Habitual Entrepreneurship in Digital Platform Ecosystems:
A Time-Contingent Model of Learning from Prior Software Project Experiences

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EXECUTIVE SUMMARY

The emergence of large-scale digital platforms such as Facebook, Google Play and Apple App Store around 2008 has created opportunities for independent entrepreneurs to offer their self-developed software applications ("apps") to large groups of platform users. The development and release of tens of thousands of apps by thousands of independent developers has created dynamic entrepreneurial ecosystems. This paper investigates whether and how learning by independent habitual entrepreneurs unfolds in substantively different ways in such dynamic platform-based environments. We argue that in these entrepreneurial ecosystems, the timing of learning efforts becomes essential. For Facebook app developers, we find that learning from their own prior app projects remains feasible. However, entrepreneurs have only a few months during which they can benefit from what they learned from a prior app project. This study supports the feasibility of time-contingent learning from prior app projects for increasingly prevalent dynamic entrepreneurial ecosystems such as digital platforms. Implications for future research and management practice are outlined.

INTRODUCTION

Digital platforms represent an increasingly prevalent type of entrepreneurial ecosystem, that are based on evolving technological systems that connect platform owners, platform users, and complementary component developers (Gawer and Cusumano 2002; Nambisan 2017; Rietveld, et al. 2019). This study builds on prior research that has examined digital platforms primarily from the platform owners' perspective (Cennamo and Santalo 2013; Schilling 1999; Zhu and Iansiti 2012). In addition, it supplements emerging research focused on the independent entrepreneurs who contribute complementary components to these platforms (Boudreau and Jeppesen 2015; Eckhardt, Ciuchta and Carpenter 2018).

Treating independent component development as a class of entrepreneurial activity, this study investigates whether and how developers learn from their own prior development projects to improve the performance of their future projects. Organizational learning research generally supports the positive performance impact of accumulated prior experiences in relatively stable learning environments (Argote and Epple 1990; Yelle 1979). However, digital platforms typically represent far more uncertain and dynamic learning contexts (Nambisan et al. 2018). Given the higher frequency, severity and unpredictability of changes (Rietveld and Eggers 2018), the timing and speed of any learning efforts are likely to be more critical. Consequently, we argue that in addition to the *number* of prior development projects, the relative *temporal proximity* of prior experiences has a strong impact on the usefulness of this experience for subsequent development projects. This study develops and tests related time-contingent hypotheses for the performance impact of prior projects and differentiates between learning from prior experiences in the recent, the intermediate and the distant past. Related hypotheses were tested using data from Facebook, which was the first main digital platform to grant free access to large numbers of independent developers to distribute their platform-complementary software applications ("apps") to a large number of end users. These digital platforms as an emergent organizational form have created open innovate ecosystems that offer framed entrepreneurial opportunities for independent entrepreneurs that differ in substantive ways from both traditional venture startup and traditional corporate entrepreneurship (Nambisan, Siegel and Kenney 2018).

This study focuses on independent habitual entrepreneurs who, individually or in groups, engaged in sequences of entrepreneurial projects (Politis, 2005; Westhead & Wright 1998). Findings support the notion that in spite of learning challenges, app developers can benefit from their prior project experiences. However, these benefits are moderate and confined to a rather narrow time window. This study expands entrepreneurial learning research into the emerging field of digital-platform ecosystems (Nambisan 2017; Rietveld et al. 2019) and contributes to the recognition of time as a crucial explanatory variable in the entrepreneurship literature (Cope 2005; Toft-Kehler et al. 2014).

THEORY AND HYPOTHESES

The importance of learning from one's own prior experiences and related positive performance effects is well documented in the organizational learning literature for individuals, groups and organizations (Argote and Levine 2020). In the relatively stable production environments that constitute the background of numerous studies, most of the lessons learned from prior experience can reasonably be applied to future activities because of the fundamental stability of the production tasks and environments. Related learning-curve effects have been broadly supported in empirical studies in the context of highly stable and repetitive tasks, such as assembly line or batch-type manufacturing (Argote and Epple 1990; Yelle 1979). Studies of slightly less repetitive tasks have reported similar, but weaker effects (Argote 2012; Reagans et al. 2005). For the execution of corporate software modifications projects, for example, empirical studies have supported the notion of positive learning-curve effects for productivity measures such as labor hours per request, post-delivery defects and schedule adherence (Boh et al. 2007; Huckman et al. 2009).

In contrast, the independent platform entrepreneurs that we studied engaged in highly unpredictable activities as they created and launched novel platform-compatible software apps. They had to decide what kind of apps to produce and how to market them. Such decisions required them to predict which type of apps users want (Eling et al. 2013; Walmsley 2010). As independent app developers, they could also change or abandon their projects at any time. Consequently, they acted as entrepreneurs who conceive, create and market new products, and many of them engaged in such app development projects repeatedly (Bergvall-Kåreborn and Howcroft 2011; Li et al. 2013; Qiu et al. 2017). Thus, two-sided digital platforms such as

Facebook provide rich empirical settings to study time-contingent learning by habitual entrepreneurs in a highly dynamic environment.

Independent Software Entrepreneurs

Software app developers represent both first-time and habitual entrepreneurs engaged in the discovery and exploitation of business opportunities (Shane and Venkataraman 2000). If they become successful developers, they can earn thousands of U.S. dollars per day (Geron 2007; Richmond 2007; Stevens 2011). The focus of their entrepreneurial activities is to develop and release a novel software app, which differentiates them from entrepreneurs engaged in traditional brick-and-mortar business startups. Digital platforms-based entrepreneurship has gained substantially in prevalence because of the digitalization of economic and social processes (Gallup 2018), further accelerated by the present global pandemic (Ip 2020).

In this study, we adopt a dynamic perspective of entrepreneurship (Cope 2005) as we focus explicitly on what habitual entrepreneurs can learn from their own prior software development projects (Politis, 2005; Westhead and Wright 1998). Despite conceptual and empirical arguments in support of opportunities to learn from prior experiences, the findings of related empirical studies have been mixed. Some studies have reported that such experience can improve the performance of subsequent ventures. However, these effects tend to be more fragile and contingent on additional factors, such as the number of prior ventures and similarity between prior and current ventures (Gimeno et al. 1997; Gompers et al. 2010; Iacobucci and Rosa 2010; Paik 2014; Toft-Kehler et al 2014). Overall, related research has so far focused primarily on traditional business-startup entrepreneurship and has mostly ignored more dynamic learning settings such as digital-platform environments.

Digital Platforms as Dynamic Entrepreneurial Ecosystems

Research on entrepreneurial learning has long highlighted the importance of industry context. The digital economy has led to the emergence of innovative platform ecosystems that connect and integrate the activities of platform owners, producers of platform-complementary products and platform users (Eckhardt et al. 2018; Gawer and Cusumano 2014; Nambisam et al. 2018). Digital platforms represent actively managed innovative ecosystems that differ from more loosely configured systems, such as Silicon Valley or Hollywood (Gawer and Cusumano 2014; Zahra and Nambisan 2012). Platform owners provide and control the foundation and frame of the ecosystem by providing an operating system and a web portal upon which entrepreneurs can offer complementary products and users can access these products (Nambisan et al. 2018). Thus, social media platforms (e.g., Facebook, LinkedIn) and smart-phone platforms (e.g., Google Android, Apple iPhone), as well as more specialized platforms such as medical record systems (e.g., Epic and Cerner), all rely on independent entrepreneurs to conceive, develop and market platform-complementary software products, called "apps." Research has identified the importance of these independent entrepreneurs for platform success (Cennamo and Santalo 2013, Schilling 2002; Zhu and Iansiti 2012).

This study defines prior experience as past involvement in the creation of a specific software app. Early app entrepreneurs on Google Play, Apple Store or Facebook were primarily skilled amateurs who, individually or in small teams, created apps as part-timers, hobbyists or professional developers (Boudreau 2019; Boudreau and Jeppsen 2015). These app entrepreneurs focused on completing a specific software project, which differentiates them from more traditional entrepreneurs engaged in creating permanent brick-and-mortar businesses (Afuah and Tucci, 2012; Bayus, 2013), as well as corporate software engineers creating software to company or client specifications (Boh et al. 2007; Huckman et al. 2009).

As indicated earlier, the success of digital platforms depends on the availability of useful apps that users can download (Zhu and Iansiti 2012). Thus, platform owners have developed various ways to motivate independent app developers: direct compensation, performance bonuses, and permission to charge users for downloads or sell advertising space on their webpages (Bump

2020; Gurevich 2020). Beyond such financial rewards, intrinsic motivations lead some entrepreneurs to regard their work as interesting, challenging, fun, or otherwise gratifying (Nieborg and van der Graaf 2008; Osterloh and Rota 2007; Roberts et al. 2006). Identity and reputation building within the platform community represent other motivators through their potential social benefits, such as social status and ego gratification, as well as economic benefits, such as future job offers and collaboration opportunities (Lerner and Tirole 2002; Zhang and Zhu 2011). Some of the entrepreneurs who developed free apps for the early iPhone, for example, became well known and were later hired by leading IT firms (Mollick 2016). Finally, app development has also been triggered by self-use motivations (Pietilä 2015). Hence, digital entrepreneurs can be motivated by a wide range of extrinsic and intrinsic factors.

Entrepreneurial Learning

Learning by habitual entrepreneurs has received substantial attention in the entrepreneurship literature with regard to the repeated creation of ventures (Aldrich and Yang 2014; Politis 2005, 2008; Westhead and Wright 2016). However, in contrast to the solid support for performance benefits of accumulated experience in stable production settings (Argote and Epple 1990; Yelle 1979), research has led to far more mixed findings in less stable settings. Empirical studies have reported positive effects (Delmar and Shane 2006; Eesley and Roberts 2012), no effect (Dencker et al. 2009; Ucbasaran et al. 2006) and even negative effects of experience (Alsos and Carter 2006; Tornikoski and Newbert 2007).

A primary challenge for the transfer of knowledge from prior ventures to new ventures is the difference between the prior and the current venture (Rerup 2005). In their study of Swedish startup entrepreneurs, Toft-Kehler, Wennberg and Kim (2014) identified several barriers that prevented entrepreneurs from extracting appropriate knowledge from their prior ventures and applying it to their new ventures. These barriers were related to differences in the content and context domains, as well as temporal distance between the prior and the current ventures. Thus, findings on learning by habitual entrepreneurs suggest that learning from prior venture experience is far from straightforward and contingent on various, sometimes ill-understood, contingencies. In general, knowledge transfers are more difficult, uncertain or potentially unfeasible if the prior ventures are substantially different and occurred longer ago (Schwab and Miner 2008, Toft-Kehler et al. 2014).

In dynamic settings, larger temporal distance becomes an even stronger barrier to learning from prior experiences. This difference is not so much because of potential “forgetting” but because changes in industry and market conditions over time make changes in content and context across sequential software apps projects more likely and more frequent. Hence, dynamic environments with their greater uncertainty and frequent changes have the potential to make prior venture experiences less valuable as learning opportunities for future ventures (Lafontaine and Shaw 2016). The frequent release of new apps, recurrent entry and exit of app developers, and rapid growth of nascent digital platforms imply dynamic changes in competing products and customer preferences. During the 2007-2008 period we studied, about 2,500 new Facebook apps were released every month by habitual and first-time entrepreneurs. Every month, on average about 34 percent of the solo apps and 29 percent of the group apps were released by novice entrepreneurs who entered the platform in this month. On average about 28 percent of the apps released in a given month were released by entrepreneurs who exited the industry during this month. Across all months, the number of Facebook users quintupled, from 20 million in April 2007 to 100 million in August 2008 (Zuckerberg, 2008).

In view of the dynamic environments of digital platforms, these arguments cast doubt on whether app entrepreneurs can learn from their prior projects. Eckhardt et al. (2018) reported that digital platforms that operate as open-innovation ecosystems can provide participating entrepreneurs with crucial information for their decision on when to commercialize a technology, meaning that information-based theories are likely essential to understanding how these open innovation systems stimulate and guide entrepreneurial activities. A few studies that focused on habitual software entrepreneurs confirmed the feasibility of knowledge transfers based on the reuse of program code developed during prior projects (Boudreau 2012; Li, Goh and Cavusoglu 2013). Other studies offered evidence for the value of app entrepreneurs' learning from relationships with customers for future projects (Baert et al. 2016; Pietilä 2015), such as learning which features end users like (Aral and Walker 2011). However, our understanding of these learning activities by independent digital-platform entrepreneurs is still very fragmented.

Because of the small number of directly relevant published studies, we also collected anecdotal evidence on learning from prior app projects by interviewing two app entrepreneurs who had released apps on Facebook around 2007 (Bunyan 2020; Kierans 2020) and by searching contemporary industry publications. We found relatively solid anecdotal evidence for the transfer of program code developed during prior projects. For example, the two Facebook app developers reused code for the feed of live data onto a webpage in a later app project that required the same function. The interviews also indicated that the entrepreneurs monitored the performance of past projects in order to learn about user preferences. User downloads indicated to them "what works and what does not." One app entrepreneur, for example, learned that "Facebook users do not like apps that require a lot of their inputs." This discovery led him to stay away from sophisticated apps and focus on developing simpler apps. Another early Facebook app developer recounted how, after releasing the first few apps, he discovered a feature that made it more likely for an app to go "viral." Subsequently, he concentrated on developing only apps with this feature. Similarly, another early Facebook app developer learned to steer away from his early shopping apps after these received low download counts. He moved to more light-hearted and entertainment-focused apps instead.

In summary, theory suggests that dynamic entrepreneurial ecosystems, such as digital app platforms, create strong challenges to learning from prior projects. The few available empirical studies, along with our anecdotal qualitative evidence, however, suggest that independent app entrepreneurs still engaged in such learning activities. To investigate whether such learning activities also led to the desired performance improvements, we tested the following hypothesis:

H1: More accumulated prior software app experiences lead on average to better performance of a current software app project.

Temporal Distance of Prior Entrepreneurial Experience

The motivation of H1 outlined how more prior entrepreneurial experience has the potential to improve future app performance (Toft-Kehler et al. 2016, 2014; Boudreau 2012), but simultaneously introduced arguments that in hyperdynamic ecosystems, such as digital app platforms, these effects are likely contingent on additional factors. When customers' preferences change and competing products emerge frequently (Rietveld and Egger 2018), learning tends to become not only more important and more challenging but also more time-contingent, as prior experience might be valuable only during a specific time window.

Drawing on concepts from the resource-based view (Dierickx and Cool 1989), Reuber and Fischer (1999) conceptualized the traditional learning-curve notion that more prior venture experience is better, as the "stock" perspective. This stock of experiences increases over time whenever an entrepreneur engages in entrepreneurial activities (Minniti and Bygrave 2001). As an alternative, they proposed conceptualizing prior experiences as a flowing "stream," with the relevance of a prior experience changing with time. This stream perspective is consistent with conceptualizations of entrepreneurial learning as a dynamic process that unfolds over time (Cope 2005; Politis 2005; Minniti and Bygrave 2001). The current study investigates the value of this time-focused conceptualization by developing time-contingent hypotheses for the performance impact of prior project experience in dynamic entrepreneurial ecosystems. For this theory-based development of hypotheses, we will conceptually differentiate among learning from prior experiences in the recent, the intermediate and the distant past. The following sections introduce our corresponding time-contingent hypotheses.

Experiences in the Recent Past

Dynamic environments imply substantive change in environmental conditions over time. These environmental changes may alter the degree to which prior experiences are still applicable. Thus, one might conclude that the more recent an experience, the better. Several arguments, however, question this simple conclusion.

For example, learning is rarely instantaneous. This notion that learning requires time has been firmly established in the individual and group learning literature and explained on the basis of time-consuming processes associated with collecting, processing and interpreting of information that typically precede the discovery of actionable knowledge (Argote 2012; Cope 2005). The results of actions in dynamic environments tend to be more indeterminate, which makes a careful and often time-consuming evaluation especially important (March, Sproul and Tamuz 1991, Van de Ven and Polley 1992). Even in cases of prior project experience leading to opportunity discovery, such entrepreneurial opportunities may not simply "jump out" in a "final, ready-made form" that allows entrepreneurs to act on them instantaneously. Instead, such discoveries often "require an iterative process of discovery, shaping and development" (Dimov 2007: 561). When entrepreneurs rush these processes, superstitious learning and inappropriate knowledge transfers become more likely, with the potential to worsen, rather than improve, performance of subsequent projects (Dencker et al. 2009; Denrell and March 2001).

Thus, dynamic entrepreneurial ecosystems such as digital platforms represent highly ambiguous and challenging learning environments (Eisenhardt, Furr and Bingham 2010). A few prior experiences can create a deceptive sense of understanding that leads one to generalize from inadequate available information (Levitt and March 1988; March et al. 1991; Musaji et al., 2020; Novick 1988). Without broader and deeper experiences, entrepreneurs may not recognize when similarities between projects are only superficial (Eesley and Roberts 2012; Toft-Kehler et al. 2014, 2016). In digital markets, customer feedback in the form of the number of downloads is available almost instantaneously, but it takes time for market signals to become reliable, and the corresponding information needs to be properly processed in order for underlying customer preferences to be identified (Pan, Aharony and Pentland 2011). A Facebook app entrepreneur we interviewed, for example, reported:

> *"After releasing an app, I would wait perhaps a few weeks before gauging its [download] performance. It might be that the first group of users did not like it very much, but a few of their friends in turn might like it. You want to give an app a fair chance to grow by exposing it to enough people before deciding whether it really performed poorly."*

Hence, in dynamic ecosystems, entrepreneurs need sufficient time to collect reliable feedback information and sufficient time to translate this information into actionable knowledge (Maitlis and Christianson 2014; Morris et al. 2012). These arguments suggest the need for an initial incubation time before prior project experiences can begin to provide valuable lessons for future similar projects. Formally, we hypothesize:

H2a: Very recent software app experiences have a weaker positive impact than experiences in the intermediate past on the performance of a current software app project.

Experiences in the Distant Past

A second well-established notion in the general learning literature is that the impact of knowledge gained from prior experiences has a tendency to diminish over time, for several reasons. First, changes in the environment will over time render past experiences 'obsolete' for future projects (Moreland and Argote 2003). Second, over time individuals will forget relevant details of their prior project experiences, and new experiences will override the memory of older experiences (Hovland 1951; Wixted, 2004). In addition, the increasing cost of retrieving information from the distant past can outweigh the expected benefits, leading to the decision not to retrieve knowledge even when it is available (Haas and Hansen 2005). Such knowledge decay effects are well established in the general organizational learning literature (Argote 2012; Argote et al. 1990; Wilson et al. 2007). For organizations engaged in stable and continuous production processes, the aforementioned learning-curve studies have reported losses of between half and all of the accumulated knowledge within a year after discontinuation of production processes (Benkard 2000; Darr et al. 1995).

The question remains: How do these knowledge decay effects play out in highly dynamic entrepreneurial ecosystems, with their frequent, substantive and unpredictable changes in customer preferences, product features, and other ecosystem conditions? When changes accumulate over time, the degree of difference from earlier ecosystem conditions increases, and knowledge from the distant past becomes increasingly outdated and less helpful (Katila 2002; Nerkar 2003). Thus, entrepreneurs in highly dynamic environments face the paradox that they must continuously decide how to adapt to these changes while at the same time whatever they just learned from their recent experiences quickly becomes outdated (Kallinikos, Aaltonen and Marton 2013; Srinivasan and Venkatraman 2018). In addition, when new experiences differ substantially from prior experiences, these new experiences may not supplement but rather interfere with and replace prior knowledge. The existence of such interference effects in highly dynamic learning environments has received substantial support in the individual psychology literature (Sadeh et al. 2016; Wixted 2004; Altmann and Gray 2002). The need to learn quickly in dynamic settings has also been linked to reduced long-term knowledge retention (Akgün et al. 2007; Tsang and Zahra 2008). Conceptually, these arguments suggest that in highly dynamic environments, prior experience will over time become outdated far more quickly than in more stable settings.

This impact of dynamic environments is also consistent with results of recent studies indicating that executives in dynamic industries show a strong tendency to discount knowledge and experiences from the distant past (Bluedorn and Ferris 2004; Chen and Nadkarni, 2017). When entrepreneurs recall the past, their biases also tend to increase over time (Cassar and Craig 2009). Moreover, entrepreneurial learning often depends on ‘lived experience’ (Morris et al. 2012; Pittaway and Thorpe 2012), which implies that entrepreneurs must be immersed deeply in the activities and events surrounding an entrepreneurial venture to fully take in the nuances and complexities of the many decisions they made and their subtle consequences (Ravasi and Turati 2005). To recall these nuances and complexities accurately can become difficult after even a relatively short time has passed (de Holan and Phillips 2004; Meschi and Metais 2013; Walsh 1995). Task complexity and interdependence has also been linked to higher forgetting rates in field studies focused on general manual and cognitive tasks (Nembhard 2000; Nembhard and Uzumeri 2000). Dynamic entrepreneurial ecosystems are rich in interdependencies and high on task complexities (Nambisan et al. 2013). In the case of collaborative entrepreneurial projects, these complexities include the distribution of knowledge across team members. If only some of the original entrepreneurs collaborate again in a future project, this can lead to memory loss with regard to the unique knowledge of the entrepreneurs who left (Thompson 2007). Anecdotal evidence from our empirical context also indicated that at least some app entrepreneurs on digital platforms deliberately paid no attention to projects that were several months in the past.

In summary, in highly dynamic entrepreneurial ecosystems, the value of prior experience over time is reduced both because environmental changes will render prior project experience obsolete and because various forms of forgetting will diminish the entrepreneur's ability to retrieve relevant information. Hence, we hypothesize:

H2b: Software app experiences in the intermediate past have a stronger positive impact than experiences in the distant past on the performance of a current software app project.

Integrating the Stream and Stock Perspectives of Prior Experience

H1 adopts the stock perspective of the established learning-curve literature and suggests that, independent of when the prior project occurred, the accumulation of prior project experience will have a positive effect on project performance, although most likely at a diminishing rate as the stock increases. A larger bundle of experiences from a larger number of prior learning events offers more helpful insights for how to execute similar future production tasks and activities (Argote and Epple 1990; Darr et al. 1995). H2a and H2b, however, reflect the fundamentally different stream perspective by proposing that the value of prior project experience changes over time. The time elapsed between a prior project and a focal project determines whether and how the prior entrepreneurial experiences will affect project performance.

As argued earlier, in dynamic environments, in which conditions change substantially over time, lessons learned from prior projects may become less applicable to a particular future project. Thus, time effects and the stream perspective become more relevant. However, we argue that within this stream perspective, stock effects remain feasible and even likely. Hypotheses 2a and 2b suggest that having entrepreneurial experience in the intermediate past would benefit a current project more than having entrepreneurial experience in either the recent or distant past. Combined, they imply that experiences in the intermediate past are the most useful prior experiences. Based on the arguments of the stock perspective, it is reasonable to expect that having more entrepreneurial experiences in the intermediate past will have a stronger positive performance impact on a current project. This time-contingent integration of the stream-based and the stock-based perspectives suggests the following hypothesis for experiences accumulated in the intermediate past:

H3: More accumulated prior software app experiences in the intermediate past will have a positive impact on the performance of a current software app project.

DATA AND METHODOLOGY

Empirical Context

This study investigates the impact of time on how entrepreneurs learn from prior project experiences in highly dynamic environments by empirically capturing how independent entrepreneurs develop software apps for a digital social media platform. In May 2007, the social media platform Facebook opened its application interface to outsiders to enable the development of software apps by independent entrepreneurs. This move created opportunities for entrepreneurs to reach a large and fast-growing number of potential users with apps that could be developed at relatively low cost and in relatively short time frames (Baldwin and Woodard 2009; Nieborg and Helmond 2019). A company official of a U.S. software firm correctly stated at the time, “This is a watershed event that is going to affect business and technology for many years” and “… many of the developers of these applications are entrepreneurs looking to start new businesses” (Richmond 2007: B4).

Facebook was one of the first major digital platforms to create such entrepreneurial opportunities, well ahead of Apple’s App Store and Google’s Play Store. The main predecessor was a far smaller digital platform created for a handheld electronic device called Palm, which also encouraged the independent development of apps, but on the basis of a fundamentally different infrastructure and functionality (Eckhardt et al. 2018; Gawer and Cusumano, 2002). The novelty of this opportunity implied that all developer entrepreneurs started without any stock of prior Facebook app development experiences. One early Facebook app developer described his initial app developing experiences as follows: “It was mostly about me learning about what I could do” and “learning as [I] went along” (Kierans 2020). The study’s intentional focus on early Facebook apps reduced left-censoring and cross-platform learning concerns.

Digital app platforms, as open-innovation ecosystems, can differ with regard to learning-relevant features (Eckhardt et al. 2018; Wareham et al. 2014; Nambisan et al. 2018). Facebook, unlike other platforms, has always allowed apps to be downloaded free of charge. Our study’s time frame pre-dated the emergence of in-app purchases as an optional revenue source (Manjoo 2009; Vision Mobile 2012: 46). App developers, however, were allowed to add links to paid advertisements to their download pages, and developers of successful apps could earn 1,000 USD or more per day (Geron 2007; Richmond 2007). Still, intrinsic and social-benefit motivations likely also play important roles (Boudreau and Jeppesen 2015; Eckhardt et al. 2018; Mollick 2016; Sproull et al. 2013).

The Facebook digital platform represented a dynamic entrepreneurial environment. The number of Facebook users quickly expanded, and each month, literally thousands of new apps were created and released (see Figure 1).

Independent app entrepreneurs tend to be college-educated individuals who work alone or in small, informal groups, typically working on one app at a time (Bergvall-Kåreborn and Howcroft 2011; Boudreau 2012; Kirk 2011; Li et al. 2013; Pietilä 2015). Many became habitual entrepreneurs and created multiple apps over time. App entrepreneurs on social media, video game and smart-phone platforms frequently started with relatively modest goals, but a substantial number of them created apps with mass-market appeal that attracted sizable numbers of downloads and potentially profits (Qiu, Gopal and Hanns 2017; Stevens 2011; Zhu and Iansiti 2012).

Data and Sampling

Facebook published annual download information on all Facebook apps released from the end of May 2007 until the end of December 2008, as well as app release information that enabled us to track an entrepreneurs' sequences of project creation. The research team identified and removed apps that represented only minor updates of earlier apps.[1] The nineteen-month time window of our sample was deemed sufficient to capture multiple learning cycles of habitual entrepreneurs, considering information documenting that simple smart-phone apps can be developed in about a day (Bergvall-Kåreborn and Howcroft 2013). Phone apps have about five times as much code as equivalent internet-based apps (Bergvall-Kåreborn and Howcroft 2011). Thus, most of the internet-based early Facebook apps could be developed in short time frames and with relatively little effort. Even for the more complicated game apps, it is estimated that a "moonlighting" entrepreneur or group of entrepreneurs would need only a couple of weeks (Manjoo 2009).

Learning the necessary Facebook-specific programming skills has been estimated to require about a week of dedicated training (Pietilä 2015: 81). Assuming a one-week app-

[1] App updates were rare at the time because apps were not technically copied onto a user's own computer. Instead, the app simply linked the users' Facebook pages to the app entrepreneurs' pages which would generate desired outputs and transfer them to the users' Facebook pages partitioned for the 'downloaded' app.

development period and a subsequent two-month feedback period, a dedicated entrepreneur could have comfortably gone through eight full learning cycles during our sampling window. The nineteen-month sampling window is also consistent with the 15-month and 25-month sampling windows used in other studies of digital-platform app development (Kapoor and Agarwal 2017; Li, Goh and Cavusoglu 2013).

This investigation focused on apps created and released by the independent app entrepreneurs who launched 59 percent of all Facebook apps during this period, with the remaining apps being launched by software firms. These firms represented a substantially different learning context and did not reveal the identity of the individuals involved in their app projects. For the investigation of learning from prior project experiences, this study focused instead on individual habitual entrepreneurs who alone or with a few others created at least two apps.

In our data set, 7,312 unique Facebook apps were released by 2,221 entrepreneurs who worked exclusively alone. On average, 24 days elapsed between consecutive app releases by the same entrepreneur. A total of 2,378 additional Facebook apps were released by 1,101 groups of entrepreneurs, with on average 34 days elapsing between consecutive app releases. 65% of the groups involved two entrepreneurs and 21% involved three. Anecdotal evidence suggested that app entrepreneurs preferred to make their apps available as soon as possible (Bergvall-Kåreborn and Howcroft 2011). Now and then, however, app entrepreneurs released more than one app on the same day, perhaps to obtain more user attention or perform launch-related activities for multiple apps simultaneously.

In the empirical analysis, we separately analyzed apps created by entrepreneurs who worked exclusively alone (solo apps) and apps created by entrepreneurs working together (group apps). These separate investigations enabled us to use appropriate control variables for each project type.

Dependent Variable

The number of downloads for a particular Facebook app represents a proxy for the app's success. As outlined earlier, app entrepreneurs were likely motivated by a mix of monetary and non-monetary incentives, including advertising revenues, social prestige, internal gratifications and future job opportunities. These benefits were download-dependent.

The distribution of the download statistics was strongly skewed, with 5 percent of apps accounting for 94.8% percent of all downloads. We used a natural logarithmic transformation to obtain a more normally distributed dependent variable (*LnDownloads*) and controlled for the time that had passed since the app's release. Data availability prevented capturing the number of downloads for a fixed time window after release.

Independent Variables

Prior app development experience is captured by the number of prior Facebook apps released by an entrepreneur or a group of entrepreneurs. Left censoring is avoided by studying the period during which Facebook first started to invite independent developers. Cross-platform learning also played no substantive role, because other similar social media platforms did not yet allow and support independent app entrepreneurs.

To capture an entrepreneur's stock of entrepreneurial experience, *LnAllPriorApps*, which contains the log-transformed sum of an entrepreneur's projects prior to a focal project, was used. This transformation implies that the effect of additional prior app experience on knowledge enhancement is particularly strong for entrepreneurs with a small stock of prior experience. For collaborative apps, we counted the number of prior apps created by all the app's entrepreneurs, avoiding any double counting. For instance, if Amy and Bert developed two prior apps together, and Bert and Cindy developed one prior app together, the focal app collaboratively developed by Amy, Bert and Cindy was coded as having three prior apps.

For the stream perspective, we differentiated between prior app experiences in the very recent, intermediate and distant past. We searched prior empirical learning studies for guidance on defining these time windows. Surveys of entrepreneurs showed that the “recent past” typically meant the past 14 days, the ‘intermediate past’ meant the past 15 to 180 days (about 6 months), and the distant past meant up to 5 years prior (Bluedorn and Martin 2008). Consistent with prior research, we expected considerably shorter time intervals for dynamic environments (Bluedorn and Ferris 2004). Anecdotal evidence from several experienced app developers indicated that although they anxiously watched app downloads during the first few weeks, they recognized the potential unreliability of this initial information. They also paid relatively little and very selective attention to apps released several months previously (Kierans 2020; Bunyan 2020). Based on the available information, we considered, for Facebook app development, the recent past to be up to 3 weeks (or 21 days) after app launch, intermediate past as weeks 4 to 8, and distant past as more than 8 weeks after launch of the focal app. This means the intermediate past captures apps released 22 to 56 days prior to the current app. App projects launched before or after this intermediate period are categorized as having been released in the "recent past" and "distant past," respectively. The variables *LnRecentApps*, *LnInterApps* and *LnDistantApps* contain the natural logarithm of the number of apps (plus one) that an entrepreneur had released during each of these periods.

Finally, we investigated how time affected the impact of prior experience without assumptions about the functional form and inflection points that informed our definition of recent, intermediate and distant periods. For these analyses, we used weekly and biweekly time spells (Starr and Goldfarb 2020). *LnPriorNappsWeek1*, for example, captures the natural logarithm of the number of apps (plus one) for the time interval 1 to 7 days prior to the focal app. *LnPriorNappsBiWeek1* captures the time interval 1 to 14 days prior to the focal app. The final weekly or biweekly interval also contains all apps created prior to this interval.

Control Variables

Because the download performance for all apps was measured at the end of the sampling period, apps released earlier had more opportunities to accumulate downloads. The variable *LnDuration* denoted the natural logarithm of the number of days (plus one) between the app's release date and the last day of 2008. Models also control for the log-transformed accumulated total number of apps (in thousands) on the date the entrepreneurs released their apps. *WeeksFirstApp* captured the number of weeks since the release of the first prior app, to account for differences in total time that an entrepreneur had been involved with this platform. *WeeksLastApp* accounted for the number of weeks since the last app was released, to control for differences in the time available to develop the focal app. We used 18 monthly fixed-effect dummy variables to control for any remaining monthly fixed effects, including occasional modifications of app privileges and other platform changes (Boudreau 2012; Claussen, Kretschmer, and Mayrhofer 2013).

Apps targeted various Facebook user needs, which implied potential differences in app features, development activities and demand characteristics. App entrepreneurs could self-assign each app to at most two app categories. The nonspecific "just-for-fun" category was most popular, accounting for 34% and 36% of apps created by solo entrepreneurs or by groups of entrepreneurs, respectively. The second and third most frequently chosen categories were gaming (11.2% and 8.5%) and education (5.1% and 5.7%). We created 22 category dummy variables to control for related fixed effects. To capture the degree to which entrepreneurs' accumulated prior app experiences were concentrated in the same category as the focal app, we calculated *HHICategory* as the Herfindahl-Hirschman Index of $\sum p_k^2$, where p_k, is the proportion of prior apps in category k for this entrepreneur.

Prior successes or failures can in complex ways affect the success of subsequent activities, independent of learning by the entrepreneurs (Deichmann and Van den Ende 2013; Eggers and

Song 2015). For this reason, this study captured *LnPriorSuccess* and *LnPriorFailure* for each entrepreneur or group of entrepreneurs when they had prior apps that had been in the top or bottom quartile in terms of download performance compared with all apps released in the same 30-day period (plus or minus 15 days of app launch date). Finally, we controlled for any remaining other fixed differences, using dummy variables for each solo entrepreneur and each group of entrepreneurs.

The control variables introduced so far were used in all regression analyses for both solo entrepreneurs and groups of entrepreneurs. For apps developed by groups of entrepreneurs, however, additional control variables were needed to account for potential alternative explanations related to the collaborative nature of these projects. *NumDev* captures the number of group members. *PriorGroupTies*, the average number of dyadic ties in past apps among the group members, controls for group-member familiarity (Reagans et al. 2005). Diversity of experience among collaborators has the potential to directly impact app performance (Reagans et al. 2005; Jain 2013;). *AppsHHI* is the Herfindahl-Hirschman Index ($\sum kq_k^2$), which captures the distribution of prior app experiences across group members, where q_k is the proportion of entrepreneur k's number of prior apps relative to the total number of prior apps developed by all entrepreneurs in the focal collaborative app. *AppsHHI* was set to 1 for apps developed by groups that had no prior app experiences.

Model Specifications

The units of analysis in this study are the Facebook apps released during the first 19 months after Facebook invited independent app entrepreneurs to their digital platform in May 2007. Apps created by either a solo entrepreneur or a group of entrepreneurs were designated "solo" or "group," respectively. These two ways of developing apps required different sets of control variables, and we therefore tested hypotheses in separate regression models.

RESULTS

Tables 1 and 2 show the means, standard deviations, ranges and bivariate correlations for the variables included in the models used for analyzing Facebook apps developed by solo entrepreneurs and groups of entrepreneurs, respectively.

-- Insert Tables 1 and 2 about here --

Discrete Time Periods Models

Table 3 reports the regression results for apps developed by solo entrepreneurs and Table 4 the results for apps developed by groups of entrepreneurs. Model 3-1 and Models 4-1 report the effects for all control variables. Hypothesis 1 predicted a simple time-independent positive impact of accumulated prior experience. Model 3-2 and Model 4-2 added the corresponding log-transformed number of prior apps variable (*LnPriorApps)*, which had no impact on a focal app's download performance for either solo entrepreneurs (*ß* = 0.027; *p* = 0.376) or groups of entrepreneurs (*ß* = 0.203; *p* = 0.239). Hence, the notion of a simple stock or learning curve effect of prior project experience was not supported (reject H1).

Model 3-6 and Model 4-6 integrate the stream with the stock perspective. The accumulated prior experience variable (*LnPriorApps*) was replaced by the three variables *LnRecentApps*, *LnInterApps* and *LnDistantApps,* which capture the log-transformed count of apps released in the corresponding three time intervals prior to the focal app’s release. Only intermediate prior experience *(LnInterApps),* which reflected a 21-day to 56-day window prior to the focal apps’ release date, had a positive effect on the performance of the current app (Model 3-6: $\beta = 0.219$; $p < 0.001$; Model 4-6: $\beta = 0.428$; $p < 0.001$). Our hypotheses predicted that experiences during the intermediate period had a stronger positive impact than experiences during the more recent (H2a) or the more distant (H2b) periods. For *LnRecentApps* and *LnInterApps*, the differences were in the expected direction (Model 3-6: $\Delta\beta = 0.252$; $p < 0.001$; Model 4-6: $\Delta\beta = 0.499$; $p = 0.010$), supporting Hypothesis 2a. For *InterApps* and *DistantApps*, the differences were also in the expected direction, but for solo entrepreneurs were only marginally statistically significant (Model 3-6: $\Delta\beta = 0.157$; $p = 0.072$; Model 4-3: $\Delta\beta = 0.584$; $p = 0.023$). These results provide moderate support for Hypothesis 2b.

H3, which predicted a positive impact of more project experiences during the intermediate past, was supported by corresponding positive regression coefficients (Model 3-6: $\beta = 0.219$; $p < 0.001$; Model 4-6: $\beta = 0.428$; $p < 0.001$). The fact that *LnDownloads* and *LnInterApps* were both natural logarithms implied that if the number of apps created in the intermediate past doubled (e.g., from 4 to 8), the user downloads (in absolute number) would increase by 10%. A change of one standard deviation in *LnInterApps* implies an 11.3% change in downloads for solo entrepreneurs and a 31.5% change in downloads for group entrepreneurs. H3 was also supported by a small but statistically significant larger variance explained of the models that integrated the stream and the stock perspective (Model 3-6 and Model 4-6), compared with the corresponding stock-only models (Model 3-2 and Model 4-2; $p < .001$).

-- Insert Table 3 and Table 4 about here --

Weekly Time Effect Models

As indicated earlier, the use of three time periods (recent, intermediate and distant past) represents a crude simplification to capture the hypothesized time-contingent effect of prior experience. In addition to the three discrete time periods, we also performed more fine-grained investigations to obtain a more continuous approximation of these time-contingent effects, using weekly time intervals. Table 5 shows the corresponding regression results for log-transformed counts of apps released during each of the prior weeks for solo entrepreneurs. The estimated coefficients for the first three weeks indicate performance effects close to zero and slightly negative. Solo entrepreneurs showed a distinct performance peak for prior experience in the fourth week (*LnPriorNAppsWeek3*: $\beta = 0.198$; $p = 0.069$) and fifth week (*LnPriorNAppsWeek4*: $\beta = 0.185$; $p = 0.077$). If these two weeks are combined, their joint effect is also clearly positive (β

= 0.218; p = 0.004). Figure 2 provides a visual representation of the time-contingent impact of prior app experiences, with the bars representing the regression coefficient for each week and the line representing their two-week moving averages.

-- Insert Table 5 and Figure 2 about here --

Table 6 reports the corresponding results for group entrepreneurs, using biweekly intervals. The switch to larger intervals was necessitated by the smaller number of observations in this sample. Again, results for the first biweekly interval indicated no systematic positive performance effects, but results for the second and third biweekly intervals showed the start of a distinct performance peak (*LnPriorNappsBiWeek2*: β = 0.292; p = 0.022; *LnPriorNappsBiWeek2*: β = 0.472; p = 0.003). The fifth biweek still showed a marginally statistically significant positive effect (*LnPriorNappsBiWeek5:* β = 0.432; p = 0.065). We speculate that the slight delay of the peak for group apps reflects the additional learning complexities groups face, as they need to share information and agree on lessons learned. For later weeks, the regression coefficients for group apps were not systematically different from zero. Figure 3 provides a visual representation of the time-contingent impact of prior app experiences, with the bars representing the regression coefficient for each biweek and the line representing their two-biweeks moving average.

In summary, the results of these more fine-grained analyses confirm the earlier reported time-contingent effects of prior project experiences for the recent, intermediate and distant time intervals. Combined, these results are consistent with the notion of a general inverse U-shaped time-moderated effect pattern.

-- Insert Table 6 and Figure 3 about here --

Additional Analyses and Robustness Tests

To probe for the robustness of our findings, we incrementally changed the definition of the intermediate past. Moving this time window up by a week (to cover weeks 3 to 7) did not substantively change the results, but further weekly shifts of the intermediate time window (e.g., weeks 2 to 6 or weeks 5 to 9) resulted in gradually weaker and less systematic effects. Similarly, shortening the intermediate interval by either dropping either the first two weeks or up to the last three weeks led to weaker but similar results for both solo and group entrepreneurs.[2] These robustness tests indicated the stability of the reported results for reasonably small changes in cut-off times. Results for larger changes confirmed the time-sensitive nature of learning effects in this dynamic environment.

Given the substantial differences among the number of prior apps across entrepreneurs, we also probed for whether results were driven by entrepreneurs with either few or many prior apps. We found consistent time-contingent effects for various subsamples containing, for example, only entrepreneurs with up to 3, more than 3, 4 to 12 and more than 12 prior apps for all models of solo entrepreneurs and most models of group entrepreneurs. Group entrepreneurs with fewer than 5 prior apps did not experience the time-contingent learning benefits, which potentially identifies an interesting additional contingency: that group learning required a minimum stock of 5 prior projects. Alternatively, however, the substantially smaller sample size for group entrepreneurs challenges this interpretation and suggests an opportunity for further empirical investigations.[3]

Some apps had only a short time to accumulate downloads because they had been released close to the end of the sampling period (December 2008). Dropping all apps released in the September-to-December period did not affect results. Finally, probing for potential multicollinearity issues revealed relatively low variance inflation factors, at below 10 for all regression models (Belsley et al. 1980; DeMaris 2004).

DISCUSSION

Learning from prior entrepreneurial experiences has emerged as a major research stream in the entrepreneurship literature (Eggers and Song 2015; Toft-Kehler et al. 2014; Wang and

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[2] Corresponding results provided in online appendix
[3] Corresponding results provided in online appendix

Chugh 2014; Westhead and Wright 1998). Conceptual arguments strongly suggest that time impacts whether and how prior entrepreneurial experiences can provide helpful knowledge for subsequent entrepreneurial activities (Davidsson, Delmar and Wiklund 2006; Cope 2005; Politis 2005). The majority of the related empirical research, however, does not take time into account as a moderating factor. Hence, most studies have assumed the stock perspective of prior experience and have used linear or log-transformed measures of accumulated experiences. The current study breaks with these common approaches.

For dynamic settings such as digital platforms, our empirical evidence confirms the theory-based expectations of time-contingent learning processes. Thus, the simple modelling of prior experience as an accumulated stock of knowledge only incompletely captures how entrepreneurs learn from their prior software app experiences. As it turns out, both very recent and very distant project experiences are mostly irrelevant, as they on average have no systematic impact on subsequent project performance. The high levels of environmental change and the rapid succession of app projects on the investigated digital platform provide robust explanations of why experiences in the more distant past quickly become outdated and irrelevant. In contrast, very recent experiences are by definition "highly up-to-date." Still, their impact is also constrained, but for other reasons. First, download information for a recent prior project may not yet be reliable because it is based on feedback from very few users. In addition, the collection, analysis and interpretation of early user feedback itself requires time. Short-circuiting these learning processes may foster superstitious learning, which hurts rather than enhances performance. We studied these time effects in a dynamic learning setting, but our functional form of the overall temporal learning pattern is consistent with findings in important recent studies that investigated learning challenges, including potential negative learning outcomes, for serial entrepreneurs engaged in traditional business start-up activities (Toft-Kehler, Wennberg and Kim

2016, 2014). The time windows in dynamic settings are, however, far more compressed because the pressure to learn quickly is strong and knowledge decays rapidly.

The reported findings confirm that during an intermediate time window, learning from prior entrepreneurial experiences remains feasible and improves performance (H2a, H2b). Beyond this support for a time stream perspective of the impact of past entrepreneurial experiences, our findings also support the notion that a larger stock of experiences during this intermediate period provides advantages (H3). Thus, our findings do not reject the stock perspective that has dominated the related literature, but rather suggest combining the stock and stream perspectives to more comprehensively and accurately capture entrepreneurial learning.

The dynamics of the Facebook digital platform created, as conceptually outlined, substantial learning challenges. Consequently, systematic performance advantages were on average moderate and limited to the relatively narrow time window of 4 to 8 weeks in the intermediate past. The identification of this time window represents an important theory contribution and enables specific evidence-based predictions. It extends prior research that has focused on entrepreneurial learning over time but that has focused on broader ecosystems, such as traditional Hollywood movie production (Schwab and Miner 2008) or the mutual fund industry (Eggers and Song 2015; Eggers and Suh 2019), and on research focused on general business-startup activities (Delmar and Shane 2006; Toft-Kehler et al. 2016, 2014). Beyond providing general support for time-contingent models of entrepreneurial learning, our study offers a few additional, more nuanced and indirect contributions that identify promising directions for future research.

Future Research Directions

Serial and portfolio entrepreneurs. This study focused on learning of habitual entrepreneurs, who by definition can be either *serial entrepreneurs*, who engage in a sequence of prior ventures, or *portfolio entrepreneurs*, who engage in multiple ventures simultaneously, or *hybrid entrepreneurs*, who combine both approaches (Hyytinen and Ilmakunnas 2007; Folta et al. 2010; Ucbasaran et al. 2006). This study lacked the information to differentiate between these types of habitual entrepreneurs, but encourages such future research, because it promises to reveal more fine-grained and potentially more pronounced time-contingent learning effects. Serial entrepreneurs, for example, may benefit from their ability and expertise to engage in deep learning efforts focused on a single app project at any point in time. In contrast, portfolio entrepreneurs may benefit from easier knowledge transfers between overlapping projects and may exploit opportunities for intentional experiments by releasing alternative apps at the same time to compare their performance directly under identical market conditions (Egelman et al., 2017). Hence, either type of entrepreneur is likely to develop different distinct learning capabilities and strategies with potentially different time contingencies. These different learning approaches may also differ in other currently unknown dimensions, such as learning scope and learning intensity (Taylor and Greve 2006). Similarly, future research should consider to what degree the observed experiential learning processes differ between entrepreneurs learning alone or as a group. Our initial and broad investigation revealed primarily similar time-contingent learning patterns for solo and group entrepreneurs. The respective vast literature on individual and group learning, however, suggests that the underlying learning processes and strategies employed by individuals or groups differ, and more nuanced future research promises to reveal these differences and extend them to entrepreneurial learning under high levels of uncertainty. Hence, the results reported in this study should trigger future deeper investigations targeted at different types of habitual entrepreneurs.

Mediating Learning Processes and Outcomes. Consistent with the majority of prior learning research, this study captured learning processes indirectly by focusing on learning inputs (prior project experiences) and learning outcomes (app downloads). Such a broad approach promises to capture a wide range of specific learning activities in which entrepreneurs engaged, in order to discover their joint overall learning effects. The evidence for such overall learning effects leads to the subsequent research step to identify and understand these underlying specific learning activities. Data availability limited our ability to identify precisely what and how entrepreneurs learned from prior projects. Our anecdotal evidence indicated that some entrepreneurs “reused” software codes and programming skills developed during prior projects. We found that some engaged in performance-feedback learning as they tried to learn about end-user preferences from download information. Some learned how to better market, launch and promote their apps. We also engaged in some post-hoc investigations focused on potentially different learning patterns for learning from prior successful or failed projects and for entrepreneurs with relatively limited versus extensive prior experience. These investigations revealed that we lacked the more detailed information necessary to identify any related differences with reasonable certainty. Our broad measurement of prior project experience clearly has the advantages for capturing the joint overall effect of all these underlying learning processes and activities, but additional future research is needed to identify what types of knowledge entrepreneurs gained from their prior projects and how they gained and exploited it. Such research also promises to reveal further details on the time contingencies of these activities. The reported support for time-contingent learning effects not only encourages, but also offers important guidance for the design of future research to capture mediating learning processes and learning outcomes potentially also employing qualitative approaches.

Vicarious learning. This study focused on the most well-established and often dominant mode of entrepreneurial learning: Learning from own experiences. The entrepreneurial learning literature, however, also provides solid evidence that entrepreneurs frequently learn vicariously, by observing other entrepreneurs and their ventures (Lévesque, Minniti and Shepherd 2009; Wang and Chugh 2014). The success of apps released by other entrepreneurs, for example, can help focal entrepreneurs to identify end user preferences (Barlow et al. 2019). This raises the question of whether and how app entrepreneurs combine learning from own experiences with learning from the projects of their competitors and whether and when they potentially switch their focus on either learning strategy (Schwab 2007). We speculate that vicarious learning in highly dynamic environments is equally affected by time effects. Hence, the results reported in this study provide a basis for investigating these more complex learning processes, for example, by suggesting a time window during which prior competitor projects are likely to be most valuable as learning opportunities.

Digital platforms. This study's empirical investigation focused on Facebook, a two-sided digital social-media platform. This raises the question of the degree to which findings are dependent on characteristics of digital platforms or even the specific digital platform that we investigated. Our understanding of digital platforms as entrepreneurial ecosystems is still very incomplete. A deep understanding, however, is crucial for assessing the generalizability and boundary conditions of the reported time-contingent learning model. Entrepreneurs on digital platforms, for example, do not create stand-alone products, but rather products that tend to be deeply integrated with the digital platform and intricately connected to other platform products (Srinivasan and Venkatraman 2018). Research has started to identify different types of entrepreneurial ecosystems and how platform complementors can strategically manage within them (Zahra and Nambisan 2012). Still, more empirical studies of these increasingly prevalent digital platform ecosystems are needed if we are to comprehend their nature and to make more solid assessments of their similarity and differences to other learning environments. Promising generalization candidates are, for example, other entrepreneurial ecosystems related to open innovation initiatives, such as comic book, movie and tv series production (Chesbrough et al. 2006; Schwab and Miner 2008; Taylor and Greve 2006).

To avoid left-censoring issues, the current study focused on one specific social-media platform in its nascent stage. Future research should explore whether and how the detected learning patterns change for more mature platforms. Rietveld and Eggers (2018), for example, reported how independent video-game developers adjust to shifts in end-user preferences as digital platforms mature. After the end of our sampling window, for example, well-funded companies entered and launched more sophisticated software on Facebook ,which raised the bar for all app entrepreneurs. The permission of in-game purchases emerged as an additional way to monetize apps. The maturing of entrepreneurial ecosystems gradually changes their learning context, which raises the question of whether these changes impact the time-contingent learning processes of independent app entrepreneurs.

In summary, future research should consider more fine-grained investigations focused on different types of entrepreneurs, learning strategies, learning outcomes and digital platform ecosystems. Such studies, with their more fine-grained measures, have the potential to reveal even stronger and more distinct time-contingent learning effects. The results reported in this study should motivate and guide this future research.

Implications for Independent Habitual Entrepreneurs

From a practitioner's perspective, the identified time windows offer some general guidance for the systematic exploitation of related learning opportunities. The first lesson addresses motivation. Although learning in dynamic environments faces specific additional challenges, it remains feasible. The second lesson is that timing plays a crucial role, but the simple adage that learning faster is better is a misleading solution strategy. Instead, it is important for practitioners to recognize that it takes some time before feedback can be usefully exploited. For example, attempts to learn from prior app projects before user feedback is reasonably reliable are unlikely to be helpful and are potentially counterproductive. After this period, however, entrepreneurs should aggressively pursue opportunities to learn from experiences they gained during a prior project, because waiting carries the risk of further shortening an already relatively short time window during which they can benefit from any lessons learned. Identifying exactly when learning becomes feasible has the potential to provide competitive advantages, as it may enable entrepreneurs to effectively pivot (Kirtley & O'Mahony, 2020). It is also noteworthy that the transition from no systematic learning effects to substantial learning effects was rapid rather than gradual, especially for solo entrepreneurs (see Figure 2). This pattern suggests a potential "sweet spot" that app entrepreneurs should attempt to hit and exploit. More broadly, we considered the degree to which rapid learning strategies can be usefully employed in this context or are already being employed by some sophisticated entrepreneurs. In general, our findings resonate with emerging entrepreneurial learning research focused on the rapid scaling of two-sided digital platforms. This research has started to identify when entrepreneurs should increase or decrease their learning pace and how to accomplish this, but so far has focused primarily on learning strategies of platform owners (Ott, Bremner and Eisenhardt 2018). The short window for learning from prior experiences also raises the question whether ad-hoc and improvisational learning approaches play especially prominent roles in such dynamic settings (Ciuchta et al., 2021).

Entrepreneurs should also be cautious and pay close attention to time when trying to learn from entrepreneurial projects from the distant past, because these experiences are far less likely to provide valuable information, and in dynamic digital platform ecosystems, the distant past might start after only two months. The reported timing patterns and related learning concerns, however, are based on average effects across all habitual entrepreneurs. Thus, these findings do not rule out actual successful learning by, for example, some seasoned entrepreneurs applying more sophisticated learning strategies. Recent research of serial business-startup entrepreneurs indicated that a substantial amount of prior experience may be needed to enable some entrepreneurs to more accurately interpret very recent venture feedback (Toft-Kehler et a. 2016). Hence, deep investigation of identified "star" entrepreneurs applying both quantitative and qualitative methodologies deserve consideration. In summary, the reported findings suggest some rudimentary learning heuristics, which might offer some valuable guidance, especially for novice entrepreneurs (Nambisan & Baron 2013). Our research suggests that these capabilities should include fast-paced time-contingent learning strategies and routines.

Implications for Digital Platforms as Entrepreneurial Ecosystems

Our study provides further evidence that we are just starting to discover the complex time-contingent and interdependent learning patterns related to digital platforms and other dynamic and innovative ecosystems (Bogers et al. 2017; Eckhardt et al. 2018; Nambisan 2017). Learning plays a crucial role in the ability of these ecosystems to exploit rapidly advancing technology and to adapt to shifts in user preferences. Facebook and other similar two-sided digital platforms depended on the quality of the constant stream of innovative apps developed by independent entrepreneurs. Hence, platform owners search for strategies on how to attract, support and retain independent producers of useful complementary platform products (Rietveld et al. 2019; Schilling 2002). Our findings resonate with Eckhardt et al.'s (2018) general recommendation that platform owners should execute information strategies that help independent entrepreneurs make inferences about the value of their complementary apps. The introduced time-contingent learning model, which integrates the stock and stream perspectives for learning from prior entrepreneurial projects, offers platform owners a deeper understanding of how the independent entrepreneurs on their platform learn.

Reported findings should guide platform owners in decisions on how to support innovation and learning among the independent entrepreneurs on their platform (Parker and Van Alstyne 2018; Van Alstyne et al. 2016). The identified time window, for example, should help them to better target their learning support activities, which often include crucial decisions related to a platform’s information-sharing agreements and policies.

CONCLUSIONS

This study investigated whether and how prior entrepreneurial experience enables habitual entrepreneurs to improve the performance of their subsequent entrepreneurial projects in dynamic digital entrepreneurial ecosystems. High levels of environmental dynamics create specific challenges for learning across entrepreneurial projects, such as knowledge obsolescence, superstitious learning and knowledge decay, among others. The reported findings confirm that, in spite of these challenges, entrepreneurs can benefit from their prior venture experience, although the resulting learning outcomes are weaker and more short-lived than learning benefits gained in more stable environments (Musaji et al. 2020). To capture these time effects, this study introduced a time-contingent learning model that integrates the stream-based and the stock-based learning perspectives. This model offers a more comprehensive understanding of entrepreneurial learning and contributes to emerging research on how to best capture and manage such learning processes (Eckhardt et al. 2018; Politis 2008; Toft-Kehler et al., 2014). Beyond its application to dynamic digital platforms, we conceptually expect the identified overall time-contingent effect pattern to generalize to other dynamic entrepreneurial ecosystems such as other creative industries (e.g., music, films, comic books, video productions, fashion, architecture, advertising) and to contribute to a more general recognition of time as a crucial explanatory variable in the entrepreneurship (Cope 2005) and the management literature (Shipp and Cole 2015).

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Table 1. Descriptive statistics and correlations for Facebook applications developed by serial solo app entrepreneurs

Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11
1 LnDownloads	3.40	3.03	0	14.36	1.00										
2 LnAllPriorApps	0.90	0.98	0	4.39	-0.22	1.00									
3 LnRecentApps	0.43	0.71	0	3.43	-0.14	0.58	1.00								
4 LnInterApps	0.17	0.49	0	3.53	-0.01	0.44	0.25	1.00							
5 LnDistantApps	0.17	0.54	0	3.47	-0.06	0.42	0.11	0.38	1.00						
6 WeeksFirstApp	4.55	9.35	0	76.29	-0.09	0.41	0.01	0.24	0.64	1.00					
7 WeeksLastApp	2.29	5.88	0	75.86	-0.05	0.07	-0.17	-0.01	0.24	0.66	1.00				
8 LnPriorSuccess	0.18	0.40	0	2.40	0.24	0.31	0.19	0.26	0.31	0.34	0.12	1.00			
9 LnPriorFailure	0.13	0.35	0	3.18	0.05	0.33	0.09	0.16	0.23	0.30	0.13	0.04	1.00		
10 LnDuration	5.01	0.90	2.40	6.32	0.74	-0.23	-0.15	-0.04	-0.09	-0.11	-0.06	0.14	0.17	1.00	
11 HHIcategory	0.76	0.29	0.09	1.00	-0.20	-0.14	-0.01	-0.13	-0.24	-0.34	-0.22	-0.21	-0.20	-0.25	1.00
12 LnAllApps	4.82	0.32	2.14	5.04	-0.42	0.15	0.07	0.02	0.07	0.11	0.07	0.03	-0.05	-0.63	0.24

N = 7312 observations by 2221 habitual solo app entrepreneurs

Table 2. Descriptive statistics and correlations for Facebook applications developed by serial group app entrepreneurs

Variables	Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 LnDownloads	5.06	3.40	0	16.69	1.00													
2 LnAllPriorApps	1.05	0.98	0	4.37	-0.07	1.00												
3 LnRecentApps	0.53	0.81	0	3.50	-0.03	0.70	1.00											
4 LnInterApps	0.34	0.62	0	3.26	0.01	0.57	0.36	1.00										
5 LnDistantApps	0.44	0.72	0	3.43	-0.14	0.55	0.17	0.38	1.00									
6 WeeksFirstApp	10.06	14.02	0	76.43	-0.19	0.48	0.07	0.17	0.64	1.00								
7 WeeksLastApp	4.83	9.54	0	71.57	-0.11	-0.01	-0.27	-0.15	0.20	0.64	1.00							
8 LnPriorSuccess	0.48	0.75	0	2.94	0.19	0.64	0.47	0.56	0.62	0.31	-0.04	1.00						
9 LnPriorFailure	0.22	0.48	0	2.77	-0.15	0.49	0.55	0.34	0.24	0.13	-0.07	0.14	1.00					
10 AppsHHI	0.79	0.27	0.14	1.00	-0.03	-0.46	-0.41	-0.45	-0.43	-0.24	0.02	-0.54	-0.20	1.00				
11 LnDuration	5.41	0.85	2.40	6.32	0.54	-0.18	-0.03	-0.11	-0.34	-0.46	-0.33	-0.06	-0.02	0.25	1.00			
12 HHIcategory	0.54	0.28	0.11	1.00	-0.15	-0.25	-0.08	-0.18	-0.32	-0.30	-0.15	-0.24	-0.10	0.19	-0.06	1.00		
13 NumDev	2.64	1.22	2.00	10.00	-0.11	-0.07	-0.03	0.07	0.13	0.05	0.08	0.01	0.06	-0.20	-0.19	0.03	1.00	
14 PriorGroupTies	2.54	5.26	0.00	40.00	-0.06	0.63	0.54	0.51	0.56	0.36	-0.05	0.64	0.28	-0.54	-0.28	-0.13	0.01	1.00
15 LnAllApps	4.67	0.40	2.14	5.04	-0.41	0.20	0.03	0.16	0.32	0.37	0.24	0.17	0.00	-0.21	-0.64	0.02	0.14	0.16

N = 2378 observations by 1101 habitual group entrepreneurs

Table 3. Regression of LnDownloads for Facebook apps developed by habitual solo app entrepreneurs

VARIABLES	Model 3-1	Model 3-2	Model 3-3	Model 3-4	Model 3-5	Model 3-6
LnAllPriorApps		0.027				
		[0.030]				
LnRecentApps			-0.033			-0.006
			[0.036]			[0.037]
LnInterApps				0.219 ***		0.218 ***
				[0.057]		[0.058]
LnDistantApps					0.062	0.059
					[0.068]	[0.070]
WeeksFirstApp	-0.154 ***	-0.154 ***	-0.154 ***	-0.157 ***	-0.157 ***	-0.16 ***
	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]	[0.031]
WeeksLastApp	0.005	0.006	0.004	0.008	0.007	0.01 †
	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]	[0.006]
LnPriorSuccess	-1.314 ***	-1.331 ***	-1.301 ***	-1.361 ***	-1.317 ***	-1.361 ***
	[0.107]	[0.109]	[0.106]	[0.106]	[0.107]	[0.107]
LnPriorFailure	0.812 ***	0.793 ***	0.818 ***	0.779 ***	0.812 ***	0.781 ***
	[0.090]	[0.093]	[0.090]	[0.089]	[0.089]	[0.089]
LnDuration	-0.281	-0.269	-0.289	-0.261	-0.282	-0.263
	[0.278]	[0.280]	[0.277]	[0.278]	[0.278]	[0.278]
HHIcategory	-0.608 ***	-0.585 ***	-0.628 ***	-0.573 ***	-0.615 ***	-0.584 ***
	[0.158]	[0.160]	[0.160]	[0.158]	[0.158]	[0.159]
LnAllApps	-0.200	-0.204	-0.195	-0.189	-0.187	-0.176
	[0.479]	[0.479]	[0.478]	[0.482]	[0.480]	[0.484]
Constant	6.949 **	6.861 **	6.995 **	6.745 **	6.92 **	6.727 **
	[2.321]	[2.333]	[2.318]	[2.326]	[2.326]	[2.331]
Developers fixed effects	yes	yes	yes	yes	yes	yes
Time periods fixed effects	yes	yes	yes	yes	yes	yes
App Categories fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.874	0.874	0.874	0.875	0.874	0.875
Test: LnRercentApps=LnInterApps (p-value)						0.0006
Test: LnDistantApps=LnInterApps (p-value)						0.0721

N = 7312 observations; robust standard errors in brackets.

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table 4. Regression of LnDownloads of Facebook apps developed by habitual group entrepreneurs

VARIABLES	Model 4-1	Model 4-2	Model 4-3	Model 4-4	Model 4-5	Model 4-6
LnAllPriorApps		0.203				
		[0.172]				
LnRecentApps			-0.071			0.050
			[0.124]			[0.148]
LnInterApps				0.428 ***		0.442 **
				[0.123]		[0.140]
LnDistantApps					-0.156	-0.017
					[0.177]	[0.207]
WeeksFirstApp	-0.184 †	-0.188 †	-0.183 †	-0.172 †	-0.177 †	-0.172 †
	[0.102]	[0.102]	[0.101]	[0.102]	[0.101]	[0.101]
WeeksLastApp	0.016	0.017	0.015	0.015	0.015	0.016
	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]	[0.012]
LnPriorSuccess	-0.507 *	-0.618 **	-0.493 *	-0.665 **	-0.469 *	-0.676 **
	[0.208]	[0.220]	[0.208]	[0.210]	[0.217]	[0.233]
LnPriorFailure	0.643 **	0.5 †	0.676 **	0.438 †	0.658 **	0.410
	[0.233]	[0.274]	[0.243]	[0.239]	[0.235]	[0.278]
AppsHHI	-1.118 *	-0.997 *	-1.16 **	-1.038 *	-1.084 *	-1.003 *
	[0.438]	[0.470]	[0.444]	[0.434]	[0.435]	[0.446]
LnDuration	-1.113	-1.107	-1.119	-1.306	-1.087	-1.305
	[1.807]	[1.847]	[1.802]	[1.814]	[1.786]	[1.804]
HHIcategory	0.834	0.916 †	0.811	0.827	0.824	0.842 †
	[0.521]	[0.519]	[0.520]	[0.513]	[0.519]	[0.509]
NumDev	0.181	0.191 †	0.180	0.198 †	0.187 †	0.201 †
	[0.111]	[0.111]	[0.112]	[0.110]	[0.111]	[0.110]
PriorGroupTies	0.002	-0.004	0.004	-0.008	0.004	-0.009
	[0.018]	[0.019]	[0.019]	[0.018]	[0.018]	[0.020]
LnAllApps	-0.164	-0.188	-0.144	-0.136	-0.189	-0.152
	[0.598]	[0.601]	[0.598]	[0.598]	[0.605]	[0.605]
Constant	5.822	5.604	5.902	7.108	5.730	7.083
	[9.032]	[9.273]	[9.017]	[9.075]	[8.937]	[9.051]
Developers fixed effects	yes	yes	yes	yes	yes	yes
Time periods fixed effects	yes	yes	yes	yes	yes	yes
App Categories fixed effects	yes	yes	yes	yes	yes	yes
R-squared	0.879	0.879	0.879	0.881	0.879	0.881
Test: LnRercentApps=LnInterApps (p-value)						0.00979
Test: LnDistantApps=LnInterApps (p-value)						0.02341

N = 2378 observations; robust standard errors in brackets.

*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table 5. Regression of LnDownloads for Facebook apps developed by habitual solo entrepreneurs

VARIABLES	Model 5-1		
LnPriorNappsWeek1	0.012		[0.043]
LnPriorNappsWeek2	-0.004		[0.053]
LnPriorNappsWeek3	0.013		[0.065]
LnPriorNappsWeek4	0.198	†	[0.109]
LnPriorNappsWeek5	0.185	†	[0.105]
LnPriorNappsWeek6	0.050		[0.125]
LnPriorNappsWeek7	0.057		[0.135]
LnPriorNappsWeek8	0.041		[0.153]
LnPriorNappsWeek9	0.037		[0.191]
LnPriorNappsWeek10	0.099		[0.132]
LnPriorNappsWeek11	0.011		[0.156]
LnPriorNappsWeek12	0.071		[0.188]
LnPriorNappsWeek13	-0.171		[0.184]
LnPriorNappsWeek14plus	0.084		[0.088]
WeeksFirstApp	-0.16	***	[0.031]
WeeksLastApp	0.010		[0.006]
LnPriorSuccess	-1.354	***	[0.106]
LnPriorFailure	0.792	***	[0.089]
LnDuration	-0.268		[0.288]
HHIcategory	-0.597	***	[0.159]
LnAllApps	-0.179		[0.482]
Constant	6.788	**	[2.367]
Developers fixed effects	yes		yes
Time periods fixed effects	yes		yes
App Categories fixed effects	yes		yes
R-squared	0.875		0.875

N = 7312 observations; robust standard errors in brackets.
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Table 6. Regression of LnDownloads for Facebook apps by habitual group entrepreneurs

VARIABLES	Model 6-1	
LnPriorNappsBiWeek1	0.233	[0.150]
LnPriorNappsBiWeek2	0.292 *	[0.127]
LnPriorNappsBiWeek3	0.472 **	[0.159]
LnPriorNappsBiWeek4	0.158	[0.185]
LnPriorNappsBiWeek5	0.432 †	[0.234]
LnPriorNappsBiWeek6plus	0.089	[0.184]
WeeksFirstApp	-0.18 †	[0.105]
WeeksLastApp	0.021	[0.013]
LnPriorSuccess	-0.719 ***	[0.208]
LnPriorFailure	0.421 †	[0.241]
AppsHHI	-0.938 *	[0.452]
LnDuration	-1.179	[1.880]
HHIcategory	0.811	[0.516]
NumDev	0.194 †	[0.111]
PriorGroupTies	-0.033	[0.021]
LnAllApps	-0.193	[0.603]
Constant	6.367	[9.367]
Developers fixed effects	yes	
Time periods fixed effects	yes	
App Categories fixed effects	yes	
R-squared	0.881	

N = 2378 observations; robust standard errors in brackets.
*** p<0.001, ** p<0.01, * p<0.05, † p<0.1

Figure 1. Number of new Facebook apps released by habitual entrepreneurs working alone or in groups

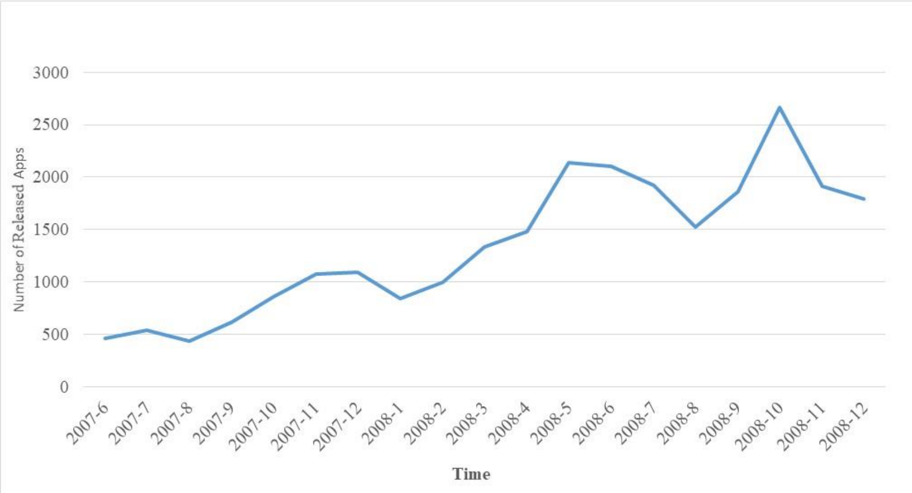
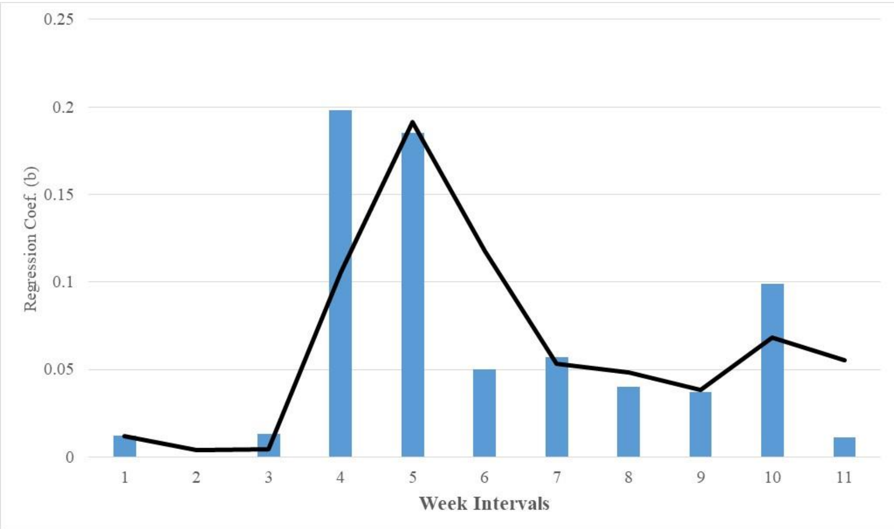
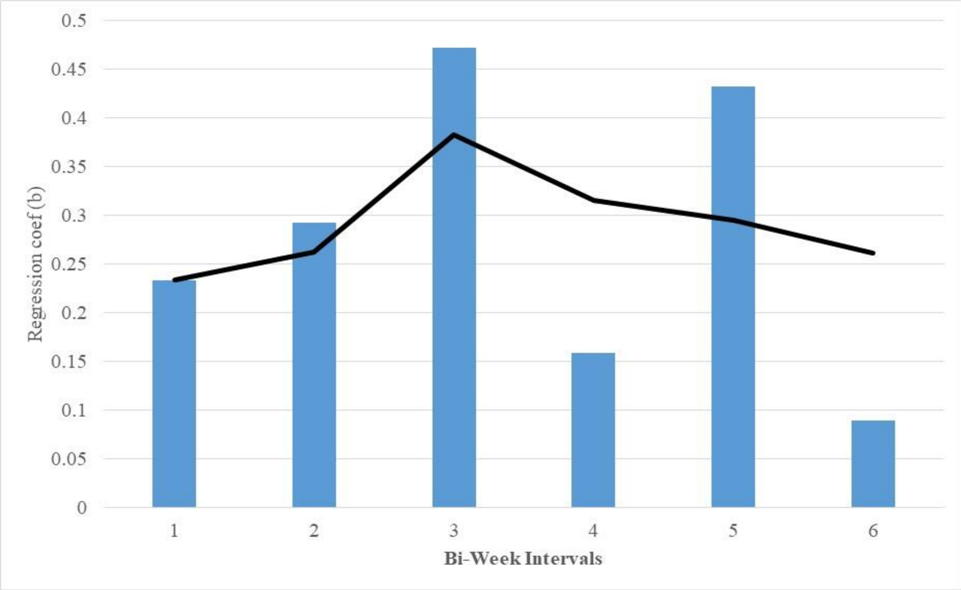


Figure 2. Estimated regression coefficients for weekly intervals for solo apps (Model 3-6)



Note: Bars represent regression coefficients and the line represent their two-week moving average

Figure 3. Estimated regression coefficients for biweekly intervals for group apps (Model 4-6)



Note: Bars represent regression coefficients and the line represent their two-biweek moving average

ONLINE APPENDIX

Table A1: Regression of LnDownloads of Facebook apps with different time-window widths for intermediate experience of solo entrepreneurs

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
LnpriorNappsWeek3-8	0.162**										
	[0.050]										
LnpriorNappsWeek4-8		0.216***									
		[0.061]									
LnpriorNappsWeek5-8			0.198**								
			[0.069]								
LnpriorNappsWeek6-8				0.138+							
				[0.080]							
LnpriorNappsWeek7-8					0.120						
					[0.106]						
LnpriorNappsWeek3-7						0.145**					
						[0.051]					
LnpriorNappsWeek3-6							0.136**				
							[0.052]				
LnpriorNappsWeek3-5								0.129*			
								[0.055]			
LnpriorNappsWeek3-4									0.077		
									[0.060]		
LnpriorNappsWeek2-4										0.019	
										[0.044]	
LnpriorNappsWeek2-3											-0.013
											[0.045]
LnpriorNappsWeek1	-0.006	-0.005	-0.005	-0.006	-0.007	-0.008	-0.007	-0.008	-0.006	-0.013	-0.008
	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.043]	[0.042]	[0.042]
LnpriorNappsWeek2	-0.033	-0.008	-0.007	-0.007	-0.008	-0.030	-0.029	-0.027	-0.016		
	[0.052]	[0.053]	[0.053]	[0.053]	[0.053]	[0.052]	[0.052]	[0.052]	[0.053]		
LnpriorNappsWeek3		0.012	0.010	0.009	0.008						
		[0.065]	[0.065]	[0.066]	[0.066]						
LnpriorNappsWeek4			0.181+	0.187+	0.187+						0.192+
			[0.102]	[0.103]	[0.104]						[0.103]
LnpriorNappsWeek5				0.176+	0.187+				0.212*	0.234*	0.188+
				[0.099]	[0.101]				[0.099]	[0.098]	[0.101]
LnpriorNappsWeek6					0.068			0.100	0.072	0.077	0.066
					[0.120]			[0.119]	[0.122]	[0.123]	[0.121]
LnpriorNappsWeek7							0.129	0.117	0.105	0.103	0.103
							[0.122]	[0.132]	[0.130]	[0.130]	[0.130]
LnpriorNappsWeek8						0.150	0.130	0.127	0.124	0.130	0.116
						[0.147]	[0.153]	[0.153]	[0.153]	[0.154]	[0.154]
LnpriorNappsWeek9	0.025	-0.012	-0.014	-0.005	-0.006	-0.028	-0.034	-0.037	-0.039	-0.038	-0.027
	[0.154]	[0.154]	[0.158]	[0.165]	[0.170]	[0.187]	[0.187]	[0.187]	[0.187]	[0.186]	[0.187]
LnpriorNappsWeek10	0.122	0.114	0.117	0.117	0.116	0.112	0.112	0.110	0.103	0.103	0.112
	[0.126]	[0.126]	[0.127]	[0.127]	[0.127]	[0.128]	[0.128]	[0.128]	[0.128]	[0.127]	[0.127]
LnpriorNappsWeek11	0.011	0.000	-0.002	-0.001	-0.002	0.006	0.003	0.002	0.009	0.007	-0.006
	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]	[0.156]
LnpriorNappsWeek12	0.076	0.081	0.077	0.083	0.077	0.077	0.076	0.078	0.081	0.083	0.074
	[0.185]	[0.185]	[0.185]	[0.186]	[0.186]	[0.185]	[0.186]	[0.187]	[0.187]	[0.187]	[0.187]
LnpriorNappsWeek13	-0.160	-0.157	-0.151	-0.154	-0.154	-0.164	-0.161	-0.163	-0.164	-0.171	-0.153
	[0.183]	[0.183]	[0.183]	[0.183]	[0.183]	[0.184]	[0.184]	[0.184]	[0.183]	[0.183]	[0.183]
LnpriorNappsWeek14plus	0.060	0.063	0.065	0.066	0.065	0.055	0.057	0.057	0.065	0.062	0.063
	[0.086]	[0.086]	[0.087]	[0.087]	[0.087]	[0.086]	[0.087]	[0.087]	[0.087]	[0.087]	[0.087]
WeeksFirstApp	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***
	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]	[0.005]
WeeksLastApp	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
LnPriorSuccess	-0.436***	-0.438***	-0.440***	-0.439***	-0.437***	-0.434***	-0.435***	-0.435***	-0.435***	-0.434***	-0.436***
	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]	[0.056]
LnPriorFailure	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***	0.060***
	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]	[0.017]
LnDuration	-0.206	-0.204	-0.201	-0.209	-0.212	-0.204	-0.204	-0.200	-0.197	-0.214	-0.210
	[0.288]	[0.289]	[0.290]	[0.289]	[0.290]	[0.288]	[0.288]	[0.289]	[0.289]	[0.287]	[0.287]
HHIcategory	-0.511**	-0.508**	-0.512**	-0.517**	-0.519**	-0.518**	-0.521**	-0.524**	-0.521**	-0.519**	-0.524**
	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]	[0.164]
LnAllApps	-0.096	-0.094	-0.093	-0.089	-0.091	-0.098	-0.097	-0.095	-0.091	-0.087	-0.091
	[0.510]	[0.511]	[0.511]	[0.511]	[0.511]	[0.510]	[0.511]	[0.511]	[0.511]	[0.511]	[0.511]
Constant	6.031*	6.009*	5.988*	6.029*	6.054*	6.032*	6.029*	6.002*	5.970*	6.057*	6.044*
	[2.422]	[2.425]	[2.428]	[2.428]	[2.430]	[2.422]	[2.424]	[2.428]	[2.428]	[2.421]	[2.421]
Developers fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time periods fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
App categories fixed effec	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.875	0.875	0.875	0.875	0.875	0.875	0.875	0.875	0.875	0.875	0.875

N=7312 observations; Robust standard errors in brackets

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A2: Regression of LnDownloads of Facebook apps with different time-window widths for intermediate experience of group entrepreneurs

VARIABLES	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
LnpriorNappsWeek3-8	0.422**										
	[0.128]										
LnpriorNappsWeek4-8		0.398**									
		[0.128]									
LnpriorNappsWeek5-8			0.328*								
			[0.149]								
LnpriorNappsWeek6-8				0.230							
				[0.163]							
LnpriorNappsWeek7-8					0.089						
					[0.180]						
LnpriorNappsWeek3-7						0.417**					
						[0.131]					
LnpriorNappsWeek3-6							0.440**				
							[0.134]				
LnpriorNappsWeek3-5								0.378**			
								[0.130]			
LnpriorNappsWeek3-4									0.300*		
									[0.131]		
LnpriorNappsWeek2-4										0.156	
										[0.139]	
LnpriorNappsWeek2-3											0.034
											[0.152]
LnpriorNappsWeek1	0.288	0.268	0.271	0.275	0.275	0.285	0.29	0.288	0.29	0.241	0.25
	[0.173]	[0.173]	[0.175]	[0.176]	[0.175]	[0.174]	[0.173]	[0.174]	[0.175]	[0.173]	[0.173]
LnpriorNappsWeek2	-0.075	-0.047	-0.046	-0.038	-0.042	-0.070	-0.075	-0.075	-0.053		
	[0.167]	[0.167]	[0.167]	[0.168]	[0.168]	[0.167]	[0.169]	[0.169]	[0.170]		
LnpriorNappsWeek3		0.153	0.149	0.153	0.155						
		[0.144]	[0.147]	[0.147]	[0.148]						
LnpriorNappsWeek4			0.285+	0.282	0.283+						0.314+
			[0.173]	[0.172]	[0.171]						[0.172]
LnpriorNappsWeek5				0.334+	0.333+				0.350*	0.387*	0.328+
				[0.176]	[0.175]				[0.172]	[0.171]	[0.174]
LnpriorNappsWeek6					0.320			0.344	0.331	0.336	0.314
					[0.219]			[0.216]	[0.217]	[0.217]	[0.219]
LnpriorNappsWeek7							0.104	0.087	0.084	0.105	0.088
							[0.245]	[0.245]	[0.244]	[0.244]	[0.242]
LnpriorNappsWeek8						0.097	0.112	0.106	0.097	0.077	0.058
						[0.214]	[0.217]	[0.219]	[0.216]	[0.215]	[0.215]
LnpriorNappsWeek9	0.337	0.346	0.357	0.382	0.399	0.349	0.368	0.373	0.391	0.395	0.406
	[0.391]	[0.392]	[0.392]	[0.388]	[0.383]	[0.388]	[0.384]	[0.382]	[0.381]	[0.380]	[0.383]
LnpriorNappsWeek10	0.270	0.264	0.280	0.291	0.325	0.282	0.297	0.303	0.319	0.296	0.317
	[0.255]	[0.255]	[0.254]	[0.255]	[0.260]	[0.255]	[0.257]	[0.259]	[0.259]	[0.261]	[0.258]
LnpriorNappsWeek11	0.127	0.105	0.108	0.103	0.118	0.134	0.134	0.138	0.111	0.108	0.121
	[0.269]	[0.269]	[0.267]	[0.268]	[0.276]	[0.274]	[0.277]	[0.281]	[0.279]	[0.280]	[0.278]
LnpriorNappsWeek12	-0.388	-0.395	-0.400	-0.404	-0.428	-0.378	-0.389	-0.422	-0.415	-0.387	-0.424
	[0.337]	[0.339]	[0.338]	[0.335]	[0.339]	[0.335]	[0.335]	[0.342]	[0.342]	[0.347]	[0.345]
LnpriorNappsWeek13	0.441+	0.434	0.447+	0.450+	0.438	0.452+	0.457+	0.451+	0.441+	0.414	0.436
	[0.267]	[0.268]	[0.270]	[0.268]	[0.267]	[0.267]	[0.265]	[0.265]	[0.265]	[0.269]	[0.269]
LnpriorNappsWeek14plus	-0.029	-0.058	-0.070	-0.063	-0.054	-0.036	-0.023	-0.033	-0.027	-0.051	-0.073
	[0.199]	[0.197]	[0.197]	[0.198]	[0.201]	[0.200]	[0.201]	[0.203]	[0.203]	[0.204]	[0.202]
WeeksFirstApp	-0.026+	-0.026+	-0.025+	-0.026+	-0.026+	-0.027+	-0.027+	-0.027+	-0.026+	-0.026+	-0.025+
	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]	[0.015]
WeeksLastApp	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]	[0.002]
LnPriorSuccess	-0.038	-0.037	-0.035	-0.037	-0.037	-0.036	-0.039	-0.037	-0.039	-0.043	-0.038
	[0.052]	[0.051]	[0.051]	[0.051]	[0.051]	[0.052]	[0.052]	[0.052]	[0.051]	[0.052]	[0.051]
LnPriorFailure	-0.029	-0.030	-0.031	-0.032	-0.032	-0.028	-0.030	-0.029	-0.031	-0.026	-0.030
	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]	[0.052]
LnDuration	-0.934	-0.921	-0.924	-0.979	-0.938	-1.030	-1.055	-0.960	-0.960	-0.916	-0.919
	[1.882]	[1.879]	[1.884]	[1.883]	[1.884]	[1.880]	[1.880]	[1.888]	[1.888]	[1.881]	[1.882]
HHIcategory	0.670	0.665	0.655	0.644	0.629	0.664	0.666	0.643	0.630	0.627	0.628
	[0.520]	[0.521]	[0.521]	[0.521]	[0.523]	[0.521]	[0.520]	[0.522]	[0.522]	[0.523]	[0.522]
AppsHHI	-0.610	-0.640	-0.667	-0.677	-0.683	-0.615	-0.635	-0.660	-0.661	-0.633	-0.675
	[0.458]	[0.457]	[0.457]	[0.457]	[0.457]	[0.459]	[0.459]	[0.457]	[0.457]	[0.458]	[0.458]
NumDev	0.205+	0.208+	0.206+	0.206+	0.205+	0.204+	0.202+	0.202+	0.203+	0.209+	0.209+
	[0.120]	[0.120]	[0.121]	[0.121]	[0.120]	[0.120]	[0.120]	[0.120]	[0.120]	[0.119]	[0.120]
PriorGroupTies	-0.030	-0.027	-0.029	-0.029	-0.030	-0.033	-0.034	-0.033	-0.033	-0.025	-0.026
	[0.022]	[0.022]	[0.023]	[0.023]	[0.023]	[0.022]	[0.022]	[0.022]	[0.023]	[0.022]	[0.023]
LnAllApps	-0.051	-0.026	-0.035	-0.038	-0.042	-0.051	-0.057	-0.056	-0.055	-0.059	-0.032
	[0.593]	[0.594]	[0.592]	[0.592]	[0.590]	[0.590]	[0.590]	[0.591]	[0.589]	[0.587]	[0.591]
Constant	4.442	4.429	4.486	4.835	4.621	4.901	5.042	4.602	4.675	4.413	4.481
	[9.426]	[9.411]	[9.435]	[9.430]	[9.439]	[9.422]	[9.420]	[9.465]	[9.464]	[9.441]	[9.445]
Developers fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Time periods fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
App categories fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
R-squared	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881	0.881

N=2378 observations; Robust standard errors in brackets

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

Table A3: Regression of LnDownloads of Facebook apps with different numbers of prior app projects for solo entrepreneurs

VARIABLES	Model 1 No. of Apps <=3	Model 2 No. of Apps >3	Model 3 No. of Apps >3 & <=12	Model 4 No. of Apps >12
LnRecentApps	0.170	-0.074+	-0.114	-0.022
	[0.121]	[0.069]	[0.109]	[0.622]
LnInterApps	0.343*	0.200***	0.188*	0.141**
	[0.031]	[0.000]	[0.031]	[0.006]
LnDistantApps	0.193	0.045	0.032	0.098
	[0.277]	[0.492]	[0.827]	[0.130]
WeeksFirstApp	-0.024***	-0.017***	-0.020**	-0.006
	[0.000]	[0.001]	[0.003]	[0.504]
WeeksLastApp	0.001	-0.001	-0.001	-0.001
	[0.349]	[0.349]	[0.606]	[0.496]
LnPriorSuccess	-1.883***	-0.244***	-0.570***	-0.009
	[0.000]	[0.000]	[0.000]	[0.781]
LnPriorFailure	1.308***	0.009	0.398***	-0.014
	[0.000]	[0.563]	[0.000]	[0.306]
LnDuration	-0.924*	0.208	-0.321	0.560
	[0.035]	[0.571]	[0.547]	[0.264]
HHIcategory	-0.537**	-0.275	-0.177	-0.623
	[0.004]	[0.243]	[0.556]	[0.116]
LnAllApps	0.028	-0.179	-0.171	-1.731
	[0.948]	[0.818]	[0.846]	[0.515]
Constant	5.396*	0.965	3.460	7.060
	[0.029]	[0.776]	[0.409]	[0.516]
Observations	4,062	3,250	2,034	1,216
R-squared	0.522	0.424	0.373	0.645
Number of devid	1,825	396	356	40

p-value in brackets

*** p<0.001, ** p<0.01, * p<0.05, + p<0.1

All models have developer, time and app category fixed effects

Table A4: Regression of LnDownloads of Facebook apps with different numbers of prior app projects for group entrepreneurs

VARIABLES	Model 1 No. Apps <=3	Model 2 No. Apps >3	Model 3 No. Apps >3 & <=12	Model 4 No. Apps >12	Model 6 No. Apps <=5
LnRecentApps	-0.208	0.045	0.255	-0.002	0.133
	[0.631]	[0.696]	[0.291]	[0.986]	[0.638]
LnInterApps	0.008	0.498***	0.720**	0.334**	0.688*
	[0.986]	[0.000]	[0.002]	[0.007]	[0.028]
LnDistantApps	-0.246	-0.098	-0.172	-0.161	0.300
	[0.662]	[0.559]	[0.620]	[0.384]	[0.415]
WeeksFirstApp	-0.010	-0.029**	-0.029+	-0.045**	-0.028*
	[0.579]	[0.004]	[0.059]	[0.001]	[0.038]
WeeksLastApp	0.004	0.003	0.004+	-0.000	0.007**
	[0.521]	[0.100]	[0.051]	[0.940]	[0.009]
LnPriorSuccess	-0.766***	-0.012	-0.197*	0.023	-0.635***
	[0.001]	[0.745]	[0.043]	[0.600]	[0.000]
LnPriorFailure	1.224**	-0.054	0.297+	0.052	0.794***
	[0.001]	[0.327]	[0.075]	[0.480]	[0.000]
AppsHHI	-1.511*	-0.585	1.013	-0.710	-1.078+
	[0.041]	[0.151]	[0.101]	[0.262]	[0.052]
LnDuration	0.713	-1.975+	-0.231	-4.143**	1.177
	[0.713]	[0.078]	[0.898]	[0.005]	[0.442]
HHIcategory	0.223	0.714	-0.018	0.381	0.794
	[0.774]	[0.173]	[0.980]	[0.674]	[0.211]
NumDev	-0.088	0.336**	0.291*	0.517*	-0.015
	[0.516]	[0.001]	[0.030]	[0.013]	[0.890]
PriorGroupTies	-0.118	-0.024	0.144+	-0.031	-0.146
	[0.642]	[0.233]	[0.092]	[0.138]	[0.333]
LnAllApps	-0.041	0.177	1.223+	-1.125	-0.464
	[0.965]	[0.743]	[0.086]	[0.194]	[0.514]
Constant	1.324	13.176*	-2.082	26.539**	-4.196
	[0.901]	[0.035]	[0.831]	[0.002]	[0.618]
Observations	1,075	1,303	731	572	1,410
R-squared	0.521	0.430	0.464	0.558	0.491
Number of devid	749	352	285	67	913

p-value in brackets
*** p<0.001, ** p<0.01, * p<0.05, + p<0.1