4-2022

Growing pains: The effect of generational product innovation on mobile games performance

Liang CHEN
Singapore Management University, liangchen@smu.edu.sg

Pengxiang ZHANG
Peking University

Sali LI
University of South Carolina

Scott F. TURNER
University of South Carolina

Citation

CHEN, Liang; ZHANG, Pengxiang; LI, Sali; and TURNER, Scott F.. Growing pains: The effect of generational product innovation on mobile games performance. (2022). *Strategic Management Journal*. 43, (4), 792-821.

Available at: https://ink.library.smu.edu.sg/lkcsb_research/7206

Published in Strategic Management Journal (2022), 43 (4), 792-821. DOI: 10.1002/smj.3338

GROWING PAINS: THE EFFECT OF GENERATIONAL PRODUCT INNOVATION ON MOBILE GAMES PERFORMANCE

Research summary: Strategy research advises firms to capture generative value by continually introducing generational improvements on their existing products. This paper considers a potential dark side of such strategy. We argue that generational innovation elicits a negative near-term response from consumers, as it distorts their ingrained behavioral patterns and imposes learning costs. Further, we propose that this negative effect of generational innovation will diminish when the product has a leading market position; and it will be more severe as the product's technological legacy lengthens. Using a difference-in-differences research design based on mobile game apps that multihome on two platforms, we find supportive evidence for our hypotheses and discuss the corresponding implications for strategy and technology innovation literature.

Managerial summary: Firms are advised to capture the value in future innovations that are spawned from their existing innovation, and they can do so by releasing improved generations of current products. This paper examines a potential dark side of such strategy — that generational innovations could alienate existing customers by unsettling their ingrained behavioral patterns. Utilizing a unique dataset of mobile game apps, we find evidence of this negative effect, which tends to be attenuated for market leaders but more damaging for those having already experienced numerous generational changes.

Keywords: innovation strategy, generative appropriability, generational product innovation, demand-side perspective, difference-in-differences design

INTRODUCTION

A central topic in strategy research concerns how firms can appropriate value from their own innovations (Teece, 1986). Recently, scholars have drawn attention to the idea of generative appropriability as an important second-order form of value appropriation, which reflects the effectiveness in capturing value through future innovations that are spawned by the current one (Ahuja, Lampert, & Novelli, 2013). A firm can appropriate generative value by continually introducing improved generations of its original innovation, before others develop substitutes based on that innovation. This is a particularly prominent practice in technology industries where existing product innovations are frequently supplanted by subsequent generations (Helfat & Raubitschek, 2000), and in the context of digital platforms where firms rely on generational innovation as a dominant appropriability strategy that preempts competitive imitation (Miric, Boudreau, & Jeppesen, 2019). It has been argued that these generational innovations account for the vast majority of economic value created by innovating firms (Pisano, 2015). Yet few studies have empirically investigated their performance implications.

This inadequacy of evidence is troubling; while the conventional view highlights generational innovation as an appropriability strategy that enables firms to sustain advantages, there are also arguments from innovation scholars that would suggest otherwise. Indeed researchers have noted that innovations that enhance firms' competencies may unwittingly destroy consumer value (Afuah, 2000). By extension, those introducing generational innovations to enhance generative appropriability could run the risk of consumer backlash against unwelcome product upgrades. This echoes the fact that firms commonly face high failure rates with their innovations (Moore, 1991). Consider a recent major app redesign by Snapchat that caused widespread anger among its users. The leading social networking app lost three million daily active users in the second quarter of 2018, for which CEO Evan Spiegel blamed the product redesign (New York Times, 2018). Likewise, the first generational upgrade of the hit game Pokémon GO sparked a significant outcry on social media (Guardian, 2016). These arguments and observations from practice suggest considerable heterogeneity in the performance outcomes of generational innovation, and underscore the need for further investigation given the corresponding implications for firms' competitiveness.

In addressing this gap, we focus on *generational product innovation* (GPI), defined as improvement of an established product that results in substantial functional and technical advances within a technological regime (Lawless & Anderson, 1996). In line with the arguments for generative appropriability, extant literature tends to emphasize the benefits of GPIs for the firm, as introducing generational innovations can help incumbents survive industry evolution and maximize returns from their initial investments in innovation (Banbury & Mitchell, 1995; Lawless & Anderson, 1996). Yet the literature has provided surprisingly little evidence as to how this pursuit of generative appropriability may affect product performance.

We draw on the demand-side perspective to examine consumers' product adoption following generational innovations (Adner & Levinthal, 2001; Priem, 2007; Wang, Aggarwal, & Wu, 2020). Because generational innovations bring changes to existing products that are already embedded in consumers' behavioral patterns, we argue that they are likely to cause frictions by altering ingrained habits and increasing learning costs for consumers. As a result, we expect that consumers will be more likely to resist generational innovation, rather than engage in behavioral adjustment, particularly in the near term. Further, we posit that the negative effect of generational product innovation will vary depending on the relative benefits of adoption for consumers vis-à-vis their required behavioral adjustment. Specifically, we argue that the negative effect will diminish when the product has a leading market position; and it will be more severe as the product's technological legacy lengthens.

Our empirical analysis focuses on the near-term ramifications of generational innovations. Our assumption is that the functional advantages offered by GPIs may themselves be short-lived because of rapid obsolescence in the wake of constant market and technological changes (Eisenhardt & Tabrizi, 1995; Tripsas, 1997). This dynamism is, in fact, the very reason for the continual release of GPIs in a bid to create long-lasting appeal for the product (Lawless & Anderson, 1996), as the accumulation of short-term advances can have profound implications for the long-term success of a firm (Helfat & Winter, 2011). Moreover, we recognize that innovation introduction is a deliberate choice made by firms. For example, seasonal holidays may breed a spike in product demand, and in response, firms are likely to introduce generational innovations in advance. To address the corresponding endogeneity issue, our analysis utilizes a unique matched difference-in-differences research design using data from the mobile games industry. The identification strategy leverages asynchronous generational innovations of multihoming mobile games (i.e., game apps available on more than one platform). By comparing the change in daily active users of the upgraded apps (i.e., treatment group) vis-à-vis the same apps that have yet to be upgraded on the rival platform (i.e., control group), we can minimize unobserved heterogeneity (e.g., developer traits, app characteristics, time effects, etc.). We find evidence in support of our hypotheses, based on 1,610 GPI events in worldwide markets.

THEORY AND HYPOTHESES

Generative appropriability and generational product innovation

Strategy research has largely focused on first-order appropriability, which refers to a firm's effectiveness in exploiting a given innovation by translating it into financial returns

(James, Leiblein, & Lu, 2013). Studies of such appropriability seek to identify, among the various possible business models, the best approach to monetizing a firm's existing innovation (Teece, 1986). Far less attention has been paid to generative appropriability as an important second-order element of appropriability, which concerns the firm's effectiveness in capturing the greatest share of future innovations that are spawned from its original innovation (Ahuja *et al.*, 2013; Alnuaimi & George, 2016).

To further understand generative appropriability, we build on previous research on generational product innovation—a prominent approach to enhancing generative appropriability (Lawless & Anderson, 1996; Turner, Mitchell, & Bettis, 2013). GPIs refer to improvements of a firm's existing products that represent significant functional extension and technical advance within a technological regime (Banbury & Mitchell, 1995; Turner, Mitchell, & Bettis, 2010). A technological regime, or trajectory, is a commonly-accepted set of technical principles for generating solutions to particular technological problems (Cohen, 2010; Nelson & Winter, 1977). Within a regime, technological development proceeds along a relatively clear path drawing on familiar methods of solution. As illustrative examples, the transition in operating systems to Windows 10 from its predecessor (Windows 8) would be within a technological regime, and therefore a GPI; by contrast, a shift from Windows to Linux represents a change of technological regime and thus would not be considered a GPI. Other examples are widely seen in automotive and consumer electronics industries where model upgrades are introduced regularly. Recently GPIs have become particularly prevalent in the digital economy, as the flexible nature of software-based products allows for continual improvements over the product lifecycle (Chen *et al.*, 2021a; Lobel *et al.*, 2016; MacCormack, Verganti, & Iansiti, 2001).

In previous work, researchers have attempted to understand whether and under what conditions firms introduce generational product innovations. The release of GPIs tends to exhibit a consistent temporal pattern given the critical role of routines in developing and introducing products (Turner *et al.*, 2013). Not only is GPI often driven by a firm's own innovation strategy featuring temporal consistency, it also can be a response to external events such as competitors' innovations (Turner *et al.*, 2010). From the view of performance implications of GPI, existing studies have emphasized the benefits of generational innovations for firms. GPIs can help them respond to consumers' changing tastes and maximize returns from firms' initial investments in innovation (Ansari, Garud, & Kumaraswamy, 2016; Lawless & Anderson, 1996). That GPIs can improve firms' competitiveness during technology evolution seems taken for granted. Yet how GPIs affect consumer utility and product performance still remains a black box.

Demand-side perspective on technology innovation

A parallel line of research in the technology innovation literature is the demand-side perspective, which concerns consumers' evaluation of products' functional performance (Priem, Li, & Carr, 2012). While often implicit, the underlying premise revolves around how consumers react to innovation. To date, demand-side studies in technology innovation research have focused on customer-oriented innovation strategy for value creation (Danneels, 2003). As with innovation diffusion studies (Rogers, 2003), this work largely follows a pro-change approach and typically presumes that technology innovations bringing novel solutions and improvements over existing alternatives tend to ultimately be adopted by consumers (Garcia, Bardhi, & Friedrich, 2007). Researchers thus are more concerned with antecedents to the diffusion of an innovation rather than focusing on factors that may inhibit its diffusion.

This is not without exceptions. Adner and Snow (2010) show that some consumer segments for an existing product may perceive little utility from the new features associated with a technological transition. Mainstream consumers are often found to be reluctant to adopt new products that are based on disruptive technologies because the attribute set being offered is misaligned with their functional preferences (Christensen, 1992; Christensen & Bower, 1996). More importantly, studies of technological changes have investigated how and why they may disrupt incumbent firms' customers (Afuah & Bahram, 1995). Using the case of the QWERTY keyboard (David, 1985), Afuah (2000) illustrates the possibility that innovations that enhance incumbents' competencies may unwittingly render obsolete consumers' accumulated skills and knowledge and thus destroy consumer value. Overall, though, scant attention has been paid to the changes that innovations may impose on consumers and the fact that consumers may have natural resistance to such changes (Heidenreich & Handrich, 2015; Oreg, 2003).

Furthermore, extant work on technology innovation is based on the assumption that consumer utility derived from a product innovation corresponds to the level of performance improvements it offers (Adner, 2002). Building on a firm's existing product, generational innovations commonly improve on the product attributes or the relationships among these attributes (Moreau, Lehmann, & Markman, 2001). This has directed much attention to the benefits of GPIs as an incremental approach for advancing along an existing technological trajectory, but not as a source of disruption. This research omission may be due to a potential conflation between incremental innovation and GPI. While both utilize established technical principles, extend the designs of existing products, and fit with the firm's current customer base (Henderson & Clark, 1990), GPIs are distinct as they incur substantial changes to consumers by altering an existing product or transforming its scope (Turner *et al.*, 2010). The potential negative consequences may only occur when changes involve new functionality and/or significant shifts of existing functionality and design (i.e., GPI). Nonetheless, because of their evolutionary nature, GPIs are subsumed under the broader literature on incremental innovation, without due consideration of the disturbances they might cause (Moreau *et al.*, 2001).

The dark side of GPI

Following the demand-side perspective, we attribute consumers' adoption of a GPI to their evaluation of the upgraded product. By definition, a GPI provides additional functional attributes for consumers, which can add to consumer utility and generate additional demand and sales (Banbury & Mitchell, 1995). However, the improvement on some performance dimensions may be accompanied by the loss of benefits on others, and as a result, the net utility change created by functional extensions should not be assumed (Mukherjee & Hoyer, 2001).

We argue that for many consumers the original product is already embedded in their existing patterns of behavior. Scholars in psychology show that individuals develop habits to engage in particular patterns of behavior in response to stable contextual cues, based on their performing activities repeatedly in similar contexts (Ouellette & Wood, 1998; Wood & Neal, 2007). As individuals often seek such stability and consistency, changes that distort habits can be disturbing (Oreg, 2003). For example, researchers find that information technology users do not willingly embrace change, but prefer innovations that cause no change to the status quo (Rivard & Lapointe, 2012). GPIs which unsettle ingrained consumption habits may elicit a negative evaluative response from consumers because changes inhibiting habitual responses demand additional cognitive resources (Quinn *et al.*, 2010) and consumers will be forced to undergo a prolonged process of behavioral adjustment before they can reach the same level of comfort as with the past product generation (Chen & Hitt, 2002; Ram, 1989).

Furthermore, we argue that while GPIs are intended to capture generative value by introducing innovative features to the market, they also impose learning costs upon consumers which can be value destroying. Generational transitions confront consumers with costs for accepting new contents, for which some accumulated knowledge may become less efficacious and new skills must be learned (Afuah, 2000). Learning costs involve cognitive efforts directed to how to operate the new product and benefit from the technical advances (Garcia *et al.*, 2007; Mukherjee & Hoyer, 2001).

Meanwhile, it is unreasonable to assume that consumers can fully exploit the functional benefits in the near term. Distracted by near-term inconvenience, consumers may be resistant to a new feature regardless of the substance of its benefits (Hong *et al.*, 2011). The reluctance for altering established behaviors and skills prompts consumers to refrain from investing in learning, even if they may subscribe to the change in principle over the long term. For average consumers, the perceived cost of enduring the adjustment period may outweigh the potential benefits to be extracted in the long term, such that consumers may view a GPI more as an immediate disruption. Commenting on the recent generational innovation, a Snapchat spokesperson admitted that "updates as big as this one can take a little getting used to…but we hope the community will enjoy it once they settle in" (CNN, 2018). Yet millions of once active users opened the app less frequently as a result of the significant redesign.

Hence we posit that the introduction of a GPI will reduce overall market demand for and adoption of the product in the near term. This is because the disturbances consumers perceive and the learning costs they assume exert a negative impact on product evaluation.

Hypothesis 1: The introduction of a generational product innovation reduces consumers' adoption of the product in the near term.

Moderation of relative benefits

Critical in demand-side understanding of innovation success is a focus on the varying extent to which consumers value technology-driven performance improvements (Adner & Levinthal, 2001; Aggarwal & Wu, 2015; Wang *et al.*, 2020). As argued, this may be based on inferences about the benefits afforded by a generational innovation relative to its potential negative effects, i.e., disturbances to consumers' established behavior. The relative (net) benefits that consumers expect to extract determine their overall evaluation of the new product generation and hence how consumers will respond to the release of a GPI. Prior research suggests that a firm's market position and experience with prior innovations can shape its tendency to engage in innovation (Ahuja, Lampert, & Tandon, 2008; King & Tucci, 2002), while paying far less attention to their impact on innovation outcomes. Extending the studies of innovation behavior, we propose that market position and technological legacy can influence innovation outcomes on the demand side. These factors, which capture salient market and technology dimensions, do so by shifting the potential benefits and costs associated with a generational innovation, thereby moderating the observed GPI effect.

Market position

As a product attains a market-leading position, we expect the negative effect of generational innovation on consumer adoption to weaken for two reasons. First, the benefits of adoption are likely to be amplified. Due to limited information processing capacity, consumers tend to rely on external signals such as rankings in adoption decisions (Rietveld & Eggers, 2018). It is reasonable to assume that the functional attributes of leading products have been configured in a way that addresses the needs of the broader base of customers (Slater & Mohr, 2006). Thus, embracing market-leading products helps to minimize search efforts, as well as the ex post uncertainty associated with generational changes. Furthermore, consumers' evaluation metrics may evolve as the product becomes increasingly successful and popular. Instead of basing product evaluation on tradeoffs between certain functional attributes, consumers may converge toward a preoccupation to satisfy social needs, i.e. "to get into the 'swim of things' [and] be fashionable or stylish" (Leibenstein, 1950: 189). From this perspective, ceasing to use the renewed product or seeking alternatives will force consumers to forego the enjoyment arising from the related social interactions. Therefore, the benefits of adopting the latest product generation are higher for market-leading products than the others, all else equal.

Second, we expect the behavioral costs of GPIs for consumers to be smaller for products that are ranked high in the market. Consumers acquire knowledge about a product via social learning, and such learning occurs commonly in consumer communities, including various online ones (Fisher, 2019). Research shows that the extent to which consumers can attain information-based learning depends on the size of the community (Hu, Yang, & Xu, 2019). For market-leading products, consumers will have a greater social community to learn from, instead of having to learn how to adapt to a new product generation on their own. Networks of friends and strangers offer knowledge about the new tools, techniques, tips and tricks. Such knowledge can reduce the barrier to acquiring new skills specific to the generational change, and enable consumers to benefit from technical advances without engaging in extensive learning. Given the increased benefits and reduced behavioral costs consumers face, products' market-leading position will weaken the negative effect of GPI.

Hypothesis 2: The decrease in near-term consumer adoption of the product in response to a generational product innovation will be weaker when the product has attained a market-leading position.

Technological legacy

We define the technological legacy of a product as the distance between the present version of the product and its foundational technological roots, and draw on the idea that a firm's legacy in old technology constrains its ability to adapt to new product generations because of technological transitions (Tripsas, 1997) and existing customer relationships (Christensen & Bower, 1996; Danneels, 2002). Focusing on the demand side, we expect the negative effect of generational innovation to be magnified, as the technological legacy of a product lengthens.

First, as the technological legacy lengthens, the benefits of consumer adoption are likely to be reduced. In developing generational product innovations, designers often introduce work-around solutions to achieve backward compatibility with one or more earlier product versions (Schilling, 2003). As the technological legacy increases, there is a greater span of technology that needs to be bridged, resulting in more challenges and complexities for a GPI to accomplish backward compatibility (Adomavicius, Bockstedt, & Gupta, 2012). These challenges and complexities may stem from "kludges" generated by an accumulation of technical advances in the product, where kludges refer to product systems that are made of poorly-matched components and contain temporary fixes on a product initially designed based on an earlier-era technological foundation (Koopman & Hoffman, 2003).[1] To address the technological distance-based challenges and complexities, designers often need to develop more and more extensive work-around solutions in the GPI to somehow, rather inelegantly, achieve backward compatibility. In turn, these updates in functionality are more likely to complicate the interface, require additional resources, and lead to integration breakdown (Hann, Koh, & Niculescu, 2016),

[1] Kludges are common in both hardware and software products, as product generational changes are often the result of adding new and imperfectly compatible design elements to an original design rather than redesigning the product completely.

such that users face more hurdles and impediments in extracting the benefits associated with the GPI.

Second, for products with longer technological legacies, we expect the behavioral and learning costs of GPIs to be higher. As the legacy lengthens, there are more likely to be users of the product who have learned and regularly utilize earlier product features. This greater base of users with skills and habits that are grounded in prior technology magnifies the risk of disrupting consumers' established skills and ingrained habits by introducing a generational innovation, given the risk of the GPI upsetting prior product features. For example, Minecraft players constantly complain that functional changes in new updates are not compatible with game mechanics in an older version, and they must fix the corresponding damage on the resources they have built cumulatively (New York Times, 2016). Research also suggests that consumers tend to associate feature additions with the difficulty of learning and using the product (Mukherjee & Hoyer, 2001). For products with long technological legacies, we expect that consumers will be more likely to associate learning and usage difficulties in connection with the feature additions that a GPI would bring. Thus, as the technological legacy of a product lengthens, the greater behavioral costs associated with GPIs are likely to be increased.

Overall, we posit that the negative effect of GPIs is amplified when the product has a longer legacy.

Hypothesis 3: The decrease in near-term consumer adoption of the product in response to a generational product innovation will be greater as the technological legacy lengthens.

DATA AND METHODS

Research context and data

In this study, we examine how generational product innovation affects near-term demand, specifically consumer adoption, in the context of the mobile app industry. This industry provides an apt empirical setting in which to investigate the interplay between generational innovations and demand side responses. Games are the largest category in the mobile app industry, both in terms of share of the total number of mobile apps (e.g., 24.9% in iOS) and revenues (e.g., in terms of revenue, seven of the top 10 apps subcategories are part of the games category). In addition, a significant group of mobile game users spend tremendous amounts of time and money to explore the gameplay and improve their skills. Such investment is game-specific, and the knowledge and credits do not transfer across games. This makes gamers relatively reluctant to switch games, so that the user disruption we seek to capture is non-trivial. More importantly, these gamers are the primary source of revenues for mobile game developers. Thus, any disruption based on existing users is a critical concern for mobile game developers.

A scope condition of our theory is that the generational innovation is a ubiquitous and important tool in firms' arsenal. This is clearly the case for mobile games. We find that the update rate of game apps is among the highest in the apps industry. To gain greater insights into the context, we conducted interviews with several developers of game apps. One described the importance of updates as follows: "Update is a question of life or death for a mobile game, because users would get bored playing the same game within a month. The best way to survive is to update new content regularly." Another developer highlighted that, "among different types of updates, those major, generational updates are the most important, as they include substantial changes to the original design, expend most firm resources, and have the highest potential to generate revenues." Thus, the mobile game category provides an ideal context to study the performance implications of GPI.

Our study focuses on generational product innovation, i.e., significant technical advances/change relative to the existing product, and we exclude minor and "bugfix" updates. Although technical performance may improve as a result of any update, prior work suggests that the significance of the advance is limited, and primarily corrective, in the case of minor and bugfix releases. To distinguish GPIs from other innovation updates, we leverage a common practice for naming the updated version of games in the mobile game industry. According to this practice, version numbers are based on three digits (i.e., Version 1.2.0, 3.7.2). When releasing a new version, there will be an increment in the first-digit if significant changes are involved in the form of new contents, new functions and features, new game designs, and new gameplay modes; an increment in the second-digit denotes minor improvements on existing features/functions, and an increment in the third-digit suggests bugfixes or marginal changes. In other words, an increment in the first-digit represents a substantial technical advance relative to the existing product design (i.e., GPI). It represents functional advances along the same technological trajectory, yet much more substantial advances than second-digit changes. We discussed the concept and measurement of GPIs with mobile game developers and product managers who are tasked with managing game updates, or "LiveOps" in their jargon. They confirmed that operationalizing GPIs as an increase in the first digit is an appropriate way to distinguish from minor, maintenance-oriented updates.[2] Doing so allows us to capture GPIs in much the same way as they suggest and as other scholars have operationalized the concept.

[2] During the interviews, practitioners suggested that there is a small portion of mobile games that do not ever change the first digit of their game version names, despite that some of the updates they release are deemed rather major ones. To this end, we consider our measurement of GPIs to be conservative.

To test our hypotheses about the effects of generational innovation on consumers' adoption of the product, we acquired data from a leading analyst firm in the mobile intelligence sector. The analyst firm tracks and archives information related to all mobile apps developed for the iOS and Android platforms. Its data are extensively used by app developers, venture capital firms, and financial analysts. Our data set comprises detailed mobile apps information for the period from Jan 1st 2015 to Dec 31th 2017 across the 58 major country markets on both iOS and Google play app stores that were available from the analyst firm. We obtained information on app updates, adoption and basic app characteristics from the analyst firm. While the intelligence firm is widely viewed as a legitimate source of industry data/information, as a further check on the validity of our data, we verified that rankings and ratings of the top 20 apps in our acquired data matched corresponding information from two other providers of mobile apps data (most mobile app data providers offer free access to select information on recent top ranked apps).

Matching and difference-in-differences approach

Given that the timing of generational innovation might be strategic and therefore endogenous, we apply a difference-in-differences (DID) approach to overcome biases related to potential time trends (Bertrand, Duflo, & Mullainathan, 2004). To construct treatment and control groups in difference-in-differences design, a common approach is to use propensity score matching, which matches the samples by trajectories of the dependent variable before the occurrence of the event (Kovács & Sharkey, 2014). However, this approach can still be subject to severe problems with unobservable variables (e.g., app theme, firm strategy, managerial composition) due to the limited availability of variables. Unobserved firm and product level characteristics may contribute to the divergence of trajectories after the GPI. In other words, the GPI decision could still be confounded by unobserved variables. Ideally, the empirical concern would be minimized if we could compare the demand of two identical apps (i.e., “twins”) produced by the same firm observed at the same time with only one experiencing treatment (i.e., experiencing generational product innovation). In fact, in the mobile app context, multi-homing/cross-platform apps can provide a “quasi” experiment context to allow for comparisons between “twins”. To a large extent, the same app on different platforms shares identical characteristics at both firm and product levels. If we control for the platform effect and some factors at the app-platform level (e.g., ranking), the decision to first update the app on one platform would be close to a random treatment. Therefore, we paired twin-apps from different platforms together so that we could address the prevailing endogeneity concerns in the examination of generational innovation outcomes (Tiwana, 2015).

Following prior literature using mobile apps datasets (Ghose & Han, 2014; Kapoor & Agarwal, 2017), we employed a “top segmentation” approach. The distribution of app revenues and downloads is heavily skewed and exhibits a long-tail shape. Based on a joint report by Prior Data and Pollen VC, more than half (55%) of the app store revenue in 2015 was generated by the top 100 apps, with the rest taken up by the other 1,500,000 apps (Macmillan, 2015). Further, when consumers are browsing apps by category, the Apple App Store only shows top apps on its page—searching by keywords is required to reach the rest—creating a huge difference in market exposure between top apps and others (Ghose & Han, 2014). Thus, top ranked apps represent a major part of the apps industry.

To construct our sample, we started with a list of top ranked apps on iOS, then found the identical twins for them on Android, and concluded by going through a series of steps to identify suitable GPI events for our study. Following Kapoor and Agarwal (2017), we first selected top grossing apps that ranked in the top 500 in each month from Jan 2015 to Dec 2017 in 58 countries in the iOS game category, generating a sample with 7,398 apps. To construct matched pairs for DID analysis, we searched for the counterparts of these iOS game apps on the Android platform from the same data source, and we found 3,187 of them that have released equivalent apps on the Android platform. That provided us with 3,187 pairs of cross-platform mobile game apps (released on both Android and iOS platforms).

To ensure that the same apps on different platforms share very similar product characteristics, we screened all 3,187 pairs of apps in the sample to identify the focal GPI events. First, we identified paired updates (GPI, minor, or bugfixes) that share the same version names between the cross-platform apps (15,115 paired updates). During our inspection of data, and consistent with our interviews with app developers, we found that the same app on different platforms may still be somewhat different from each other in update progress and product design. However, when version names (e.g., 3.4.2) for the same app on different platforms are the same, the update progress and product characteristics are most likely to be very similar. To ensure that the focal updates take place when both treatment and control groups share very similar product characteristics, we started by focusing on the paired updates that share the same version names on different platforms. Second, we dropped out those paired updates if one of them had experienced any type of updates shortly after the matched updates (less than 7 days), so as not to confound the influence of paired updates with the focal update.[3] That led to 2,032 paired updates. Third, we kept the pairs if either one of them experienced the focal update, while the other one was not updated for at least 7 days after the counterpart's focal update. To isolate the effect of the focal update, we also excluded pairs that have experienced additional updates right after the focal update within one week. In doing so, we generated a 7-day period after the

[3] Most mobile game users update new versions within the first 4-5 days.

focal update in which the counterpart app was yet to update, leaving us with 1,706 paired updates. Finally, we kept the paired updates corresponding to focal updates that are qualified as generational product innovations based on the criteria mentioned earlier. These focal updates must have increments in the first-digit of their version names compared to the version names of the paired updates. In summary, we had a final sample of 1,610 focal GPI events occurring across apps and country markets. Figure 1 helps illustrate our sampling procedures. We treated the date of a focal GPI as day 0 and kept data that ranges from day -7 to day 7 for each selected pair. In this way, the matched samples are equivalent in unobserved covariates at the firm level, product level and even product-day level.

[Insert Figure 1 here]

In econometrics terms, our regressions follow the difference-in-differences approach. The identification of the treatment effect relies on comparing changes in adoption over time between apps that experienced a generational product innovation during our observation window and the matched apps that are identical but operate on different platforms and did not experience the GPI event. In statistical modeling, we followed previous studies to conduct pooled regressions that include matched-dyad fixed effects, or in other words, app fixed effects (Kovács & Sharkey, 2014; Singh & Agrawal, 2011).

Variables

Dependent variable. To capture the change in near-term demand around GPI, we measured *consumer adoption* of a mobile game by the number of consumers that use the app on a specific day in the focal country market. To normalize its distribution, we log-transformed the measure such that consumer adoption equals to ln (number of daily active users + 1). By log-transforming the number of consumers, we capture the within-app percent change in consumer adoption as a function of the GPI event and change in covariates (Greene, 2003; Wang *et al.*, 2020). Similar measures of count within a specific time interval (e.g., day, week, month) have been frequently adopted to gauge consumers' usage of online games, mobile apps, or social networking services (Kovács & Sharkey, 2014; Tiwana, 2015; Toubia & Stephen, 2013).

Independent variables. Given that we seek to examine research questions with the matched difference-in-differences design, we are interested in the coefficient, p-value and magnitude of the difference estimator (Bertrand *et al.*, 2004). The difference estimator is the interaction of the treatment and post dummy variables. The *treatment* variable is a dummy variable, which is coded as 1 for the app-platform that experiences a GPI in the observation window and 0 for the control group. The *post* variable is also a dummy variable, which receives a value of 1 from day 0 to day 7 and 0 from day -7 to day -1. In essence, the difference estimator captures whether the dependent variable has changed at a significantly different rate for the treated group as compared to the control group.

Moderators. According to our theory development, the treatment effect of GPIs would vary based on the relative benefits consumers can extract from GPIs. Therefore, we included market position and technological legacy as moderators to construct triple differences models.

First, we expect that market position on a platform will influence the negative effect of a GPI event. While market share, market growth or other related variables are often employed to characterize the market position in traditional industries (e.g., Hopkins, 1987), market position in digital platforms is straightforward. Mobile app ranking lists capture the market positions of different apps based on their recent demand, rewarding popular apps with salient market visibility and a trendy appeal (Chen *et al.*, 2021b). Since ranking lists aggregate information about the usage decisions of all other app users, they reduce the uncertainty consumers face regarding the value of apps they have not used. Given that most ranking lists only show the top 30 ranked apps in a category list, we included an indicator of market position *(top market ranking)* for the focal app on the focal country-platform, coding as 1 if the focal app has reached top 30 in the local market ranking, 0 otherwise.

Second, we expect that the technological legacy of a product will also moderate how a GPI affects consumer adoption. Our primary operationalization of technological legacy is an event-based measure of technological distance, which captures a product's cumulative innovation history and demand dynamics (Kretschmer & Claussen, 2016). Specifically, we operationalized technological legacy using the number of *prior GPIs* before the focal day (log-transformed), which captures the temporal/technological distance between the present version and initial product introduction as measured by the number of prior generational innovation events. As a secondary operationalization for technological legacy, we utilize a calendar time-based measure of technological distance, which centers on *product age*. For this operationalization, we measured technological legacy as the amount of time (in days, log-transformed) since the initial product introduction, which offers an alternative means of capturing the temporal/technological distance between the present product version and the initial introduction of the product. We view these two operationalization approaches as providing similar measures, which capture technological legacy in somewhat different ways. In our view, the number of prior GPIs is the more salient measure because it directly captures technological increments (i.e., technological distance), as opposed to product age which we view as a less direct measure based on founding era. Yet both effects may be present, and therefore our empirical analysis considers both measures.

Controls. While matching "twin" apps together obviates the need for app and developer level controls (Foerderer & Heinzl, 2017; Kovács & Sharkey, 2014), we must take into account the idiosyncrasy between the "twin" apps due to platform differences. Since upstream interventions may lead to a shift in the technological environment, we controlled for *platform generational transition* using a dummy variable, which equals 1 if the focal platform has undergone a major update in the past month and 0 otherwise (Kapoor & Agarwal, 2017). We included *competition* to account for innovation by competing apps across time (Turner *et al.*, 2010). We used the number of major updates in the same subcategory as the focal app to measure competition (log-transformed). To control for the influence of different platforms, we included a dummy variable of *platform*, which is coded as 1 if the app is operating on iOS platform, 0 otherwise. In addition, we included *product age* and *time since the last update*, and their square terms, to account for the influence of app lifecycle and update recency. Specifically, we measured product age as the log-transformed number of days since the first day of app release on the platform, and we measured time since last update as the log-transformed number of days since the date of the most recent update of the product on the same platform.

Analysis

We conducted DID regressions to estimate the adoption difference between treatment and control apps at the app-country-platform level, with app-country fixed effects and platform fixed effects. Specifically, we estimate the DID effect from the following equation:

$$Y_{ip} = \alpha + \alpha_i + \alpha_p + \beta T_{ip} + \gamma t_{ip} + \delta\,(T_{ip} \cdot t_{ip}) + \varepsilon_{ip}$$

By inspecting the equation, we can see that the coefficients have the following interpretation: α = constant term; α_i = app-country fixed effects; α_p = platform fixed effects; β =

treatment group specific effect (treatment/control); γ = time trend common to control and treatment groups (pre/post-focal update); δ = true effect of treatment.

RESULTS

Table 1 presents summary statistics and the correlations between covariates. While cross-platform twins provide us with a unique context that eliminates heterogeneities in developer-level characteristics (size, age, experience, etc.) and app-level characteristics (genre, contents, quality, etc.), they may exhibit different adoption trajectories over time, mostly due to the platform effect (platform governance, consumers' preferences for app features, consumers' willingness to pay, etc.). Therefore, we must first examine the common trend assumption (also known as the parallel path assumption) that underpins the validity of DID estimation. In line with prior research (Asgari, Singh, & Mitchell, 2017), we employed the statistical assessment of the common trend assumption and found supportive evidence.[4] In addition, we followed recent DID studies by plotting the DID estimates from a lead and lag model (Alonso & Andrews, 2019; Wen & Zhu, 2019; Zhang, Li, & Tong, 2020).[5] Figure 2 shows that before the introduction of GPI, the difference in DAU between treatment and control groups remains stable, supporting the prerequisite for a DID design. In comparing the DAU trends after the GPI event, we found that the DID estimate does not become negative and significant ($p<0.05$) until day 3 and then the negative effect stays salient till day 7. This suggests that, during day 0 to day 2, there could be a mix of quitting users, new downloads, and users' delayed installation of the update. When the dust has settled (i.e., from day 3 to day 7), the general declining trend dominates in our data as

[4] We performed Stata procedure "didq" to assess the plots statistically (Mora & Reggio, 2015). The results indicate that the null hypotheses of a common trend cannot be rejected, supporting the validity of the assumption.
[5] The lead and lag model includes interactions between the treatment dummy and lead and lag terms for the introduction of GPIs (Autor, 2003; Bertrand & Mullainathan, 2003). This approach allows us to compare the treatment and control groups during the pretreatment period and test for any potential anticipatory effects before the introduction of GPI.

the user base becomes clearly disrupted after most users have experienced the updated game. Thus, Figure 2 provides preliminary evidence in support of our main hypothesis.

[Insert Table 1, Figure 2, and Figure 3 here]

To further examine the general impact of GPIs over a longer time horizon, we investigated changes in DAU before and after GPI events (see Figure 3).[6] Specifically, we expanded our data to illustrate the DAU difference between treatment and control groups, ranging from Week -5 (prior to the occurrence of GPI) to Week 9 (past the GPI event). The relatively stable trend in the pre-GPI weeks and the sharp drop following the GPI event are evident, and provide further visual support for our main hypothesis. In addition, in post-GPI weeks, it takes around 3 to 4 weeks for the DAU difference to recover the level prior to the GPI, implying substantive loss and risk the innovating firm must bear. Then, the relative DAU growth continues for another 3 to 4 weeks, reaches a plateau in around week 7, and then starts to decline again. While the pattern of near-term disruption aligns well with our hypothesis, it also reveals the longer-term upward trend which may be the very motivation for firms' continual engagement in GPIs despite the near-term risk that this study focuses on.

[Insert Table 2 here]

Table 2 presents results in Models 1-4 that examine Hypothesis 1, which suggests that GPIs decrease consumers' usage of the product in the near term. In Model 1, we only included observations that are before GPI events (day -7 to -1 in our 15-day observation window), and we controlled for app, country and platform fixed effects separately. The coefficient of treatment suggests that before GPI, the treatment group has 33.4% higher DAU than the control group. There is a significant difference between treated and control groups regarding usage level with a

[6] To facilitate interpretation, we included control variables in the model underlying the depicted DAU pattern.

p-value of 0.000. Developers may prefer to introduce a GPI first on the platform with more active users. In Model 2, we only included observations that are after GPI events (day 0 to +7 in our 15-day observation window). The coefficient of treatment suggests that after the GPI, the treatment group has only 16.3% higher DAU than the control group. Compared with the coefficient in Model 1, the DAU gap between treatment and control groups significantly shrinks, which is consistent with our H1 prediction. In Model 3, we adopted the classic difference-in-differences estimator to report results. The term of interest is Treatment*Post, as the coefficient of this interaction term indicates the treatment effect of GPI on the outcome variable. The coefficient of Treatment*Post is negative and has a p-value of 0.000, and it suggests that apps that just experienced a GPI event will see a 9.2% drop in DAU, relative to apps that did not experience GPI events.[7] This is consistent with the results in Models 1 and 2. In Model 4, we further controlled for app-country fixed effects, which accounts for unobserved heterogeneity in consumers' preferences across different countries. The results remain consistent. Thus, our results support Hypothesis 1. Table 2 also reveals a surprising result that can help to enrich our understanding of the near-term effects associated with GPIs. Specifically, the results in Models 3 and 4 show that the coefficient for Post is positive, and that it is larger in magnitude than the coefficient for Treatment*Post. These results indicate that for both groups (control and treatment), there is an increase in DAU from the pre-GPI to post-GPI period, and that the magnitude of the increase is significantly lower for the treatment group. As described, these results provide evidence in support of Hypothesis 1, but they also reveal an unexpected upward trend for both groups. While we did not anticipate such an effect *ex ante*, our *ex post* conjecture

[7] We employ the semi-log specification as discussed in Greene (2003) and Wang, Aggarwal, & Wu (2020). When the dependent variable ln(y) is a natural log and the independent variable x is left unlogged, the coefficient on the (unlogged) independent variable is interpreted as semi-elasticity of that independent variable, which is the within-app percent change in consumer adoption.

is that this reflects a marketing effect, where promotional investments focus consumer attention on the product in general, thereby positively influencing DAU on both platforms in a similar fashion. To explore this idea, we conducted interviews with several senior managers in the mobile gaming industry, and their accounts supported our conjecture. Specifically, they indicated that publishers often engage heavily in promotion for a GPI event, with related investments frequently beginning approximately a week before the GPI event and continuing for several weeks afterwards. The practitioners also suggested that while at times promotional investments can be specific to the platform for GPI, for the most part, they are investments through third parties (e.g., social networks, video-sharing sites) and even offline events (e.g., gatherings/parties), and therefore the effect of marketing/promotion would be expected to be similar for the control and treatment groups. Overall, this unanticipated result provides additional support for our use of a DID design, as it can help to account for potential conflations and enables us to tease out the near-term impact of GPI, which is consistent with our argument around behavioral disruption and learning costs.

[Insert Table 3 and Figure 4 here]

To test under what conditions GPIs would be more or less disruptive, we employed a difference-in-difference-in-differences (DDD) design. Table 3 investigated the moderating effects of market position (H2) and technological legacy (H3), respectively. We predicted that the negative effect of GPIs on consumer adoption would be mitigated by market position and amplified by technological legacy. In Model 5, the coefficient of Treatment*Post*Top market ranking is positive and has a p-value of 0.009. Figure 4 provides graphical illustration. For non-top 30 apps, consumer adoption decreases by 10% after a GPI update, as compared to the control group; for top 30 apps, consumer adoption increases by 8.5% after a GPI update, as compared to the control group. The flip of the main effect from negative to positive is driven by a very strong moderating effect of market position.[8] These results are consistent with our theoretical arguments and also square well with the inferred marketing effect. Specifically, for products with a low market position, there is an increase in DAU for the control group for the period before the GPI event to the period afterwards (i.e., the marketing effect), while for the treatment group, there is a weaker increase (i.e., GPI-based disruptions on top of the marketing effect). For products with a market-leading position, we see a mild increase in DAU for the control group from pre-GPI to post-GPI, which is consistent with the idea that for well-known, market-leading products, the marketing effect would be weaker; and for the treatment group, we see an increase in DAU that is of greater magnitude than that of the control group, suggesting that consumers perceive greater benefits of GPI for market-leading products relative to their disruptive effects. Thus, consistent with Hypothesis 2, we found that the near-term negative effect of GPIs is mitigated by the market position of the game, and that for market-leading games, the benefits of GPIs could in fact outweigh the potential costs.

[Insert Figure 5 here]

Model 6 reports the coefficient of Treatment*Post*Prior GPIs, which indicates a negative moderating effect with a p-value of 0.001. Figure 5 assists in interpretation. For apps with a relatively low level of prior GPIs (mean – 1 standard deviation, which is 1.75 prior generations), consumer adoption decreases by 3.5% after a GPI update, as compared to the control group; for apps with a high level of prior GPIs (mean + 1 standard deviation, which is 5.70 prior generations), consumer adoption declines by 14.3% after a GPI update, as compared to the control group. Specifically, these results suggest that for products with few prior GPIs, there is a

[8] Such flips are not uncommon in prior empirical studies examining moderating effects (e.g., Benischke, Martin, & Glaser, 2019; Chae, Song, & Lange, 2021).

general increase in DAU from the period prior to GPI to the period following it (i.e., the marketing effect), while there is a slight decrease for the treatment group as compared to the control group (i.e., signs of a weak disruptive GPI effect). For products with many prior GPIs, there is also a general increase in DAU from pre-GPI to post-GPI, consistent with a marketing effect; and for the treatment group, we observe a considerable decrease in DAU relative to the control group, suggesting that consumers perceive greater disruptive effects relative to potential benefits. Therefore, consistent with Hypothesis 3, we found that the negative effect of GPIs is amplified by technological legacy.

In Models 7-9, we tested the moderating effect of product age as an alternative measure that taps into a different aspect of technological legacy. For this test, we included the interaction terms involving product age and its squared term, given that both terms are included and statistically significant as control variables in the initial models (see Table 2). In Model 7, we entered the set of product age interaction terms separately, while in Models 8 and 9, they are entered alongside the interaction terms for our other focal measures (Prior GPIs, Top market ranking). Specifically, in Model 8, we included the product age interaction terms in the same model with the interaction terms for our primary measure of technological legacy, i.e., the number of prior generations; and in Model 9, we entered the full set of interaction terms. Overall the models offer little support for a negative moderating effect of product age, while they provide consistent evidence in support of a negative moderating effect of prior generations.[9] Hence, we

[9] In testing for the moderating effect of product age (i.e., its effect on the GPI effect), we noted the potential for curvilinearity (in Model 7, the p-value for the Treatment*Post*Product age^2 coefficient is 0.039), suggesting that the moderating effect of product age may depend on its level. Therefore, we examined the moderating effect of product age at three levels: when product age is low (i.e., mean – 1 s.d., which is 455 days since the release date), at the mean of product age (which is 765 days since the release date), and when product age is high (i.e., mean + 1 s.d., which is 1,287 days since the release date). In the full models (Models 8 and 9), the moderating effect of product age was not statistically significant at conventional levels for any of the three focal levels of product age.

find support for H3 when using our primary measure of prior generations, but not with the alternative measure of product age.

Robustness tests

We conducted a series of robustness tests using alternative samples, measures and analysis techniques to verify the main findings. First, to assess whether our theoretical arguments only apply to GPIs rather than other types of updates, we conducted placebo tests based on minor updates and bugfixes. We constructed samples of minor updates and bugfixes using the same sample selection criteria and then reexamined our hypotheses. The empirical details and results are reported in Appendix A. We found that minor updates exhibit a significant and negative effect on consumer adoption. But since a portion of mobile games (20.1%) have never changed their first digits and do not distinguish GPIs and minor updates in their version names, the effect we found for minor updates could well be driven by this confounding factor. Thus, we excluded those observations and re-ran the tests. The results suggest that the effect of "true" minor updates is positive but lacks statistical significance, whereas bugfixes have a positive and significant effect on adoption. Therefore, the consumer disruption effect is only observed in GPIs in our sample, providing empirical support for our theoretical focus on GPIs.

Second, to verify whether the negative effect of GPI is truly due to disruptions to existing consumers as theorized, we created an alternative dependent variable that excludes those daily active users who have just downloaded the game. We did so by constructing a proxy for existing users, which is the difference between DAU and new downloads on the focal day (log-transformed). The results with this alternative dependent variable remain qualitatively the same for all the hypotheses (see Appendix B). Third, fixed effects and random effects models are both widely used in twin studies. While the fixed-effects model is often used in difference-in-differences "twin" design to control for time-invariant unobserved heterogeneity, twin studies can also employ random-effects models (Carlin *et al.*, 2005), which treat twin effects as randomly selected from a normal distribution. Accordingly, we reexamined all our hypotheses using random-effects models at the app-country level. As reported in Appendix C, the results remain consistent with our main specification.

Finally, while most mobile game users update to new versions within 4-5 days, a portion of existing users may not have updated to the new version within the 7-day time window. In this case, our results of the DAU drop would be conservative, as those users who have yet to update the focal game are still playing the old version and should not be disrupted. To further account for late adopters of GPI, we expanded our post-GPI time window from 7 days to 14 days after the day of the GPI update. The results (see Appendix D) suggest that our findings are robust to the alternative time window, indicating that users' update delay does not confound our theorized effect.

DISCUSSION

In this paper, we seek to investigate the performance outcome of generational product innovations. Extant literature has examined extensively the implications of technology evolution for firm competition (Tushman & Anderson, 1986), and it has emphasized the value of frequent, generational innovations in sustaining competitive advantage during industry evolution (Banbury & Mitchell, 1995; Lawless & Anderson, 1996). Our study instead examines the effect of generational innovation on consumer adoption. This is a key dimension of innovation outcome since the commercial success of any innovation ultimately depends on adoption. Using a difference-in-differences "twin" design, we find that generational innovations reduce product adoption in the near-term, in line with our argument that the changes introduced are likely to cause disturbances by altering ingrained behavioral patterns and increasing learning costs for consumers. Furthermore, consistent with the idea that the dark side of GPIs is conditioned by the relative benefits of adoption vis-à-vis the disruptions, we find that market position dampens the negative effect, while technological legacy amplifies it.

Our study makes three contributions to the literature. First, our analysis points to tension in pursuing generative appropriability. Researchers advise that firms create new innovations that build on their own existing innovations (Ahuja *et al.*, 2013). However, while developing improved products incorporating features that build on a firm's current innovation can enhance generative appropriability, an emphasis on this form of continual renewal and seeking out new adopters could also destroy value for existing consumers and damage the firm's primary appropriability, i.e., the commercialization of the innovation. In fact, if one views innovation as a type of organizational change, it seems fitting to describe it along content and process dimensions (Barnett & Carroll, 1995). While innovation, viewed through the lens of content, involves new products delivering improved technical performance and serves as a source of competitive advantage for innovating firms, the very process behind the creation of such content may incur significant disruptions to organizational routines partly due to the structural adjustments in the firm's relationships with co-opetitors (Carroll & Teo, 1996; Leonard-Barton, 1992). We resonate with the idea of disruptive process effects inside the organization, and we extend it to the demand side. Generational product innovation is simultaneously a value-creating outcome and a value-destroying process for consumers. While the content effect of GPIs may lead to higher generative appropriability for the firm, the process itself incurs significant near-term costs and may prevent potential benefits from realization.

Utilizing a novel identification strategy, our analysis can minimize unobserved heterogeneity associated with innovation behaviors and better investigate the causal effect of generational innovation. Focusing on process, while the immediate negative impact may decline over time, the accumulation of shocks could have profound implications for the firm's competitiveness. That is particularly notable for firms in dynamic environments (e.g., the digital economy) where GPIs are ubiquitously used for competitive responses or to preempt imitation (Helfat & Raubitschek, 2018; Miric *et al.*, 2019). One may view introducing GPIs as related to innovation-based firm adaptation in changing environments, yet extant research such as that based on NK models tends to assume a zero cost of adaptation for analytical clarity (Levinthal, 1997). Our findings imply that adaptation incurs costs; put at a more abstract level, firms must first climb down the current local peak in order to relocate to a higher peak. We show that adaptation can trigger self-disruption in that it erodes the customer base of incumbents and creates room for rivals' competitive attack. These ideas can play a role in understanding how successful firms could possibly die out. On the other hand, the findings also reveal a unique challenge for entrepreneurial firms seeking to emerge from the low end of the market and appropriate generative value arising from their original innovation, given that they may find themselves more vulnerable to consumer backlash than market-leading incumbents.

Second, we extend the literature on technology evolution. Prior research tends to link disruption with discontinuous technological transition or novel business models (Henderson & Clark, 1990), not with GPI. This is partly because the perceived discontinuity is assumed to be low for GPIs, given no change of technological regime. Moreover, research on technology evolution emphasizes that incumbent firms and industry structures are primarily disrupted by new entrants bringing about competence-destroying changes (Tushman & Anderson, 1986); yet it still begs the question of how successful firms get to the point where their products no longer appeal to consumers. We argue that, just as incumbents demonstrate inertia to technological changes (Rosenbloom, 2000; Tushman & Anderson, 1986), consumers may be reluctant to adopt generational innovations because of the distortions on their ingrained behavioral patterns. We also stress the possibility that innovations enhancing competence for incumbents may unwittingly render obsolete their consumers' accumulated skills and knowledge and hence destroy consumer value (Afuah, 2000; David, 1985). Our view echoes but extends the idea that product failures arise from firms' inability to effectively manage customer relationships (Levinthal, 1991).

Lastly, we enrich the demand-side perspective on technology innovation. Since innovation outcomes are closely related to consumers' adoption decisions, extant research examines extensively the role of the demand environment. That perspective may be particularly relevant for generational innovations with which firms can continually adjust to changing demand conditions (Henderson, 1999; Lawless & Anderson, 1996). To date demand-side research primarily focuses on preference heterogeneity in explicating why certain technology innovations are adopted (Danneels, 2004). The less noted fact is that the vast majority of new product ideas suffer commercial failure. One of the key reasons is the resistance from consumers (Claudy, Garcia, & O'Driscoll, 2015), which has been documented in the information systems literature (Rivard & Lapointe, 2012).

Instilling a new dimension to the demand-side view, our study shows how and why the demand environment may present an impediment to product innovations. That impediment is attributed to the fact that consumers may be overwhelmed by the near-term costs associated with behavioral adjustments and learning. This is similar to the foundational idea in the disruptive innovation literature that a technological change is often perceived as inferior to existing technologies by the mass of consumers (Danneels, 2004). Moreover, the demand-side perspective allows us to explore conditions under which the GPI effect varies, as consumers' benefits of adoption may outweigh costs and vice versa. By focusing on important market and technology factors, we predict product demand as a function of the barriers that consumers face in utilizing the GPI. Overall, our analysis departs from the customary view of the diffusion of a fixed innovation, and instead it depicts consumers' changing tendency of adoption as the product's features and functions continually evolve through its lifecycle.

The findings and inferences from this study are subject to a number of caveats that offer opportunities for future research. First, our empirical analysis is based on a single industry setting. Whether and to what extent the findings would be observed in other empirical contexts remains to be seen. Second, while our DID estimates and the associated figures show that the post-GPI decline is beyond a continuation of recent performance trends, it is still plausible that the timing of the GPI is strategically determined by the firm in response to sluggish performance. We encourage future research to delve into the rhythm of GPIs and the implications of temporal patterns of innovation, which would be of interest to strategy scholars. Lastly, our findings, and particularly Figure 3, suggests that GPIs may lead to longer-term growth of consumer adoption, which may be the very reason why firms continue to engage in GPIs despite the risk of near-term disruptions. We encourage future research to tease out the direct, longer-term consequences of a generational innovation while controlling for the unobserved changes in complementary assets and other organizational activities (Helfat & Raubitschek, 2000).

In conclusion, this study extends our understanding of technology evolution. In adopting a demand-side lens, it brings theoretical nuance to research on generational innovation, and we enrich the view of disruption in the innovation literature. These insights should shed new light on the risks associated with product redesign, regardless of the innovation content.

References

Adner R. 2002. When are technologies disruptive? A demand-based view of the emergence of competition. *Strategic Management Journal* **23**(8): 667-688.

Adner R, Levinthal D. 2001. Demand heterogeneity and technology evolution: Implications for product and process innovation. *Management Science* **47**(5): 611-628.

Adner R, Snow D. 2010. Old technology responses to new technology threats: Demand heterogeneity and technology retreats. *Industrial and Corporate Change* **19**(5): 1655-1675.

Adomavicius G, Bockstedt J, Gupta A. 2012. Modeling supply-side dynamics of IT components, products, and infrastructure: An empirical analysis using vector autoregression. *Information Systems Research* **23**(2): 397-417.

Afuah A. 2000. How much do your co-opetitors' capabilities matter in the face of technological change? *Strategic Management Journal* **21**(3): 397-404.

Afuah AN, Bahram N. 1995. The hypercube of innovation. *Research Policy* **24**(1): 51-76.

Aggarwal VA, Wu B. 2015. Organizational constraints to adaptation: Intrafirm asymmetry in the locus of coordination. *Organization Science* **26**(1): 218-238.

Ahuja G, Lampert CM, Novelli E. 2013. The second face of appropriability: Generative appropriability and its determinants. *Academy of Management Review* **38**(2): 248-269.

Ahuja G, Lampert CM, Tandon V. 2008. Moving beyond Schumpeter: Management research on the determinants of technological innovation. *Academy of Management Annals* **2**(1): 1-98.

Alnuaimi T, George G. 2016. Appropriability and the retrieval of knowledge after spillovers. *Strategic Management Journal* **37**(7): 1263-1279.

Alonso JM, Andrews R. 2019. Governance by targets and the performance of cross-sector partnerships: Do partner diversity and partnership capabilities matter? *Strategic Management Journal* **40**(4): 556-579.

Ansari S, Garud R, Kumaraswamy A. 2016. The disruptor's dilemma: TiVo and the U.S. television ecosystem. *Strategic Management Journal* **37**(9): 1829-1853.

Asgari N, Singh K, Mitchell W. 2017. Alliance portfolio reconfiguration following a technological discontinuity. *Strategic Management Journal* **38**(5): 1062-1081.

Autor DH. 2003. Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics* **21**(1): 1-42.

Banbury CM, Mitchell W. 1995. The effect of introducing important incremental innovations on market share and business survival. *Strategic Management Journal* **16**: 161-182.

Barnett WP, Carroll GR. 1995. Modeling internal organizational change. *Annual Review of Sociology* **21**: 217-236.

Benischke MH, Martin GP, Glaser L. 2019. CEO equity risk bearing and strategic risk taking: The moderating effect of CEO personality. *Strategic Management Journal* **40**(1): 153-177.

Bertrand M, Duflo E, Mullainathan S. 2004. How much should we trust differences-in-differences estimates? *Quarterly Journal of Economics* **119**(1): 249-275.
Bertrand M, Mullainathan S. 2003. Enjoying the quiet life? Corporate governance and managerial preferences. *Journal of Political Economy* **111**(5): 1043-1075.
Carlin JB, Gurrin LC, Sterne JA, Morley R, Dwyer T. 2005. Regression models for twin studies: A critical review. *International Journal of Epidemiology* **34**(5): 1089-1099.
Carroll GR, Teo AC. 1996. Creative self-destruction among organizations: An empirical study of technical innovation and organizational failure in the American automobile industry, 1885–1981. *Industrial and Corporate Change* **5**(2): 619-644.
Chae H, Song J, Lange D. 2021. Basking in reflected glory: Reverse status transfer from foreign to home markets. *Strategic Management Journal* **42**(4): 802-832.
Chen L, Wang M, Cui L, Li S. 2021a. Experience base, strategy-by-doing and new product performance. *Strategic Management Journal* **in press**.
Chen L, Yi J, Li S, Tong TW. 2021b. Platform governance design in platform ecosystems: Implications for complementors' multihoming decision. *Journal of Management* **in press**.
Chen P-Y, Hitt LM. 2002. Measuring switching costs and the determinants of customer retention in Internet-enabled businesses: A study of the online brokerage industry. *Information Systems Research* **13**(3): 255-274.
Christensen CM. 1992. The Innovator's Challenge: Understanding the Influence of Market Environment on Processes of Technology Development in the Rigid Disk Drive Industry. In *Graduate School of Business Administration.* Harvard University: Cambridge, MA.
Christensen CM, Bower JL. 1996. Customer power, strategic investment, and the failure of leading firms. *Strategic Management Journal* **17**(3): 197-218.
Claudy MC, Garcia R, O'Driscoll A. 2015. Consumer resistance to innovation—a behavioral reasoning perspective. *Journal of the Academy of Marketing Science* **43**(4): 528-544.
CNN. 2018. Snapchat faces backlash after app redesign. Retrieved from https://money.cnn.com/2018/02/12/technology/snapchat-update-backlash/index.html.
Cohen WM. 2010. Fifty years of empirical studies of innovative activity and performance. In *Handbook of the Economics of Innovation.* Hall BH, Rosenberg N (eds.), North-Holland.
Danneels E. 2002. The dynamics of product innovation and firm competences. *Strategic Management Journal* **23**(12): 1095-1121.
Danneels E. 2003. Tight–loose coupling with customers: The enactment of customer orientation. *Strategic Management Journal* **24**(6): 559-576.
Danneels E. 2004. Disruptive technology reconsidered: A critique and research agenda. *Journal of Product Innovation Management* **21**(4): 246-258.
David PA. 1985. Clio and the economics of QWERTY. *American Economic Review* **75**(2): 332-337.
Eisenhardt KM, Tabrizi BN. 1995. Accelerating adaptive processes: Product innovation in the global computer industry. *Administrative Science Quarterly* **40**(1): 84-110.
Fisher G. 2019. Online communities and firm advantages. *Academy of Management Review* **44**(2): 279-298.
Foerderer J, Heinzl A. 2017. Product updates: Attracting new consumers versus alienating existing ones. *SSRN Working Paper 2872205*.
Garcia R, Bardhi F, Friedrich C. 2007. Overcoming consumer resistance to innovation. *MIT Sloan Management Review* **48**(4): 82-88.

Ghose A, Han SP. 2014. Estimating demand for mobile applications in the new economy. *Management Science* **60**(6): 1470-1488.

Greene WH. 2003. *Econometric Analysis* (5th ed.). Pearson: New Jersey.

Guardian. 2016. Pokémon Go players outraged after maps shut down by game update. Retrived from https://www.theguardian.com/technology/2016/aug/01/pokemon-go-maps-shut-down-game-update-tracking.

Hann I-H, Koh B, Niculescu MF. 2016. The double-edged sword of backward compatibility: The adoption of multigenerational platforms in the presence of intergenerational services. *Information Systems Research* **27**(1): 112-130.

Heidenreich S, Handrich M. 2015. What about passive innovation resistance? Investigating adoption-related behavior from a resistance perspective. *Journal of Product Innovation Management* **32**(6): 878-903.

Helfat CE, Raubitschek RS. 2000. Product sequencing: Co-evolution of knowledge, capabilities and products. *Strategic Management Journal* **21**(10-11): 961-979.

Helfat CE, Raubitschek RS. 2018. Dynamic and integrative capabilities for profiting from innovation in digital platform-based ecosystems. *Research Policy* **47**(8): 1391-1399.

Helfat CE, Winter SG. 2011. Untangling dynamic and operational capabilities: Strategy for the (n)ever-changing world. *Strategic Management Journal* **32**(11): 1243-1250.

Henderson AD. 1999. Firm strategy and age dependence: A contingent view of the liabilities of newness, adolescence, and obsolescence. *Administrative Science Quarterly* **44**(2): 281-314.

Henderson RM, Clark KB. 1990. Architectural innovation: The reconfiguration of existing product technologies and the failure of established firms. *Administrative Science Quarterly* **35**(1): 9-30.

Hong W, Thong JYL, Chasalow LC, Dhillon G. 2011. User acceptance of agile information systems: A model and empirical test. *Journal of Management Information Systems* **28**(1): 235-272.

Hopkins HD. 1987. Acquisition strategy and the market position of acquiring firms. *Strategic Management Journal* **8**(6): 535-547.

Hu MM, Yang S, Xu DY. 2019. Understanding the social learning effect in contagious switching behavior. *Management Science* **65**(10): 4771-4794.

James SD, Leiblein MJ, Lu S. 2013. How firms capture value from their innovations. *Journal of Management* **39**(5): 1123-1155.

Kapoor R, Agarwal S. 2017. Sustaining superior performance in business ecosystems: Evidence from application software developers in the iOS and Android smartphone ecosystems. *Organization Science* **28**(3): 531-551.

King AA, Tucci CL. 2002. Incumbent entry into new market niches: The role of experience and managerial choice in the creation of dynamic capabilities. *Management Science* **48**(2): 171-186.

Koopman P, Hoffman RR. 2003. Work-arounds, make-work, and kludges. *IEEE Intelligent Systems* **18**(6): 70-75.

Kovács B, Sharkey AJ. 2014. The paradox of publicity: How awards can negatively affect the evaluation of quality. *Administrative Science Quarterly* **59**(1): 1-33.

Kretschmer T, Claussen J. 2016. Generational transitions in platform markets—The role of backward compatibility. *Strategy Science* **1**(2): 90-104.

Lawless MW, Anderson PC. 1996. Generational technological change: Effects of innovation and local rivalry on performance. *Academy of Management Journal* **39**(5): 1185-1217.
Leibenstein H. 1950. Bandwagon, snob, and veblen effects in the theory of consumers' demand. *Quarterly Journal of Economics* **64**(2): 183-207.
Leonard-Barton D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal* **13**: 111-125.
Levinthal DA. 1991. Random walks and organizational mortality. *Administrative Science Quarterly* **36**(3): 397-420.
Levinthal DA. 1997. Adaptation on rugged landscapes. *Management Science* **43**(7): 934-950.
Lobel I, Patel J, Vulcano G, Zhang J. 2016. Optimizing product launches in the presence of strategic consumers. *Management Science* **62**(6): 1778-1799.
MacCormack A, Verganti R, Iansiti M. 2001. Developing products on "Internet time": The anatomy of a flexible development process. *Management Science* **47**(1): 133-150.
Macmillan M. 2015. The Millionaires Index. *Pollen VC* (Retrieved from https://insights.pollen.vc/articles/the-millionaires-index/).
Miric M, Boudreau KJ, Jeppesen LB. 2019. Protecting their digital assets: The use of formal & informal appropriability strategies by app developers. *Research Policy* **48**(8).
Moore GA. 1991. *Crossing the Chasm: Marketing and Selling Technology Products to Mainstream Customers*. HarperCollins: New York.
Mora R, Reggio I. 2015. didq: A command for treatment-effect estimation under alternative assumptions. *Stata Journal* **15**(3): 796-808.
Moreau CP, Lehmann DR, Markman AB. 2001. Entrenched knowledge structures and consumer response to new products. *Journal of Marketing Research* **38**(1): 14-29.
Mukherjee A, Hoyer WD. 2001. The effect of novel attributes on product evaluation. *Journal of Consumer Research* **28**(3): 462-472.
Nelson RR, Winter SG. 1977. In search of useful theory of innovation. *Research Policy* **6**(1): 36-76.
New York Times. 2016. The Minecraft generation. Retrived from https://www.nytimes.com/2016/04/17/magazine/the-minecraft-generation.html.
New York Times. 2018. Snap's drop in active users could signal a social media peak. Retrived from https://www.nytimes.com/2018/08/07/technology/snapchat-users.html.
Oreg S. 2003. Resistance to change: Developing an individual differences measure. *Journal of Applied Psychology* **88**(4): 680-693.
Ouellette JA, Wood W. 1998. Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological Bulletin* **124**(1): 54-74.
Pisano G. 2015. You need an innovation strategy. *Harvard Business Review* **93**(6): 44-54.
Priem RL. 2007. A consumer perspective on value creation. *Academy of Management Review* **32**(1): 219-235.
Priem RL, Li S, Carr JC. 2012. Insights and new directions from demand-side approaches to technology innovation, entrepreneurship, and strategic management research. *Journal of Management* **38**(1): 346-374.
Quinn JM, Pascoe A, Wood W, Neal DT. 2010. Can't control yourself? Monitor those bad habits. *Personality and Social Psychology Bulletin* **36**(4): 499-511.
Ram S. 1989. Successful innovation using strategies to reduce consumer resistance: An empirical test. *Journal of Product Innovation Management* **6**(1): 20-34.

Rietveld J, Eggers JP. 2018. Demand heterogeneity in platform markets: Implications for complementors. *Organization Science* **29**(2): 304-322.
Rivard S, Lapointe L. 2012. Information technology implementers' responses to user resistance: Nature and effects. *MIS Quarterly* **36**(3): 897-920.
Rogers EM. 2003. *Diffusion of Innovations* (5th ed.). Free Press: New York.
Rosenbloom RS. 2000. Leadership, capabilities, and technological change: The transformation of NCR in the electronic era. *Strategic Management Journal* **21**(10-11): 1083-1103.
Schilling MA. 2003. Technological leapfrogging: Lessons from the U.S. video game console industry. *California Management Review* **45**(3): 6-32.
Singh J, Agrawal A. 2011. Recruiting for ideas: How firms exploit the prior inventions of new hires. *Management Science* **57**(1): 129-150.
Slater SF, Mohr JJ. 2006. Successful development and commercialization of technological innovation: Insights based on strategy type. *Journal of Product Innovation Management* **23**(1): 26-33.
Teece DJ. 1986. Profiting from technological innovation: Implications for integration, collaboration, licensing and public policy. *Research Policy* **15**(6): 285-305.
Tiwana A. 2015. Evolutionary competition in platform ecosystems. *Information Systems Research* **26**(2): 266-281.
Toubia O, Stephen AT. 2013. Intrinsic vs. image-related utility in social media: Why do people contribute content to Twitter? *Marketing Science* **32**(3): 368-392.
Tripsas M. 1997. Unraveling the process of creative destruction: Complementary assets and incumbents survival in the typesetter industry. *Strategic Management Journal* **18**(S1): 119-142.
Turner SF, Mitchell W, Bettis RA. 2010. Responding to rivals and complements: How market concentration shapes generational product innovation strategy. *Organization Science* **21**(4): 854-872.
Turner SF, Mitchell W, Bettis RA. 2013. Strategic momentum: How experience shapes temporal consistency of ongoing innovation. *Journal of Management* **39**(7): 1855-1890.
Tushman ML, Anderson P. 1986. Technological discontinuities and organizational environments. *Administrative Science Quarterly* **31**(3): 439-465.
Wang T, Aggarwal VA, Wu B. 2020. Capability interactions and adaptation to demand-side change. *Strategic Management Journal* **41**(9): 1595-1627.
Wen W, Zhu F. 2019. Threat of platform-owner entry and complementor responses: Evidence from the mobile app market. *Strategic Management Journal* **40**(9): 1336-1367.
Wood W, Neal DT. 2007. A new look at habits and the habit-goal interface. *Psychological Review* **114**(4): 843-863.
Zhang Y, Li J, Tong TW. 2020. Platform governance matters: How platform gatekeeping affects knowledge sharing among complementors. *Strategic Management Journal* **in press**.

Table 1 Summary statistics and correlation

		Mean	S.D.	Min	Max	1	2	3	4	5	6	7	8	9	10
1	Consumer adoption	6.621	2.454	0.000	14.755	1.000									
2	Treatment	0.527	0.499	0.000	1.000	-0.015	1.000								
3	Post	0.533	0.499	0.000	1.000	0.009	0.000	1.000							
4	Top market ranking	0.069	0.254	0.000	1.000	0.441	-0.009	0.019	1.000						
5	Prior GPIs	1.153	0.589	0.000	2.890	0.255	-0.043	0.000	0.220	1.000					
6	Platform generational transition	0.096	0.294	0.000	1.000	-0.007	-0.035	-0.006	-0.089	-0.066	1.000				
7	Competition	1.686	0.652	0.000	3.296	0.120	-0.017	0.100	0.122	0.061	-0.173	1.000			
8	Platform	0.472	0.499	0.000	1.000	-0.096	0.112	0.000	0.023	-0.023	-0.217	-0.448	1.000		
9	Product age	6.648	0.520	3.807	7.627	0.063	-0.035	0.011	0.194	0.305	0.006	-0.080	0.163	1.000	
10	Time since the last update	4.081	0.797	1.386	6.426	-0.205	0.151	0.104	-0.177	-0.113	0.017	0.088	-0.062	0.021	1.000

Table 2 Influence of GPIs on consumer adoption

	(1) Pre-update	(2) Post-update	(3) All sample	(4) All sample
Treatment*Post			-0.097	-0.096
			(0.026)	(0.018)
			[0.000]	[0.000]
Treatment	0.288	0.151	0.264	0.268
	(0.022)	(0.020)	(0.020)	(0.014)
	[0.000]	[0.000]	[0.000]	[0.000]
Post			0.177	0.176
			(0.021)	(0.014)
			[0.000]	[0.000]
Top market ranking	0.727	0.555	0.619	0.365
	(0.066)	(0.060)	(0.044)	(0.040)
	[0.000]	[0.000]	[0.000]	[0.000]
Prior GPIs	0.013	-0.216	-0.058	-0.060
	(0.070)	(0.066)	(0.047)	(0.033)
	[0.857]	[0.001]	[0.219]	[0.072]
Platform generational transition	0.124	0.200	0.170	0.166
	(0.053)	(0.049)	(0.035)	(0.025)
	[0.019]	[0.000]	[0.000]	[0.000]
Competition	0.271	0.302	0.216	0.209
	(0.027)	(0.030)	(0.018)	(0.013)
	[0.000]	[0.000]	[0.000]	[0.000]
iOS platform	-0.297	-0.323	-0.356	-0.366
	(0.030)	(0.030)	(0.021)	(0.014)
	[0.000]	[0.000]	[0.000]	[0.000]
Product age	6.839	4.564	6.271	6.290
	(0.638)	(0.642)	(0.447)	(0.321)
	[0.000]	[0.000]	[0.000]	[0.000]
Product age^2	-0.566	-0.378	-0.507	-0.508
	(0.047)	(0.047)	(0.033)	(0.024)
	[0.000]	[0.000]	[0.000]	[0.000]
Time since the last update	-1.074	-1.959	-0.391	-0.332
	(0.269)	(0.376)	(0.171)	(0.119)
	[0.000]	[0.000]	[0.022]	[0.005]
Time since the last update^2	0.035	0.136	-0.040	-0.045
	(0.035)	(0.045)	(0.023)	(0.016)
	[0.326]	[0.002]	[0.074]	[0.004]
App FE	YES	YES	YES	YES
Country FE	YES	YES	YES	YES
App-country FE	NO	NO	NO	YES
Observations	21399	24456	45855	45855
R^2	0.688	0.698	0.691	0.855

Standard errors are included in parentheses. P-values are in square brackets. All tests are two-tailed.

Table 3 DDD-moderation effects on the relationship between GPI and consumer adoption

	(5)	(6)	(7)	(8)	(9)
Treatment*Post	-0.105	0.020	4.673	2.538	2.360
	(0.019)	(0.039)	(2.216)	(2.238)	(2.252)
	[0.000]	[0.619]	[0.035]	[0.257]	[0.295]
Treatment*Post*Top market ranking	0.187				0.215
	(0.072)				(0.075)
	[0.009]				[0.004]
Treatment*Top market ranking	-0.434				-0.248
	(0.057)				(0.061)
	[0.000]				[0.000]
Post*Top market ranking	-0.151				-0.151
	(0.052)				(0.054)
	[0.004]				[0.005]
Treatment*Post*Prior GPIs		-0.100		-0.102	-0.119
		(0.030)		(0.032)	(0.032)
		[0.001]		[0.001]	[0.000]
Treatment*Prior GPIs		0.030		0.240	0.256
		(0.024)		(0.026)	(0.026)
		[0.216]		[0.000]	[0.000]
Post*Prior GPIs		0.029		0.061	0.075
		(0.022)		(0.023)	(0.023)
		[0.178]		[0.007]	[0.001]
Treatment*Post*Product age			-1.433	-0.783	-0.711
			(0.681)	(0.688)	(0.692)
			[0.035]	[0.254]	[0.304]
Treatment*Product age			-9.254	-9.242	-9.581
			(0.661)	(0.662)	(0.672)
			[0.000]	[0.000]	[0.000]
Post*Product age			0.035	-0.779	-0.807
			(0.600)	(0.610)	(0.611)
			[0.954]	[0.202]	[0.187]
Treatment*Post*Product age^2			0.107	0.061	0.054
			(0.052)	(0.053)	(0.053)
			[0.039]	[0.248]	[0.308]
Treatment*Product age^2			0.662	0.652	0.680
			(0.051)	(0.051)	(0.052)
			[0.000]	[0.000]	[0.000]
Post*Product age^2			-0.006	0.054	0.057
			(0.046)	(0.046)	(0.046)
			[0.892]	[0.242]	[0.220]
Controls	Included	Included	Included	Included	Included
App-country FE	YES	YES	YES	YES	YES
Observations	45855	45855	45855	45855	45855
R^2	0.855	0.855	0.859	0.859	0.859

Standard errors are included in parentheses. P-values are in square brackets. All tests are two-tailed.

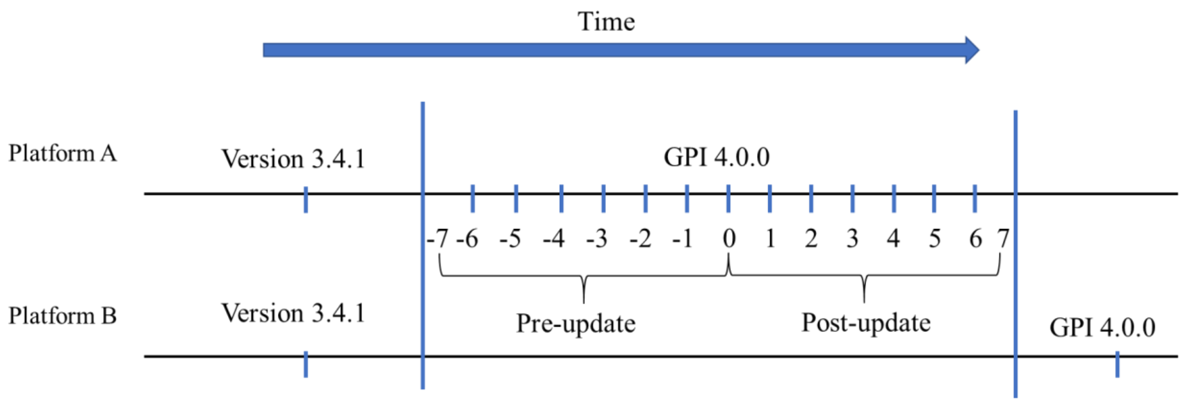
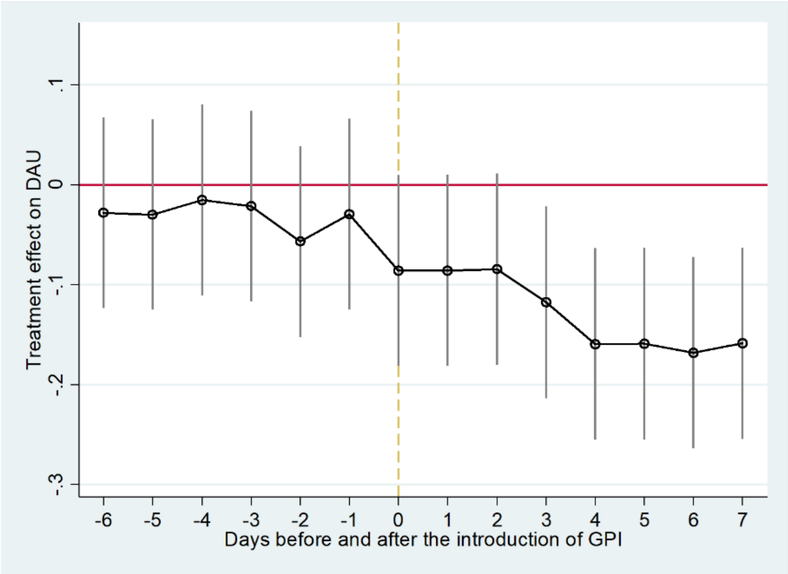


Figure 1 DID sample matching



Notes: The circles represent the coefficients of the DID estimates (the interaction terms). The grey vertical lines represent the 95% confidence intervals of the DID estimates.

Figure 2 The treatment effect on log-transformed DAU for days before and after the introduction of GPI

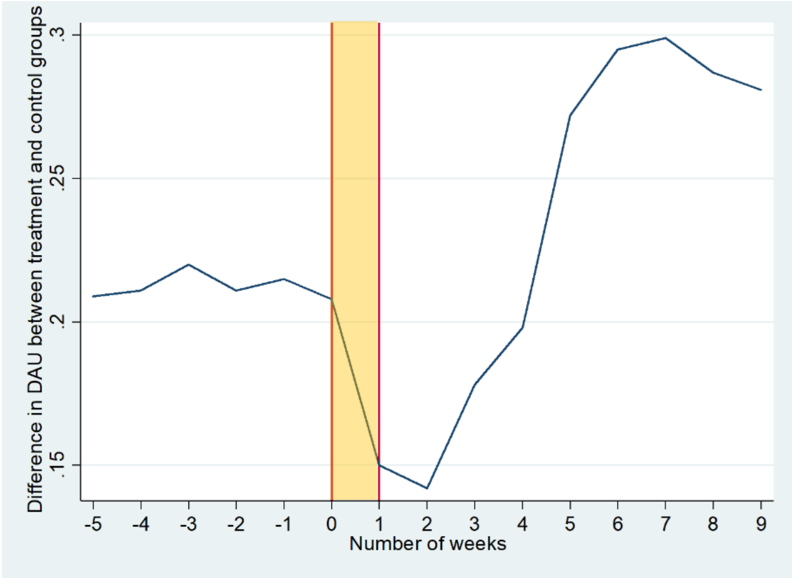
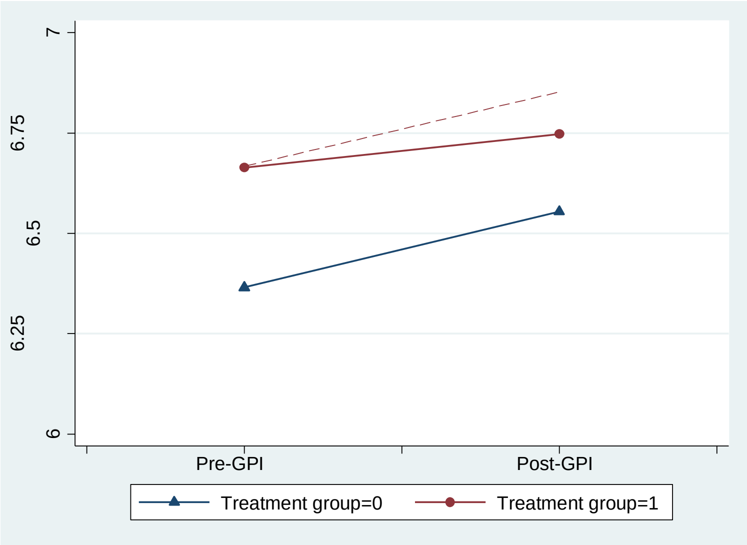


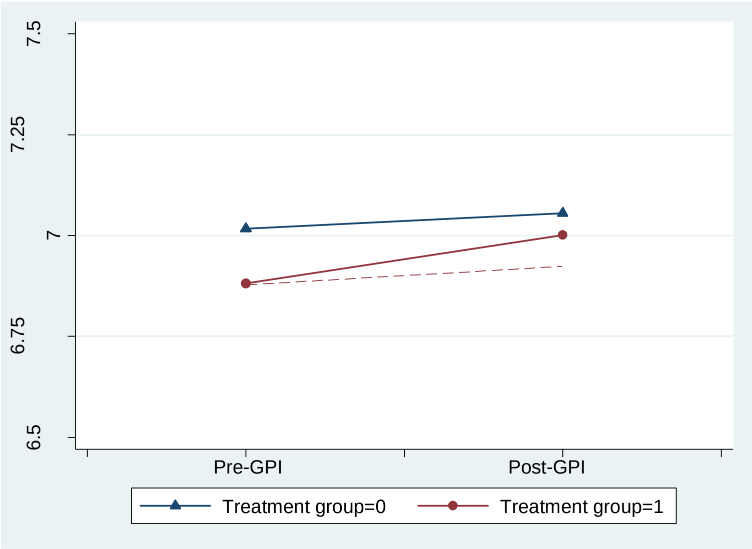
Figure 3 The difference in log-transformed DAU between treatment and control groups at the weekly level

(Shaded area represents the near-term effect of GPI)



*Note: the dashed line represents the counterfactual trend should the GPI have no effect.

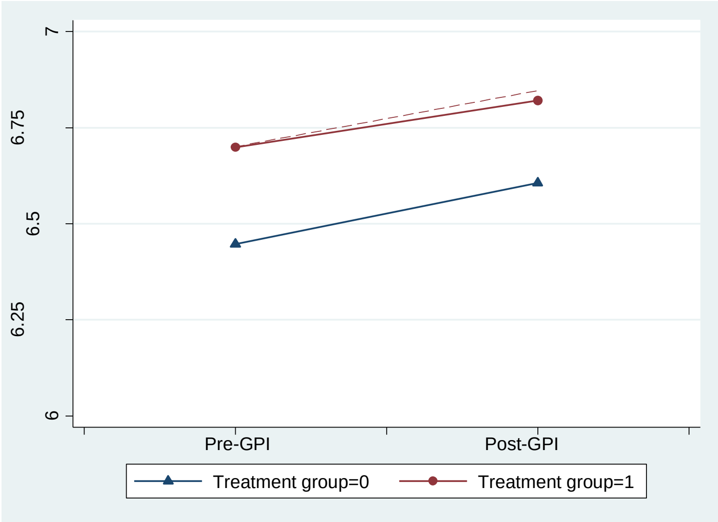
Low market ranking (not ranked in top 30)



*Note: the dashed line represents the counterfactual trend should the GPI have no effect.

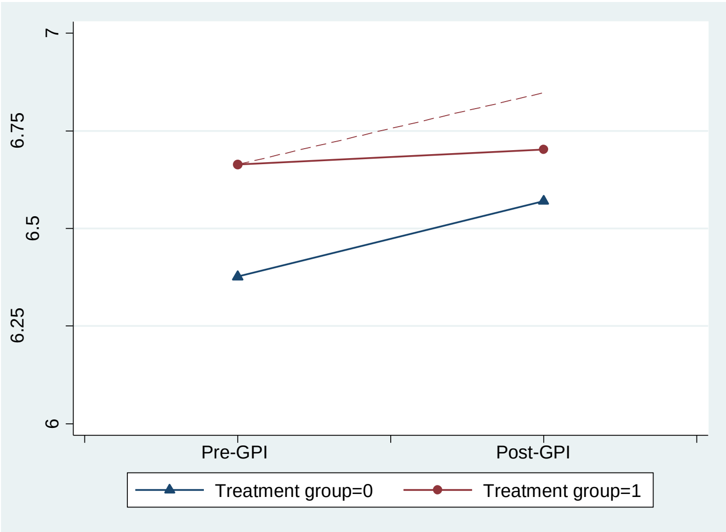
High market ranking (ranked in top 30)

Figure 4 Moderating effect of market position



*Note: the dashed line represents the counterfactual trend should the GPI have no effect.

Apps with low level of prior GPIs, mean – 1s.d.



*Note: the dashed line represents the counterfactual trend should the GPI have no effect.

Apps with high level of prior GPIs, mean + 1s.d.

Figure 5 Moderating effect of technological legacy