

Sequential Innovation in Mobile App Development

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Problem Definition: In today’s highly dynamic and competitive app markets, a significant portion of development takes place after the initial product launch via the addition of new features and the enhancement of existing products. In managing the sequential innovation process in mobile app development, two key operational questions arise: i) What features and attributes should be added to existing products in successive versions? and ii) How should these features and attributes be implemented for greater market success? We investigate the implications of three different types of mobile app development activities on market performance. **Academic/Practical Relevance:** Our study contributes to the operations management literature by providing an empirically based understanding of sequential innovation and its market performance implications in mobile app development, an important industry in terms of size, scope and potential. **Methodology:** Using a novel dataset of mobile apps in the Productivity category, we leverage text-mining and information retrieval techniques to study the rich information in the release notes of apps. We then characterize product development activities at each version release, and link these activities with app performance in a dynamic estimation model. We also incorporate an instrumental variables analysis to substantiate our findings. **Results:** We find that greater update dissimilarity (i.e. dissimilarity of the features and attributes of a new update from those of previous updates) is associated with higher performance, especially in mature apps. We also find that the greater the product update market-orientation (i.e. the greater the similarity of the focal firm’s new features and attributes with respect to the recent additions of its competitors), the higher is the market performance. This finding suggests that the market rewards those developers who have a responsive policy to their competitors’ product innovation efforts. Our results also suggest that a rapid introduction of updates dampens the potential market benefits that the mobile app developers might gain from market-orientation. We find no evidence of a beneficial effect of product update scope (i.e. incorporating features and attributes from other product sub-categories) on market performance. **Managerial Implications:** Our study offers managerial insights into mobile app development by exploring the sequential innovation characteristics that are associated with greater market success in pursuing and implementing new features and attributes.

Keywords: mobile apps, product development, sequential innovation, market performance

1. Introduction

The steady rise in the adoption and use of smartphones has led to the explosive growth of mobile applications which have multiplied the capabilities of the mobile internet and transformed business models across a range of industries including retail, banking, and media (Kavadias and Ladas 2015). With growing demand from consumers on the one side and a large number of producers (mobile app developers) on the other side, mobile app stores such as Apple’s App

Store and the Google Play Store have been pivotal to innovation in the mobile apps industry. As of Q4 2020, there were 2.09 million apps available for download on the Apple App Store and 3.14 million apps available on the Google Play store (Statista 2021). In 2021, the app economy was worth \$6.3 trillion, the main driver being the purchase of goods and services through mobile applications (Ceci 2021). As mobile application development becomes a crucial part of the digital business strategy for firms (Bharadwaj et al. 2013), understanding the process and implications of app development becomes essential.

A large number of app developers compete with one another through dynamic and mostly transparent (both to customers and to competitors) product innovation efforts by continuously pursuing new features and attributes through software updates. While developing successive versions of the same product, mobile app developers retain the core innovation and incrementally add new features and attributes with a hope to generate value and attract new customers.¹ For example, as of May 2021, the popular social media app Instagram has released 189 version updates Apple (2021), including many smaller versions since its initial launch in October 2010. In Jan 2011, Instagram introduced “hashtags” to help users discover photos posted by other users. In September 2011, it added live filters, instant tilt shift, a border option and one-click rotation. In August 2017, it has added multi-image posts, allowing users to combine 10 images or videos at a time. Through updated versions of the same product with additional features and attributes, Instagram generated value and was able to attract a significant number of new customers over time.²

If new features and attributes can have such significance in providing value and attracting new customers, two key operational questions for mobile app developers arise: i) What features and attributes should be added to existing products in successive versions? and ii) How should these features and attributes be incorporated for greater market success? We seek to address these questions with a particular focus on the developers’ implementation of new features and attributes in introducing successive versions of their products. In such a “high-velocity” (Brown and Eisenhardt 1995) and “hyper-competitive” (Datta and Kajanan 2013) environment with a high degree of product transparency, low barriers for creating content, and a weak Intellectual property (IP) regime, firms can turn to their direct competitors as a source of innovative ideas, they can explore other broad product domains, or they can simply build on their own previous

¹ While our study focuses on new features and attributes in successive versions of applications, a notable portion of version updates also involve corrective maintenance (i.e., bug fixing). We control for such retrospective changes in our models while examining the market implications of new features and attributes.

² See Online Appendix A.1

versions by recombining existing features and attributes. While each of these strategies might make the resulting product more appealing to consumers, in contrast, they could be a hindrance for market success. Additionally, considering the importance of consumer attitudes in product sales (Brown 1950), the way developers implement new features can be a significant driver or barrier for market success. In this study, we empirically address these questions by employing a unique dataset of Productivity apps from the Apple App Store and using novel text-mining and information-retrieval techniques to examine the relationship between three types of product development activities in sequential innovation (namely, dissimilar app updates, app update scope, and market-orientation of the app update) and market performance.

First, developers can incorporate previously unexplored and distant paths (Ahuja and Katila 2004) and potentially make novel and dissimilar improvements in the new versions. Alternatively, considering the potential risks and uncertainties associated with market response, developers can resort to variations of existing features and attributes (Katila and Ahuja 2002) which can be very effective (Fleming 2001) and can lead to highly useful innovations (Utterback 1996). Consequently, our study examines these contrasting perspectives and sheds light on the relationship between the degree of app update dissimilarity and market performance.

Secondly, developers can consider a broad scope and turn to other domains to source innovative ideas for the next version of their apps to bring distinctive new variations (Katila and Ahuja 2002). However, such variety can also bring additional uncertainty, reliability concerns and noise for the consumers (Fleming 2001, Martin and Mitchell 1998) while introducing inefficiencies to the innovation process (Henderson and Clark 1990). Considering these, it is not clear whether update scope, i.e., incorporating features and attributes from other domains, would be an asset or liability for mobile app developers.

Thirdly, and more importantly, in introducing successive versions of their products, either developers might keep a close eye on their competitors and try to incorporate their competitors' new features and attributes into their own releases, or they might be less reactive. While the former responsive policy (i.e., market-orientation) could help firms remain competitive and relevant in the marketplace, it might also result in diminished novelty and lack of focus (Köhler et al. 2012) from the consumers' viewpoint. Consequently, such market orientation could be a help or hindrance for the app developers.

Our study contributes to the operations management literature by providing an empirically based understanding of the sequential innovation process in mobile app development and its market performance implications. Despite the significance of the mobile app industry in terms

of size, scope and potential³, mobile app development has received little attention in the existing operations management literature. While sequential innovation has been studied in other technology-based industries such as industrial products or consumer electronics (Bessen and Maskin 2009, Kornish 2001, Ramachandran and Krishnan 2008, Krishnan and Ramachandran 2011), novel characteristics of the mobile application development call for new scholarly attention. In addition, the availability of highly granular data for successive versions of mobile apps over time as well as corresponding market data allows us to link and empirically investigate sequential innovation efforts with market performance.

Our findings reveal that greater update dissimilarity in successive versions of mobile applications is associated with greater market performance, especially in mature apps. That is, during the later stages of an app’s life cycle, firms can significantly benefit by incorporating ideas far from the neighborhood of paths previously explored. As there may be a limit to deriving benefits from refining or recombining existing features, introduction of original and fresh features over time result in market success. However, we find no evidence of beneficial effects of broad updates. Interestingly, we find that the greater the market orientation, that is, the greater the similarity of the focal firm’s new features and attributes with respect to the recent additions of its competitors, the higher the market performance. This finding suggests that the market rewards those developers with a responsive policy to its competitors’ product innovation efforts. Our results also indicate that rapid introduction of an update reduces potential market benefits that mobile app developers may gain from market orientation. That is, while incorporating competitors’ recent features into their own apps seems to be beneficial for developers, rushing to incorporate such features reduces the benefits.

2. Related Literature and Hypotheses

Our work is related to the literature on sequential innovation which is broadly defined as an ongoing process in which firms engage in sequential experimentation (Thomke 2003) by introducing new versions of the same product over time (Brown and Eisenhardt 1995). The extant literature on sequential innovation is focused on the implications of technological advances in relatively stable industry structures with defined market boundaries, such as industrial products or consumer electronics. In order to minimize the cost incurred by the customer in keeping up with new technology, firms design their products to be “modularly upgradeable” (Ramachandran and Krishnan 2008), allowing customers to select the desired components for upgrade which

³ By 2022, the mobile app economy is expected to be worth \$6.3 trillion (Ceci 2021).

might also potentially reduce waste (McDonough and Braungart 2002). A stream of literature has studied the decisions made by firms while managing rapid sequential innovation through modular upgradability, such as those related to product design (Ramachandran and Krishnan 2008), release timing, and pricing (Kornish 2001), and while assessing the appropriateness of modular upgradability for different types of markets and products (Krishnan and Ramachandran 2011), mostly by using analytical models.

Another stream of literature in operations management explores the innovation management strategies of firms in dynamic environments when faced with uncertainty (Sommer and Loch 2004, Sommer et al. 2009, Pich et al. 2002), namely trial and error learning and selectionism. Other studies highlighted the quick evolution of technologies in certain products and examined how firms should update (i.e., reposition) their product design based on the timing of the underlying technology (Jain and Ramdas 2005) and what technology levels should be incorporated in successive product generations over a product’s life cycle (Gjerde et al. 2002). Several analytical studies concentrated on optimizing the initial product development process by focusing on the trade-offs between the benefits and the costs of concept testing (Dahan and Mendelson 2001), parallel vs. sequential testing of design alternatives (Loch et al. 2001) and collaborative prototyping and contracting (Terwiesch and Loch 2004). Unlike prior research that focuses on the development of entirely new products or designs, we explore the series of activities performed by app developers after the initial launch of the product. Such updates can help preserve the product’s core features while simultaneously generating new value for the consumers (Kim and Kogut 1996). In a sense, our setting is akin to “trial and error learning”, but involves incremental improvements to the same product as adjustments are made to the development process based on new information. In addition, while development cost is a major concern in the aforementioned literature, due to the digital and sequential nature of development in mobile apps, we are less concerned about the development cost and are more interested in the product’s appeal to prospective customers.

Mobile app firms release sequential app updates involving “rapid and sequential” reuse and recombination (Cohen and Lemley 2001) in which it is easy to have the entire product upgraded (as opposed to modular upgrades) at no additional cost to existing customers. Furthermore, since mobile apps tend to be stand-alone products, backward compatibility is minimized, unlike in the case of products such as cameras that consist of several components such as the main body and lenses.

Next, we next develop our hypotheses which seek to explore the nature and effects of different types of product development activities related to mobile apps. App developers can incorporate

previously unexplored features and attributes to make major improvements in the new versions (Katila and Chen 2008) which can be introduced with ease due to the relatively low development cost of mobile apps. In contrast to an update with minor improvements to existing features and functionality, the addition of new and novel attributes and functionality could be viewed as an “dissimilar” update. Given the ease of product development and low switching costs for the consumers of mobile apps, we posit that an increase in novelty through new attributes and dissimilar features would make the product more appealing and would lead to an increase in market performance.

Hypothesis 1 *The greater the update dissimilarity, the higher the app’s market performance.*

New and novel features in a mobile app can make it appealing for prospective customers. However, such features might also result in possible resistance and anxiety which might lead customers to delay or abandon their purchase (Castaño et al. 2008). Firms can reduce consumer anxiety about resistance toward new products by providing additional information and familiarizing customers with the product (Goering 1985, Heiman and Muller 1996). Through the new release notes that accompany new versions, mobile app firms not only communicate with their existing users, but more importantly, they also inform prospective customers about the features and attributes of their products and their latest updates. We propose that the anxiety and risk aversion of prospective customers would be particularly high for early versions of a new and innovative product. However, such concerns would be mitigated as the product gets more mature and hence more stable and dependable over time. We expect update dissimilarity to be particularly helpful for market success during the later stages of an app’s life cycle.

Hypothesis 2 *The relationship between update dissimilarity and an app’s market performance is positively moderated by the app’s maturity.*

While firms vary in the degree of use and reuse of their existing knowledge, they also vary in the way they explore other domains for new knowledge (Katila and Ahuja 2002). Recombination of different kinds of knowledge outside of a firm’s usual domain can enhance innovation (Fleming and Sorenson 2004) and produce novel ideas of high economic value (Ahuja and Lampert 2001). Overall, for a focal app, we expect that incorporating elements and features from other domains would enhance the market performance of the focal app through useful re-combinations of the knowledge gained (Jung and Lee 2016).

Hypothesis 3 *The greater the product update scope, the higher the app’s market performance.*

An important source of new product ideas and features is the product market itself (Köhler et al. 2012). Market-driven knowledge, such as the knowledge of competitor activity, is embodied in the products and services that are available in the market. The convenience of inspecting competitor apps to identify features that are worth imitating and a weak IP regime makes the mobile app setting suitable for firms to be responsive to market changes. Furthermore, the value of imitation increases in dynamic “high velocity” environments (Brown and Eisenhardt 1995) where industry the structure is unclear, there are no dominant models of success, and there is a constant flux of firms and products. Indeed, such environmental uncertainty has been suggested to be conducive for the efficacy of imitation (Ross and Sharapov 2015). Moreover, customers of mobile apps face low switching costs due to the ease of comparing apps and substituting apps due to relatively low prices. We expect app developers that actively pursue market driven updates and incorporate competitors’ recent attributes and features into their own products to exhibit greater performance.

Hypothesis 4 *The greater the market-orientation of the update, the higher the app’s market performance.*

While market orientation might help drive performance, the timing of such updates can also be important. Timing has been highlighted as a critical decision in introducing new product attributes, especially for technology products (Gjerde et al. 2002, Jain and Ramdas 2005). On the one hand, by delaying an update, the firm can learn more about innovations introduced by competitors and can ensure high quality implementation (Ethiraj and Zhu 2008). In dynamic environments where product features constantly evolve and market response might be uncertain, it might seem sensible to delay market oriented features until the uncertainty is resolved. On the other hand, because competitor knowledge can quickly lose its value, speed might matter. Indeed, slow incorporation of competitor knowledge was found to deteriorate innovation performance in the R&D activities of robotics firms and optical disc firms (Katila 2002, Rosenkopf and Nerkar 2001). In sum, the existing literature offers a mixed view. By rapidly updating a mobile app, a firm might avoid the risk of losing market opportunity and lagging behind competitors. In contrast, a rapid update might result in a rushed and possibly inadequate product which might limit the value generated by market orientation. We therefore present two competing hypotheses:

Hypothesis 5a *The relationship between market orientation and the app’s market performance is negatively moderated by a rapid update.*

Hypothesis 5b *The relationship between market orientation and the app’s market performance is positively moderated by a rapid update.*

3. Data and Empirical Approach

Our sample consists of data from 588 mobile applications in the ‘Productivity’ category that appear in the top 500 Paid apps list for the iPhone in the US Apple App Store⁴. We observed these apps weekly over 23 months, from January, 2013 through November, 2014. There are two types of data available for apps- 1) static data that typically does not change over time such as the app name, category, and pp publisher name; and 2) dynamic data that changes over time such as the app rank, version description, price, and ratings. Since Apple only displays data for the most recent update of apps, we obtain historical data on daily ranks over our observation period from a mobile analytics firm. We included apps that have two or more version updates in the observation period because we would need two or more updates within the observation period to leverage the panel structure for estimation. While our study focuses on the top 500 paid apps, some of these apps naturally dropped from the top 500 list at times and others entered the list (which is why our final sample consists of 588 apps). For those apps that dropped from the top 500, if they remained within rank 1500, we are still able to retain them in our sample because we could estimate their sales (downloads) from the actual rank data that we obtained for them (within 1500) from the analytics firm with which we collaborated. However, the small number of apps that dropped beyond 1500 were excluded from our study as we had no rank information⁵. Apart from the paid model, freemium is also a popular monetization strategy that relies on an ad-supported model. For consistency, we chose to focus only on *paid* apps rather than *free* apps because additional or premium functionality in free apps is charged via in-app purchases and free apps heavily rely on advertising for revenue generation. These additional features are otherwise typically accessible for paid apps.

Productivity apps are a suite of apps aimed at enhancing an individual’s productivity in life and work. There are various sub-categories within the productivity category, such as note-taking, calendar, organizer and password management, pomodoro apps, and so on. Examples of some popular productivity apps include Scanner Pro and WunderList (Heath 2015). A WordCloud depicting the most frequently used words across all the app descriptions in our sample is given

⁴ Like in many other online marketplaces, the mobile app market exhibits a power law distribution where a large portion of sales is generated by a small fraction of top ranked apps (Wang et al. 2016, Zhong and Michahelles 2013).

⁵ The total number of apps that dropped below 1500 in the sample was 33.

in Online Appendix A.5. We chose the Productivity category because of the utilitarian nature of the apps in this category (in contrast to the hedonic nature of apps in the gaming category, for example). Productivity is also a fairly good representative of utilitarian app categories in terms of the nature of underlying product development activities and customer dynamics. Our semi-structured interviews with five developers in five categories including Health and Fitness, Productivity, Business, Wearables and Graphics & Design revealed that a similar set of product development activities takes place across these categories including iterative development, transparent product design, competitor observation, and the use of release notes to communicate product updates to customers. The interviews also revealed broadly similar customer dynamics across categories in terms of purchase decisions. (See the Online Appendix D for the details of the interviews including the main excerpts and emerging themes.) We would expect that within the Productivity category, features would be utilitarian and a common vocabulary would be shared across firms. Indeed, we find that features across apps tend to use similar terminology, such as “Dropbox support”, “organizer”, and “password manager”. In categories such as gaming, on the other hand, developers tend to use self-generated creative names for features, which would have made it difficult to find a common feature vocabulary for our study.

3.1. App purchase process

Given the utilitarian nature of Productivity apps, we expect their purchase to be driven largely by “need”, which is different from the case of consumption of hedonic apps such as games. When making a purchase decision for a particular product category, prospective customers typically look at a small set of competing products that they consider seriously, which is known in the literature as the “consideration set” (Armstrong et al. 2014). A consideration set typically involves 3-5 products that remain after a person has narrowed down their choice based on personal screening criteria. We expect that for a digital product such as a mobile app, after identifying the need (e.g., a note taking app), a prospective customer would filter available alternatives and undertake a detailed analysis of the reduced (consideration) set before making a final decision (Roberts and Lattin 1991). Prospective customers browse through the overall description and other attributes of the app (e.g., previous download numbers, rating, price, etc.) that are readily available, and review the descriptions of multiple competing products to get a sense of the state-of-art product offering. Such information is provided in an app’s update release notes with the latest changes and features. (For general background on the app purchasing process see Online Appendix C).

3.2. Main variables of interest

We provide a brief description of our variables in Table 4 in the Online Appendix F.

Dependent Variable: Our dependent variable is the sales performance of the apps as measured by *Downloads*, the log of estimated weekly download volume⁶ for the mobile apps. Although download volume data is not publicly available in the App Store, rank information based on product downloads (sales) is released publicly. Apple releases sales rank information for the top few hundred apps in each category. Following the work of Goolsbee and Chevalier (2003) and Brynjolfsson et al. (2003), we assume that the relationship between sales rank and sales volume follows a Pareto distribution. This relationship has been shown to hold in various settings such as books, software, and electronics where sales volume information is not reported publicly, but rank information is available. Furthermore, Garg and Telang (2013) provide a methodology to calibrate the relationship between daily app download volume and app download rank. Based on their approach, we calibrate the relationship between the sales rank and download volume in our study using the actual sales data that we obtained from a select group of developers. By contacting developers and using their actual rank and download data, we were able to calibrate the scale and shape parameters of the distribution⁷ Based on the estimates of the parameters of the Pareto distribution, we infer the sales (i.e., download) quantities of the apps over time⁸. This strategy is very similar to the one employed by Ghose and Han (2014).

Independent Variables: The three main independent variables are *UpdateDissimilarity* (H1, H2), *UpdateScope* (H3), and *MarketOrientation* (H4, H5). We discuss the operationalization of each of our key independent variables in the next section.

Control Variables: Sales performance can be affected by several app-specific characteristics. In addition to including app fixed effects, we include the following control variables in our model:

Price: Given that changes in the price of apps can affect consumers' purchase decisions, which in turn would affect downloads, we control for the price of an app in a given week.

AgeofApp: This variable controls for the endogenous time effects of an app's survival in the market, and is measured as the number of weeks elapsed since the app's initial release.

⁶ We also conducted robustness analysis by logging independent variables such as Price, Age, Timesincelastversion, etc. and found no qualitative change in the results.

⁷ We obtained actual rank and corresponding purchase data from seven different developers at different points in time to successfully calibrate our estimates. Consistent with the findings of Garg and Telang (2013), we estimate the shape parameter to be 1.04.

⁸ This includes new purchases only.

UpdateSize: The overall size⁹ of the app update could be expected to have an impact on app performance. We use an indicator *UpdateSize* which takes on the value of 1 if the size of the focal update, operationalized as the total count of words in the update, is greater than the mean size of its previous updates.

NumRetrospective: This variable is a measure for the number of retrospective activities in the app update. This essentially captures the corrective maintenance (bug-fixing) changes, which can affect an app’s market performance.

TimeSinceLastVersion: We also control for the time since an app update was last made. For this we use, *TimeSinceLastVersion*, which is a count of the number of weeks since the last app update was released.

Rating: We also control for the app’s overall review rating from user reviews from the previous week because this can influence a prospective customer’s decision to purchase the app.

RapidUpdate: This is an indicator variable that captures whether the app update is introduced rapidly or not in comparison to the updates of its competitors. In order to operationalize this, we first calculate the release frequency (based on *TimeSinceLastVersion*) of all the version updates of the focal app’s competitor group. We then create an indicator variable that is equal to 1 if the focal app’s update is in the top quartile of its competitor group. Since we are not interested in the specific release time of a version update per se (which is noisy because it is influenced by many external factors), we try to identify whether an update was released rapidly or not in comparison to the competitors’ updates (because we are primarily interested in the moderating effect of *RapidUpdate*), and operationalize this as a discrete variable rather than a continuous variable.

HasUpdate: This controls for the effect of an update on the performance in a particular week.

VersionsTillNow: This is a proxy for the degree of maturity of the app operationalized as the number of distinct versions of an app since its initial release.

3.3. Operationalization of Independent Variables

It is a standard practice in the software industry to distribute ‘release notes’ with every new software update to summarize the nature of changes that are made in that particular version which is found to be an accurate indicator of the activities at the underlying software level (Baysal and Malton 2007, Yu 2009). We employ text-mining and information retrieval techniques to study the rich information in the release notes of apps. Text mining is the process of extracting

⁹ The actual size of updates in bytes is not known, therefore, we use the the number of words in the update as a proxy.

information of value from unstructured or semi-structured text such as descriptions or comments. It involves collecting data in a parse-able format, pre-processing (to remove noise), extracting the items of interest and analytics (i.e., modeling) (Fan et al. 2006).

Following the software engineering literature, we call the keywords related to software maintenance activities (bug-fixing) as ‘maintenance’ or ‘retrospective’ keywords and the keywords related to new features and functionality as ‘prospective’ keywords (Yu 2009). Examples of maintenance keywords are terms such as “bug”, “fix”, “error”, and “crash”, while terms such as “improve”, and “feature” (see Appendix A.4) are prospective keywords¹⁰. More details on text analysis are included in Appendix B. While there would be heterogeneity in the level of detail used by firms to describe their changes, we assume that for the same firm, the reporting style would remain consistent over time.

3.3.1. Operationalization of Update Dissimilarity: We have historical version update data for each app in our dataset from the time the app was initially released (i.e. prior to the observation period). Our analysis is based on the idea that new functionality and attributes (prospective changes) will introduce new terminology that would not have appeared in previous updates. In contrast, improvements to existing features would re-use terminology that was previously used. One of the simplest and intuitive measures of similarity between documents is the Jaccard index, which measures document similarity as the intersection divided by the union of the objects (Huang 2008). The Jaccard distance measured as 1 minus the Jaccard index in Equation 1, is our measure for *UpdateDissimilarity*.

$$\text{UpdateDissimilarity} = 1 - \frac{|X \cap Y|}{|X \cup Y|} \quad (1)$$

where X is the set of words used in the current update and Y is the set of words in the previous updates of the app.

3.3.2. Identifying Sub-Categories Using Topic Modeling: To operationalize Market Orientation in the next section, we first need to identify the sub-categories of apps (in which the apps compete with one another) within the ‘Productivity’ category. Since no such classification existed at the time of collecting this data, we employ a topic modeling approach or Latent Dirichlet Allocation (LDA) (Blei et al. 2003) to determine the sub-categories of productivity apps. Using this approach, we arrive at 15 sub-categories^{11 12} We have used a majority rule

¹⁰ After the initial classification of changes into prospective and retrospective, we filter commonly occurring words such as “feature” as mentioned below and in Appendix B

¹¹ For robustness, we do sub-sample analysis on apps that have a single topic with 50 percent or more assigned weight, see Table 5, Columns 5-7 of Online Appendix F.

¹² The Silhouette coefficient is 0.46.

to assign a topic (category) to an app. Each topic is labeled with representative words such as password/security management, calendar, goal/habit tracking, note-taking, file transfer, and timer apps. A list of keywords associated with the topics and the full set of topics are given in Online Appendix A.6. Our identified topics are qualitatively similar to those listed by Sensor Tower (Kimura 2014), a mobile analytics company.

3.3.3. Operationalization of Update Scope: To measure the scope of an app update in Hypothesis 3, we assess the extent to which there was variety in an app update in the form of discriminating keywords from other domains. For this, we use an entropy based measure of diversity (Harrison and Klein 2007) given in Equation 2 to operationalize *UpdateScope*.

$$\text{UpdateScope} = - \sum_{i=1}^K p_i \times \ln(p_i) \quad (2)$$

where p_i is the weight of topic i . Updates in which topics are spread evenly across a greater number of clusters will have a higher value of *UpdateScope*.

3.3.4. Operationalization of Market Orientation: To capture similarity between a focal firm’s update and the updates of its competitors, we use a keyword similarity approach, following Criscuolo et al. (2007), Haas and Criscuolo (2015). Since apps in the Productivity category are utilitarian in nature, a common vocabulary to describe features such as “dropbox support” and “retina display” would be prevalent. Our similarity measure captures how similar the keywords in the focal firm’s update are to the keywords used by its competitors in the period between the focal firm’s current update and its last update.

For each competitor category, we first construct an App-by-Keyword asymmetric matrix X where element $ij = 1$ if app i has keyword j . From the content of all the apps in our sample, we extracted keywords excluding stopwords. We construct a keyword-by-keyword matrix, K , the ij th cell of which is a measure of similarity between keywords i and j . We use the Salton cosine metric in Equation 3 to measure the similarity between keywords. The numerator denotes the co-occurrence of each pair of keywords in the focal firm’s update and the update of the competitor, and the denominator is the product of the square root of the respective frequencies of the two keywords across all the updates. In essence, pairs of keywords that co-occur frequently would have similarity closer to 1, while keywords that rarely co-occur would have a value close to 0. The ij th element of the App-by-App matrix is the similarity between keywords in app i ’s change and in app j ’s change. Each ij th element is divided by the product of the total number of keywords in app i ’s change and in app j ’s change. From this, we derive the average similarity between App i ’s current update and the updates made by all other competitors since app i ’s

last update, as given in Equation 4. A focal firm’s update that contains keyword combinations that are similar, on average, to those keyword combinations in competitor changes will have a higher average similarity score. We define this as *MarketOrientation*. (See Online Appendix A.3 for more details.)

$$\text{cosine}(i,j) = \frac{\text{cooccurrence}(i,j)}{\sqrt{\text{occurrence}(i) \times \text{occurrence}(j)}} \quad (3)$$

$$\text{MarketOrientation}_i = \frac{\sum_{j=1}^J \frac{q_{ij}}{kw_i \times kw_j}}{J} \quad (4)$$

4. Results

The correlations between the variables are reported in Table 1 and the descriptive statistics are reported in Table 2¹³. We log-transform our dependent variable, the weekly downloads, because this variable is highly skewed (Afifi and Clark 1999).

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Log(downloads)	1												
Price	-0.11	1											
AgeofApp	0.05	0.16	1										
TimeSinceLastVersion	-0.11	0.00	0.23	1									
NumRetrospective	0.05	0.01	-0.05	-0.06	1								
MarketOrientation	0.04	0.00	-0.05	0.00	0.44	1							
UpdateDissimilarity	0.02	-0.01	-0.16	-0.03	0.27	0.42	1						
UpdateScope	0.04	0.01	-0.02	-0.04	0.29	0.38	0.19	1					
VersionsTillNow	0.14	0.19	0.62	-0.16	0.05	0.03	-0.12	0.06	1				
Rating	0.10	0.00	0.04	-0.09	0.01	0.02	0.00	0.02	0.11	1			
RapidUpdate	0.10	0.01	-0.15	-0.44	0.08	0.01	0.06	0.05	0.10	0.05	1		
HasUpdate	0.05	0.01	-0.08	-0.07	0.54	0.83	0.46	0.47	0.05	0.02	0.09	1	
UpdateSize	0.04	-0.01	-0.03	0.05	0.09	0.13	0.08	0.08	-0.04	0.03	0.02	0.16	1

Table 1 Correlations matrix, N = 49114, unit of observation is appid-week

4.1. Estimation Strategy: Dynamic Panel analysis

Our data consists of an unbalanced¹⁴ panel of the weekly data of the firms’ market performance (i.e., downloads) and co-variates outlined earlier. Because the performance of an app in one week would be highly correlated with its performance in the previous week, we estimate a dynamic autoregressive model in the Equation 5:

¹³ We find 8 instances of an app having price of 0. This can happen if the app changed from paid to free for that week.

¹⁴ Our panel is unbalanced because app launch times are different. Some apps were launched before the start of our observation period, and some apps were released during our observation period.

Variable	Mean	Std. Dev	Min	Max
Log(downloads)	7.09	1.29	3.96	12.8
Price	4.26	4.9	0	99.99
AgeofApp	114	68	0	331
TimeSinceLastVersion	16	19	0	213
NumRetrospective	0.08	0.55	0	21
UpdateDissimilarity	0.06	0.24	0	1
MarketOrientation	0.017	0.076	0	0.76
UpdateScope	0.14	0.46	0	2.19
NewWords	0.5	3.5	0	175
RapidUpdate	0.28	0.45	0	1
VersionsTillNow	13.8	9.27	1	57
Rating	3.63	1.5	1	5
UpdateSize	0.08	0.28	0	1
HasUpdate	.06	.25	0	1

Table 2 Descriptive Statistics for all App firms, N = 49,114, unit of observation is appid-week

$$Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \beta_2 X_{it} + \beta_3 \delta_i + \beta_4 \gamma_{it} + \epsilon_{it} \quad (5)$$

$$\Delta Y_{it} = \beta_1 \Delta Y_{it-1} + \beta_2 \Delta X_{it} + \beta_4 \Delta \gamma_{it} + \Delta \epsilon_{it} \quad (6)$$

where Y_{it} is the log of aggregated weekly downloads of app i in week t and Y_{it-1} is the log of aggregated weekly downloads of the same app in the previous week. X_{it} is a set of our covariates, δ_i is the app fixed effect, γ_{it} is the set of controls and ϵ_{it} is the error term. Included in X_{it} are our variables of interest, namely, *UpdateDissimilarity*, *UpdateScope* and *MarketOrientation*. Any seasonal variation is also controlled for using weekly time dummies. We also add controls for the age of the app and its squared value, time since the last update and its squared value, size of the update, and the number of retrospective changes. We also include a dummy, *HasUpdate*, that captures whether or not there is an update in a particular week to discern the effects of updating on app performance.

In an autoregressive model such as ours, the inclusion of the lagged dependent variable might give rise to biased estimates and lead to endogeneity concerns. Standard OLS estimates of the lagged dependent variables in a dynamic panel are biased and inconsistent due to the correlation between the individual fixed effect and the lagged dependent variable (Nickell 1981). This bias is not caused by an autocorrelated error process ϵ , but arises even if the error process is iid. Furthermore, the lagged dependent variable y_{it-1} is mechanically correlated with the ϵ_i for time period $s < t$, such that the standard fixed effects estimator is also biased (Wooldridge 2010). Anderson and Hsiao (1981) were the first to demonstrate that the issue with the within estimator can be solved by differencing to eliminate unobserved effects. As differencing shown in Equation

6 induces a correlation with the error term and the lagged dependent variable, instrumental variables in the form of the differences of the lagged dependent variable, such as ΔY_{it-2} , can be constructed in order to obtain unbiased estimates. Dynamic panel estimators based on the lagged instruments have been widely used in recent economics and management research to address similar endogeneity concerns, see for example Suarez et al. (2013), Acemoglu et al. (2008), Bhargava and Mishra (2014). Therefore, we opt for the Anderson-Hsiao estimator in a 2SLS procedure which is based on the first-differencing approach to instrumental variables in a GMM framework. This is due to certain characteristics of our sample: 1) the need to control for fixed app-level effects, 2) a linear functional relationship between the outcome variable and regressors, and 3) a dynamic outcome variable (current performance depends on its own past realizations).

Table 3 summarizes the results for our dynamic panel estimation. Although the use of a dynamic panel estimator is more appropriate for estimation due to the inclusion of lags in our model, we also replicate the analysis with simpler estimators such as OLS and Fixed effects.

We expected corrective maintenance activities to impact performance, for which we added a control *NumRetrospective*. Furthermore, an increase in price is expected to have a negative impact on downloads which is confirmed by the negative and significant coefficient of *Price*. Each of the regressions includes an indicator variable, *HasUpdate*, which is set to 1 for weeks when there was an update.

In H1, we proposed that the greater the *UpdateDissimilarity* with respect to the firm's past activities, the higher the performance. To test this, we examined the coefficient of *UpdateDissimilarity* with the OLS, Fixed Effects and Anderson Hsiao estimators in Table 3. We find partial support for H1 with a positive and significant coefficient across Columns 1-2 with the OLS and Fixed effects estimators. In terms of the magnitude of the effect, a one unit increase in the update dissimilarity results in a 15% increase in estimated downloads ($\beta * 100$).

We find that the app's maturity is positively associated with market performance, as indicated by the positive and significant coefficient on *VersionsTillNow*. In H2, we proposed that the app's maturity, operationalized as *VersionsTillNow*, positively moderates the relationship between *Update Dissimilarity* and an app's market performance. We find support for this in Columns 4-5 with the positive and significant coefficient on the interaction term *UpdateDissimilarity x VersionsTillNow* in Table 3. Update dissimilarity is indeed particularly helpful for market success during the later stages of an app's life cycle.

In H3, we proposed that greater *UpdateScope* would be associated with higher performance. We do not, however, find support for this hypothesis with any of the estimators (Columns 1-12).

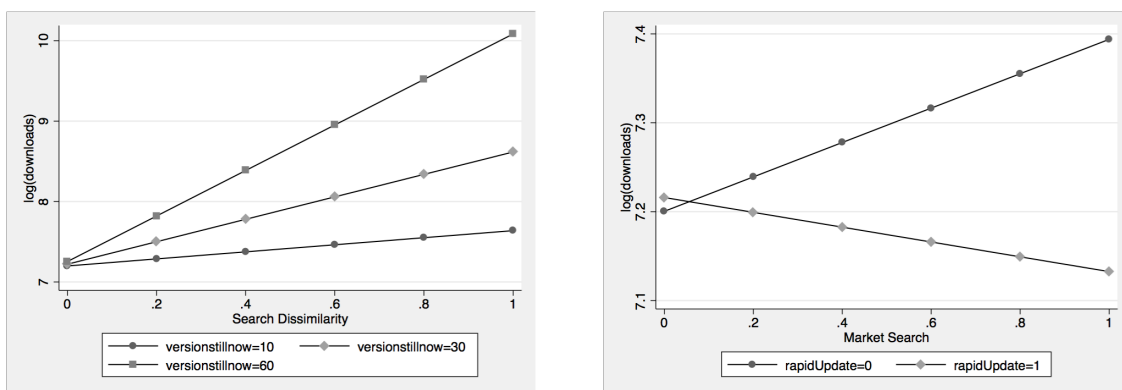
Table 3

Variables	Dependent Variable = Performance in log(downloads)											
	OLS (1)	FE (2)	A-H (3)	OLS (4)	FE (5)	A-H (6)	OLS (7)	FE (8)	A-H (9)	OLS (10)	FE (11)	A-H (12)
log(Downloads) _{t-1}	0.5009** (0.0088)	0.3943** (0.0111)	0.4287+ (0.2451)	0.5009** (0.0088)	0.3943** (0.0111)	0.4342+ (0.2457)	0.5010** (0.0088)	0.3944** (0.0111)	0.4230+ (0.2449)	0.5010** (0.0088)	0.3944** (0.0111)	0.4288+ (0.2455)
Price	-0.0034** (0.0008)	-0.0402** (0.0081)	-0.1833** (0.0239)	-0.0034** (0.0008)	-0.0402** (0.0081)	-0.1833** (0.0238)	-0.0034** (0.0008)	-0.0402** (0.0081)	-0.1829** (0.0238)	-0.0034** (0.0008)	-0.0402** (0.0081)	-0.1829** (0.0238)
AgeOfApp	0.0003+ (0.0002)	0.1360** (0.0473)	0.0000 (0.0001)	0.0002 (0.0002)	0.1369** (0.0474)	0.0000 (0.0001)	0.0003+ (0.0002)	0.1356** (0.0474)	0.0000 (0.0001)	0.0002 (0.0002)	0.1365** (0.0474)	0.0000 (0.0001)
Age_sq	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)
TimeSinceLastVersion	-0.0007** (0.0002)	-0.0013** (0.0005)	-0.0019* (0.0008)	-0.0007** (0.0002)	-0.0013** (0.0005)	-0.0018* (0.0008)	-0.0007** (0.0002)	-0.0013** (0.0005)	-0.0023** (0.0008)	-0.0007** (0.0002)	-0.0013** (0.0005)	-0.0022** (0.0008)
UpdateScope	-0.0002 (0.0011)	-0.0001 (0.0008)	0.0004 (0.0005)	-0.0008 (0.0012)	-0.0007 (0.0008)	-0.0002 (0.0005)	-0.0001 (0.0011)	0.0000 (0.0008)	0.0004 (0.0005)	-0.0007 (0.0012)	-0.0006 (0.0008)	-0.0002 (0.0006)
HasUpdate	-0.0048 (0.0220)	-0.0054 (0.0226)	-0.0364+ (0.0208)	-0.0222 (0.0244)	-0.0226 (0.0245)	-0.0507* (0.0219)	0.0020 (0.0223)	0.0022 (0.0229)	-0.0268 (0.0210)	-0.0147 (0.0247)	-0.0143 (0.0248)	-0.0414+ (0.0222)
UpdateDissimilarity	0.1227+ (0.0662)	0.1599* (0.0627)	0.0764 (0.0651)	-0.0397 (0.0886)	-0.0045 (0.0794)	-0.0745 (0.0802)	0.1177+ (0.0657)	0.1553* (0.0624)	0.0661 (0.0649)	-0.0309 (0.0882)	0.0053 (0.0790)	-0.0759 (0.0802)
MarketOrientation	0.1375* (0.0678)	0.1315* (0.0638)	0.1578* (0.0644)	0.1179+ (0.0658)	0.1104+ (0.0623)	0.1382* (0.0636)	0.1768* (0.0704)	0.1731** (0.0660)	0.1968** (0.0669)	0.1543* (0.0676)	0.1491* (0.0639)	0.1743** (0.0658)
RapidUpdate	0.0015 (0.0063)	0.0054 (0.0071)	0.0039 (0.0128)	0.0024 (0.0062)	0.0064 (0.0071)	0.0050 (0.0129)	0.0058 (0.0063)	0.0096 (0.0072)	0.0104 (0.0131)	0.0061 (0.0063)	0.0101 (0.0072)	0.0108 (0.0131)
NumRetrospective	-0.0060 (0.0050)	-0.0047 (0.0051)	-0.0035 (0.0042)	-0.0059 (0.0050)	-0.0045 (0.0050)	-0.0035 (0.0043)	-0.0039 (0.0050)	-0.0024 (0.0050)	-0.0023 (0.0042)	-0.0040 (0.0050)	-0.0025 (0.0050)	-0.0024 (0.0043)
UpdateSize	0.0080 (0.0059)	-0.0171 (0.0193)	0.0039 (0.0183)	0.0080 (0.0059)	-0.0187 (0.0192)	0.0027 (0.0182)	0.0080 (0.0059)	-0.0200 (0.0194)	0.0034 (0.0182)	0.0079 (0.0059)	-0.0212 (0.0193)	0.0024 (0.0181)
VersionsTIIINow	0.0010* (0.0004)	0.0069** (0.0020)	0.0183 (0.0133)	0.0009* (0.0004)	0.0070** (0.0020)	0.0197 (0.0134)	0.0010* (0.0004)	0.0068** (0.0020)	0.0146 (0.0134)	0.0009* (0.0004)	0.0069** (0.0020)	0.0163 (0.0135)
Rating	0.0101** (0.0014)	0.0145** (0.0022)	0.0025 (0.0032)	0.0102** (0.0014)	0.0145** (0.0022)	0.0027 (0.0032)	0.0101** (0.0014)	0.0144** (0.0022)	0.0025 (0.0032)	0.0101** (0.0014)	0.0145** (0.0022)	0.0027 (0.0032)
Time_sq	0.0000** (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)	0.0000** (0.0000)	0.0000* (0.0000)	0.0000 (0.0000)
UpdateDissimilarity X VersionsTIIINow				0.0475* (0.0215)	0.0485* (0.0198)						0.0436* (0.0214)	0.0392** (0.0136)
MarketOrientation X RapidUpdate												
Intercept	0.3158** (0.0378)	-20.0337** (7.7156)	-0.0279 (0.0242)	0.3086** (0.0462)	-20.1929** (7.7211)	-0.0283 (0.0243)	0.3065** (0.0460)	-19.9780** (7.7205)	-0.0269 (0.0241)	0.3076** (0.0461)	-20.1300** (7.7248)	-0.0274 (0.0242)
Week Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
App Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	44005	44005	41716	44005	44005	41716	44005	44005	41716	44005	44005	41716
R ²	0.8425	0.8571		0.8425	0.8571		0.8425	0.8571		0.8426	0.8571	

ⁱ Notes: Standard errors are clustered at the app-level. ^a

ⁱⁱ **p < 0.01, *p < 0.05, +p < 0.1

^a Clustering standard errors at firm level does not change the main results



(a) Interaction plot between VersionsTillNow and Update Dissimilarity

(b) Interaction plot between RapidUpdate and MarketOrientation

Figure 1 Interaction plots

While update scope has been found to affect innovation and market performance positively in the extant product development literature, this finding appears to not hold in our rapid sequential innovation setting. We discuss this result along with our main findings in Section 6.

In H4, we proposed that the higher the *MarketOrientation*, the higher the market performance. Estimates from the OLS, Fixed Effects and Anderson-Hsiao estimator are presented in Columns 1-3. We find a positive and significant effect of *MarketOrientation* on app performance. This suggests that closely following and incorporating competitors' recent features and attributes into one's own products is associated with increased market success. In terms of magnitude, a one unit increase in *MarketOrientation* results in a roughly 13% increase in estimated downloads ($\beta * 100$). For H5, we find that the coefficient on the interaction term *MarketOrientation* \times *RapidUpdate* estimates in Columns 7-9 in Table 3 is negative and significant. That is, our results indicate that a rapid update dampens the positive relationship between market orientation and performance.

Figure 1a graphs the margins plot for the interaction of *Update Dissimilarity* and *Version-sTillNow*, and shows that the slope gets steeper as the product matures, implying that greater benefits are accrued from dissimilar updates as the product matures. Figure 1b graphs the margins plot for the interaction of *MarketOrientation* and *RapidUpdate*, and shows that the slope is positive when *RapidUpdate* is 0, whereas the slope is negative when *RapidUpdate* is 1, implying that firms that do not update rapidly derive greater benefits from market orientation, all else being equal.

We have controlled for immediate past performance by including the lagged dependent variable in our models. For performance in the subsequent period, we only look at the effects of the

main variables *UpdateDissimilarity* and *MarketOrientation* that are not already explained by the lagged performance, and find these to be significant. The estimates of the lagged dependent variable from OLS and the Fixed-effects estimator can be used as bounds for the true parameters to assess the validity of the Anderson-Hsiao estimator. The OLS estimate is expected to be positively correlated with the error term, resulting in an upward bias. On the other hand, the lagged dependent variable should be negatively related to the error term in a Fixed-effects estimator, biasing the coefficient downward (Roodman 2009, Bond 2002). In other words, if the Anderson Hsiao model is valid, the coefficient on the lagged dependent variable from FE should be a lower bound, and the coefficient of the OLS regression should be an upper bound. The Anderson-Hsiao estimate for the coefficient of the lagged dependent variable across the different models is indeed within the credible range. For example, the OLS and FE estimates for the lagged dependent variable are in the range of 0.50 and 0.39. This supports the validity of our estimation strategy. Finally, in Columns 10-12, we add the fully interacted models for OLS, Fixed effects and Anderson-Hsiao estimators, and find that our results are consistent with the non-interacted estimators in the previous columns.

4.2. Possible Endogeneity of Market Orientation: Instrumental variable analysis

Our previous dynamic panel estimation included app fixed effects to account for time-invariant unobservable app characteristics. However, time-varying unobservables might be correlated with market orientation and market performance. Hence, they might bias the results. To address potential endogeneity concerns, we use the release of iCloud Drive in 2014 as a technology shock to our main variable of interest *Market Orientation*. iCloud Drive, Apple’s cross-platform file hosting platform and app, allows users to store any type of file and access the file on any compatible device. While Google and Microsoft both had complete document creation and collaboration suites, and Dropbox had a competitive cloud storage service, Apple lagged in a complete document creation and collaboration suite (Apple introduced its own document creation suite called iWork in 2013 but lacked a competitive cloud storage service such as Google Drive or SkyDrive). Through iCloud Drive, Apple expanded its capabilities in Cloud services by allowing seamless synchronization of changes to documents across multiple devices while also making changes accessible through multiple apps. Our extensive study of the mobile app setting and the institutional details allowed us to use the introduction of iCloud Drive as a plausible instrument and to support exclusion restriction. iCloud Drive was introduced by the platform (i.e., Apple) and not by the app developers. However, app developers were affected by it because a key feature of iCloud Drive was that users can access files from other apps “as long as app developers

have integrated it in their apps” (Shaik 2014). On the other hand, because iCloud Drive is a complementing service provided by the App Store to simply support existing mobile apps (the apps’ core functionality remain unchanged), we believe it is unlikely that customers will start making a new app purchase just because iCloud Drive has been introduced. One might also argue that the introduction of iCloud Drive could affect app purchases through other channels because of its effect on the size of an update or possibly by generating new bugs and issues in the apps. We already accounted for these possible paths by controlling for update size and corrective maintenance (bug-fixing) changes in our models. We define our first instrument, *iCloudDrive* as an indicator variable that is turned on during the 8 weeks after the release of iCloudDrive.

Using multiple IVs improves the efficiency of the estimation (Wooldridge 2010). Therefore, we also identify a Hausman-style instrument. With the transparent development environment, app developers are likely to be influenced not just by other developers in their own category, but also by the developments in other categories. Building on this, we make use of the average-market oriented update in all other categories as an instrument to focal market-oriented update. The rationale is that while market-oriented update activity in other categories is likely to influence a developer’s update behavior (relevance criterion), such changes in other categories would have no direct effect on their sales in the focal category (exclusion restriction).

We implement the IV analysis in a parsimonious 2-stage estimation procedure (Wooldridge 2010) in Table 4. In Column 1 in 4, we show the first stage results of our 2SLS wherein we estimate *Market Orientation* using the *iCloudDrive* instrument and the Hausman style instrument, *OthersMarketOrientation*. As indicated, both of our instruments are significant in predicting Market Orientation. We also perform a number of underidentification and weak identification tests for our instruments (please see Online Appendix F for details), all of which confirm their validity. In the second stage, we use the estimated exogenous increase in Market Orientation to estimate its impact on market performance. In Column (2), we report the second-stage estimates examining the impact of instrumented Market Orientation on performance. Column (2) shows that Market Orientation has a positive influence on app performance ($\beta = 0.2393, p = 0.06, SE = 0.13$).

Next, to incorporate the interaction of Rapid Update and Market Orientation, we instrumented *MarketOrientation* and the interaction *MarketOrientation X RapidUpdate*, with both the iCloudDrive and Hausmann style instruments, and the interaction of the instrumental variables with RapidUpdate as outlined in (Wooldridge 2010). In Column 3 in Table 4, we show the first stage of our 2SLS wherein we instrument *Market Orientation* and the interaction *MarketOrientation X RapidUpdate* using the *iCloudDrive* instrument and the Hausman style instrument,

OthersMarketOrientation, and the interactions *iCloudDrive X RapidUpdate* and *OthersMarketOrientation X RapidUpdate*. For our instruments in the interaction model, we run a similar set of underidentification and weak identification tests (see Online Appendix F) which confirm their validity. Next, in Column 4, we instrument *MarketOrientation X RapidUpdate* with the *iCloudDrive* instrument and the Hausman style instrument, and the interactions *iCloudDrive X RapidUpdate* and *OthersMarketOrientation X RapidUpdate*. The results in Column 5 of Table 4 supports our earlier findings in that the coefficient of the interaction term *MarketOrientation X RapidUpdate* is negative and significant suggesting that a rapid update reduces the positive effect of market orientation on market performance.

4.3. Robustness Analysis

In our dynamic panel models, we test for serial correlation in the errors over time with the Arellano-Bond Z-test. As expected by construction, the AR(1) test on differences reveals first-order serial correlation. However, the AR(2) test for serial correlation is not statistically significant ($p=0.14$) suggesting that serial correlation does not pose a significant threat to our findings. To address concerns of potential multi-collinearity in the analysis, we checked include the Variance Inflation factors and found none of the variables to have VIFs close to or larger than 10.

An alternative explanation for the effect of market-orientation could be that one firm might be an innovator in its sub-category and introduces new features, while others in the same category are imitators. In this case, the innovating firm's subsequent incremental updates might appear to be similar to the other apps' features due to overlapping terminology (as our approach hinges on textual similarity). As such, the innovator firm's own incremental changes might be incorrectly perceived as its market-orientation (i.e., imitation of other firms). In order to address this, in the models where we estimate the effect of market-orientation, we control for *UpdateDissimilarity*.

One could also argue that over time, an app's developers might improve app quality as they get better at understanding their market or implementing functionality in better ways, reducing defects, and marketing the product as the product matures. This could then improve market performance in a way that is not accounted for in our analysis. To investigate this, we regress the count of defects (*NumRetrospective*) on the number of versions thus far (*VersionsTillNow*) and find a U-shaped relationship between defect count and version count. We interpret this as follows: In the early stages of an app's life, we might expect more defects, as the app stabilizes gradually the defects reduce over time. However, in later stages there is an increase in defect count again. Since defect count increases in later stages, we can rule out improvement in handling defects

Table 4 Two-Stage Least Squares Regressions of Market Performance: Instrumental Variable Analysis

Dependent Variable	(1)	(2)	(3)	(4)	(5)
	1st stage <i>MarketOrientation</i>	2ndstage	1st stage <i>MarketOrientation</i>	1st stage <i>MarketOrientationXRapidUpdate</i>	2nd stage
$\log(\text{downloads})_{t-1}$	0.0001 (0.0003)	0.5528** (0.0059)	-0.0000 (0.0003)	-0.0001 (0.0003)	0.5528** (0.0059)
Price	0.0001 (0.0001)	-0.0375** (0.0030)	0.0000 (0.0001)	-0.0002* (0.0001)	-0.0375** (0.0030)
AgeOfApp	-0.0040+ (0.0023)	0.1766** (0.0470)	-0.0038+ (0.0023)	-0.0025 (0.0016)	0.1753** (0.0470)
Age_sq	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-0.0000 (0.0000)	0.0000 (0.0000)
TimeSinceLastVersion	-0.0003** (0.0000)	-0.0016** (0.0004)	-0.0003** (0.0000)	0.0000 (0.0000)	-0.0016** (0.0004)
Time_sq	0.0000** (0.0000)	0.0000** (0.0000)	0.0000** (0.0000)	-0.0000 (0.0000)	0.0000** (0.0000)
UpdateScope	0.0020** (0.0003)	-0.0004 (0.0007)	0.0019** (0.0003)	0.0014** (0.0002)	0.0003 (0.0007)
UpdateDissimilarity	-0.0475** (0.0071)	0.2425** (0.0544)	-0.0565** (0.0075)	-0.0382** (0.0065)	0.2380** (0.0545)
RapidUpdate	0.0027** (0.0005)	0.0125+ (0.0068)	-0.0012* (0.0005)	0.0084** (0.0003)	0.0229** (0.0071)
NumRetrospective	0.0187** (0.0018)	-0.0052 (0.0061)	0.0164** (0.0017)	0.0107** (0.0012)	0.0034 (0.0058)
UpdateSize	0.0516** (0.0034)	-0.0169 (0.0204)	0.0537** (0.0033)	0.0273** (0.0024)	-0.0088 (0.0202)
VersionsTillNow	-0.0003* (0.0001)	0.0082** (0.0012)	-0.0002 (0.0001)	-0.0004** (0.0001)	0.0080** (0.0012)
Rating	-0.0001 (0.0001)	0.0155** (0.0019)	-0.0000 (0.0001)	0.0000 (0.0001)	0.0155** (0.0019)
MarketOrientation		0.2393+ (0.1323)			0.3467* (0.1502)
MarketOrientation X RapidUpdate					-0.5707** (0.1512)
<i>iCloudDrive X RapidUpdate</i>			-0.0098 (0.0135)	0.1216** (0.0107)	
<i>OthersMarketOrientation X RapidUpdate</i>			0.2477** (0.0208)	0.6062** (0.0194)	
<i>OthersMarketOrientation</i>	0.3000** (0.0110)		0.2478** (0.0114)	-0.0625** (0.0047)	
<i>iCloudDrive</i>	0.1122** (0.0067)		0.1136** (0.0080)	-0.0026 (0.0026)	
Week Dummies	Yes	Yes	Yes	Yes	Yes
R^2		0.3494			0.3496
F -statistic		111.0280			110.2938

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

as a potential explanation for the positive moderation effect we observe. In fact, we observe a positive moderating effect of later versions (i.e., an app’s maturity) on the relationship between update dissimilarity and market performance despite the increase in defects in the later versions. Going back to our proposed mechanisms based on consumer anxiety for new and novel features earlier, we contend that defects in this setting are not perceived as “product failures” as they are in traditional product development settings such as in the automotive industry. Instead, defects are likely to be viewed by customers as glitches that are resolvable in a relatively short span of time and they do not cause irreversible damage. That is, despite the increasing trend in defects, consumers would have greater confidence in the products at later stages, and therefore, would experience lower purchase related anxiety when they face new and novel features in a product.

It is worth noting that our sample in this study consists of top-performing apps (ranked between 1-1500). Therefore, we would be unable to observe cases where an app in our sample might imitate the features of a poorly performing app. While such an imitation might occur in our setting, it would make our current estimates for *MarketOrientation* more conservative.

Our dataset includes only paid apps. Conceptually, for paid apps, a download clearly corresponds to a new product sale because customers are likely to carefully evaluate a product before purchasing it. However, for free apps, it is harder to establish a direct connection between downloads and sales, as a customer can quickly and easily download a free app, before quickly uninstalling it. That is, while we think downloads is a good proxy for market (sales) performance in paid apps, it is less so for free apps. For the free apps, measures such as ad revenue or in app purchase frequency can be possible proxies for their market performance, but unfortunately this data is not available to us. One possibility is that an app might copy or mimic a ‘free’ app out of our existing sample. First, conceptually this would not change our conclusions for *UpdateDissimilarity* because this variable focuses on the extent to which an update is dissimilar to an app’s own previous features or attributes, and it is not concerned about the source of the new attribute (i.e., how or where it was acquired). Second, with regards to Market Orientation, similar to the previous point about the possible imitation of a poorly performing app, the presence of such imitation would likely increase the true effect size of *MarketOrientation*.

In addition, to ensure the robustness of our results for *UpdateDissimilarity*, we consider an alternative measure. One of the best-performing sentence novelty measures in the literature uses a simple measure that assigns a score based on the number of words a new document contains that have previously not appeared (Allan et al. 2003). This can be extended to document novelty, given by Equation 7 where W_{d_i} is the set of words in document d_i . We call this new variable *NewWords*.

$$\text{NewWords}(d_i|d_1, \dots, d_{i-1}) = |\text{W}_{d_i} \cap \overline{\bigcup_{j=1}^{i-1} \text{W}_{d_j}}| \quad (7)$$

The estimate of *NewWords* in Table 5 in the Online Appendix F, Column 1 is positive and significant consistent with that of *UpdateDissimilarity*, which further supports our second hypothesis. We attribute the difference in the magnitude of the two variables to their different levels of granularity of measurement. While *NewWords* is a raw measure of the number of new words in a new document, *UpdateDissimilarity* is based on the Jaccard similarity between two sets of words.

We also use an alternative measure for UpdateScope based on the Herfindahl–Hirschman Index in Equation 8.

$$\text{UpdateScopeHHI} = \sum_{i=1}^K p_i^2 \quad (8)$$

where p_i is the proportion of keywords in cluster i . The estimate of *UpdateScopeHHI* in Table 5 (Online Appendix F), Column 2 is insignificant. To ensure the robustness of our results pertaining to rapid updates, we introduce a continuous measure for speed of updating, *UpdateSpeed*, which is operationalized as the difference between the time since the app’s last update, *TimeSinceLastVersion* and the mean time of updating of rival apps in the same category. The positive and significant coefficient on the interaction term *MarketOrientation* \times *UpdateSpeed* in Column 3 of Table 5 (Online Appendix F) shows that the relative timing of the update compared to updates of rival apps positively moderates the relationship between *MarketOrientation* and performance. If a competitor introduces significant features to their apps, the focal firm might take time to incorporate these into their apps, and these changes might manifest in updates further down the road rather than in immediate updates. For robustness, we ran our analysis considering only large updates (i.e., those in the 3rd and 4th quartile of the update size distribution). We present the results of the fully interacted model in Column 4 of Table 5 (Online Appendix F). Our findings are consistent with those from our previous analyses.

Another concern for our analysis could be that our instrumental variables might not perfectly satisfy exclusion restriction. We conducted sensitivity analysis by adopting the plausibly exogenous estimation developed by (Conley et al. 2012) which assumes that the exclusion restriction does not hold precisely. Using this approach, we examine possible violations of the exclusion restriction that produces confidence intervals on the main coefficient at a chosen level of significance. We find that the second-stage estimate of the impact of market orientation on performance is bounded away from zero even when allowing for upto 30% violation of the exclusion restriction (i.e. the direct (endogenous) effect of the instrument on performance is not more than 30% of the

reduced form effect). Therefore, our sensitivity analysis indicates that the positive effect of market orientation on downloads remains robust even with sizable departures from strict exogeneity (for details of the sensitivity analyses, see Online Appendix E).

5. Limitations and Discussion

Based on our interviews we believe the Productivity category is a fairly good representative of utilitarian app categories in terms of the nature of underlying product development activities and customer dynamics. Thus, we expect our results in the Productivity category to be broadly generalizable to other utilitarian categories. However, future work could collect and use app data from multiple categories to confirm our findings. To gain a possibly more nuanced understanding of the product development activities across different categories, future work could also consider conducting large scale qualitative studies. Most online marketplaces, including the app market, have been found to display a power law distribution, where a large portion of sales is generated by a small fraction of high performing apps. The top 500 apps in our study represent the vast majority of the economic activity in the Productivity category. Minor, possibly experimental apps at the very tail of the sales distribution are not the focus of this study. As such, our focus on the top 500 apps might limit the generalizability of our findings to new upcoming or less popular apps, where the market dynamics might be different, or where developers might not frequently update their apps, or follow the competition so closely due to the poor performance.

Another limitation of our study is that, like in many other online markets, we are unable to directly obtain downloads (sales) data for the apps. Hence, we adopted the common approach of estimating weekly sales from the available rank data (Chevalier and Goolsbee 2003, Brynjolfsson et al. 2003, Garg and Telang 2013, Ghose and Han 2014) and then calibrated our estimates with the real rank and corresponding sales data obtained from several developers. While well-established, this approach relies on a particular functional form assumption as it assumes a linear relationship between the logarithm of app ranks and the logarithm of sales. Although this linear relationship (i.e., the power law distribution) has been consistently observed in various online markets such as books, electronics, software, and mobile apps (Wang et al. 2016, Zhong and Michahelles 2013), and our own field data from mobile app developers in the Productivity category confirms this relationship, the violation of this assumption might lead to possible measurement error in sales. However, if such a measurement error in the dependent variable is random (which is likely the case in our study which only uses top performing apps), it would not be a threat to our findings as it would just inflate the standard errors and bias against finding statistical relations (Hausman 2001, Cameron and Trivedi 2005). Nevertheless, despite the

difficulty due to the typically confidential nature of the sales data, future work could attempt to directly obtain sales data for apps, which would reduce measurement error and enable researchers to directly observe this important measure of market performance.

Another limitation of our study is that our original data is from a single app store, and the data was collected more than five years ago. We believe the essence and nature of product development activity as well as customers' app purchase are broadly consistent across different platforms and over time. Yet, as one of the first papers in this domain, we acknowledge that our paper has a limited scope and future research could examine whether and to what extent our findings would hold, for example, for the Android app market. One also has to be cautious with a strong causal interpretation of our results. In the absence of field experiments (which are difficult to implement in highly competitive and dynamic business settings such as mobile app development) or truly exogenous variation in product development strategies, we addressed our research questions and examined the relationship between various product development strategies and market performance by exploiting the longitudinal nature of our data set and making use of plausible instruments. Future work could explore the feasibility of field-experiments to study the market implications of sequential app development efforts.

Innovation has been characterized as a search process (Katz and Allen 1982, Clark and Fujimoto 1999, Cusumano and Nobeoka 1992, Iansiti 1998, Katila 2002) in the previous new product development literature. In our study, we are only able to observe the end-points of search that manifest as feature improvements and new feature introductions and not the search process itself ("adding a new feature" might be somewhat different from "searching" for a new feature). Future work could take up the search perspective of the product innovation process in mobile apps and by deeply engaging with the app developers in a field setting, researchers could examine how existing characterizations of the nature of search in product development (local search, distant search and search breadth) might be consequential for app market performance. Additionally, as an initial attempt to explore the link between app features and market success, the characterization of app update development in our paper is limited to the previous activities of firms and those of their competitors. We do not investigate particular reasons behind firms' update dissimilarity or their market-orientation. For instance, customers might play a role in influencing various product development strategies with their comments and feedback (e.g., "your competitor has added this feature, you should do it, too"). Future research could deepen our understanding by building on the current work and exploring the implications of such mechanisms.

6. Conclusion

While mobile apps have been around for many years, barring recent work such as (Allon et al. 2022), not much research has examined new product development for apps. In their review article on product development decisions, Krishnan and Ulrich (2001) observed that product development is highly contingent on market uncertainty and other environmental characteristics and called for new research to provide insights on customizing product development practices to diverse environments such as small entrepreneurial firms and varied industries. Responding to this call, our study investigated sequential product development and its market implications for the productivity apps in the mobile industry. Unlike traditional product development environments that have been studied (Sommer and Loch 2004, Sommer et al. 2009, Pich et al. 2002) where R&D activities are mostly kept secretive and revealed only upon product launch, in dynamic mobile apps setting, the activities of one’s immediate competitors are visible through updates. Moreover, unlike traditional NPD settings with multiple products and sufficient time between successive releases, in emerging hypercompetitive settings such as mobile apps, the typical firm is a resource-constrained startup with no established innovation processes where knowledge management activities change throughout the venture’s life (Gaimon and Bailey 2013). In such settings, it becomes even more critical to identify appropriate product development strategies to generate value and make products appealing to consumers. Our study sheds new light into this by identifying several product development strategies for mobile app developers to achieve greater market success. Our access to detailed longitudinal data and the use of text-mining and information-retrieval techniques allowed us to monitor and quantify both continuous development (i.e. product evolution) and the corresponding market performance of the mobile apps over the course of their sequential updates.

We find empirical evidence for the positive effects of (i) update dissimilarity i.e. dissimilarity between the contents of the focal firm’s update and the content of its previous updates and (ii) market orientation i.e. similarity between the focal firm’s update with respect to the recent updates of its competitors on market performance. Additionally, the functional maturity of an app positively moderates the relationship between update dissimilarity and market performance. Put differently, there are greater benefits accrued to introducing novel content at later stages, rather than in the early stages of the app’s life cycle. Thus, unlike the common emphasis on the advantages of early innovations and gains for the success of products, our study highlights the greater value potential of new and novel features during the later stages of an app’s life cycle where such features might no longer be perceived as risky by the prospective customers.

Moreover, we find that rapid update negatively moderates the relationship between market orientation and market performance, indicating that a rapid release dampens the potential benefits of market orientation. This suggests that while incorporating competitors' recent features into their own apps seems to be beneficial for developers, rushing to incorporate such features is not a good idea as it might limit the value generated by market orientation. We do not find support for our hypothesis on product update scope. This could be due to several reasons. Incorporating broad knowledge sources might increase the complexity to manage the variety and relationships between the sources (Leiponen and Helfat 2010). Moreover, it could become difficult to combine technology components as the number of interactions between them grows (Fleming and Sorenson 2004). As a result, firms might avoid pursuing features and attributes too broadly from highly diverse sources since greater update scope might be confusing for customers and potentially risky in a setting with a fluid customer base.

Our findings from Productivity category apps suggest that it does not help to be a lone wolf in this environment and that keeping up with the competitors' ideas and incorporating these into one's own products could help performance by mitigating obsolescence. This is consistent with and complements prior work which showed that in mobile app platforms with a large number of producers, innovation occurs through the diversity of the population of producers and not by the heroic efforts of any one innovator (Boudreau 2012). In the continuous product development efforts of Productivity apps, our results suggest that turning to competitors as a source of innovative ideas and carefully evaluating and implementing them is conducive for market success.

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