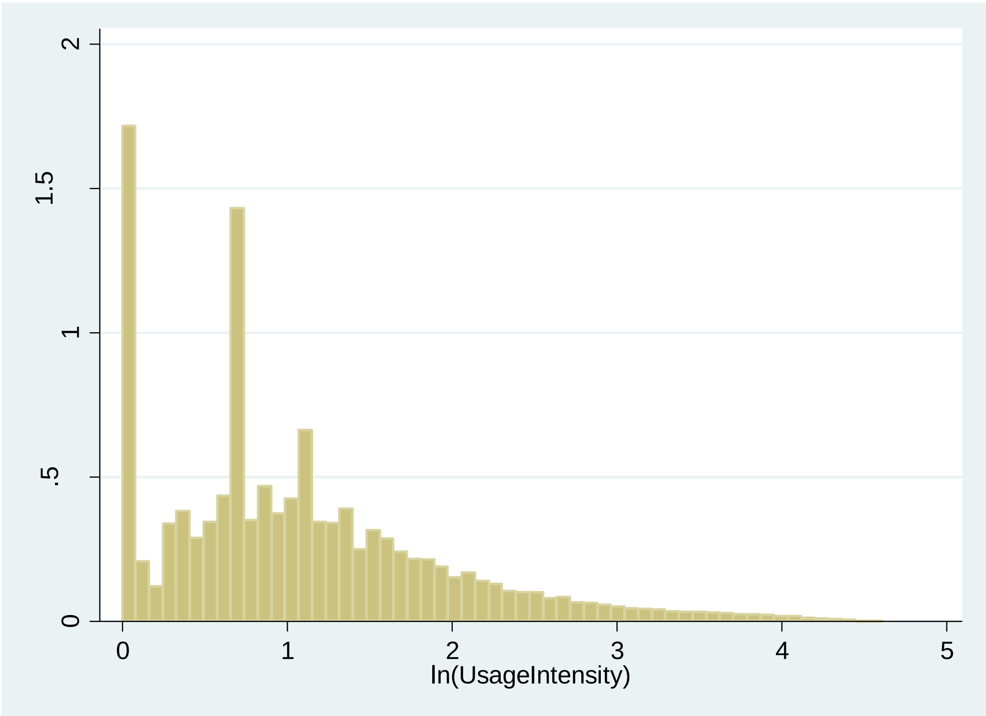

Figure B. 3: Histogram of the transformed dependent variable $ln(UsageIntensity_{it} + 1)$

Table B. 1: Correlation Table

	$NumUsers_{it}$	$WeeksActive_{it}$	$HHIcat_{it}$	$HHIccat_{it}$	$NumSisterApps_{it}$
$NumUsers_{it}$	1.0000				
$WeeksActive_{it}$	0.0872	1.0000			
$HHIcat_{it}$	0.0069	0.0481	1.0000		
$HHIccat_{it}$	0.0232	0.0130	0.6081	1.0000	
$NumSisterApps_{it}$	-0.0242	0.0075	-0.0281	-0.1017	1.0000
$NumUsersSisterApps_{it}$	0.1025	0.0921	-0.0744	-0.1358	0.4246
$UpdateFreq_{it}$	-0.0308	-0.5751	-0.0114	0.0058	-0.0435
$Christmas_{t}$	0.0001	-0.1072	0.0131	0.0068	0.0022
$DiffStage_{it}$	0.0127	0.1803	-0.0257	-0.0320	0.0510
$PolicyChange_{t}$	0.0006	0.3684	-0.0374	-0.0274	0.0229

	$NumUsers$ $SisterApps_{it}$	$UpdateFreq_{it}$	$Christmas_{t}$	$DiffStage_{it}$	$PolicyChange_{t}$
$NumUsers_{it}$					
$WeeksActive_{it}$					
$HHIcat_{it}$					
$HHIccat_{it}$					
$NumSisterApps_{it}$					
$NumUsersSisterApps_{it}$	1.0000				
$UpdateFreq_{it}$	-0.0697	1.0000			
$Christmas_{t}$	0.0115	0.0394	1.0000		
$DiffStage_{it}$	0.0493	-0.2810	-0.0644	1.0000	
$PolicyChange_{t}$	0.0004	-0.2182	-0.3364	0.2853	1.0000

Table B. 2: Variance inflation factors for model (4)

Variable	VIF	1/VIF
$HHIcat_{it}$	3.91	0.255531
$HHIccat_{it}$	3.51	0.285199
$WeeksActive_{it}$	1.96	0.511022
$NumSisterApps_{it}$	1.39	0.717508
$UpdateFreq_{it}$	1.38	0.723462
$NumUsersSisterApps_{it}$	1.38	0.723646
$Christmas_{t}$	1.05	0.947922
$NumUsers_{it}$	1.03	0.969996
Mean VIF	1.95	