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The differential impact of types of app innovation on customer evaluation

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ABSTRACT

Digital innovation literature seldom considers the effects of innovation from app developers' perspective. Even when it does, the findings on the value of app innovation are mixed. Based on technological innovation and early-mover advantages literature, we delineate types of app innovation and their impacts on customer evaluations. Our empirical results indicate that adding new business functions to provide new categories of product or service offerings increases customer evaluations, whereas, adding new supporting service functionalities (SSFs) decreases customer evaluations. For followers that "imitate" innovations, the effect of adding SSFs on customer evaluations is negatively contingent on the quality of early-mover apps.

1. Introduction

Because of recent advancements in digital technologies and pervasive digitization, digital innovation has transformed industries and created substantial economic value. As of 2018, digital innovation accounted for about 11 percent of GDP in advanced economies and is viewed as the backbone of economic growth[1] . In conjunction with this trend, mobile software apps are particular forms of digital innovation that drive much industry revolution [1,2]. Mobile software apps are predicted to impact the global economy to the tune of $6.3 trillion by 2021, five times greater than in 2016[2] . Organizations and individuals can readily leverage widely accessible tools and resources offered by software platforms, such as app programming interfaces and software development kits, which allows them to participate in innovation and create novel apps that have a tremendous impact on society, industry, firms, and individuals. In Apple's App Store alone, as of July 2019, approximately 3.97 million apps covered twenty-four categories, such as games, business, education, and entertainment[3] .

In contrast with the wide recognition of the positive aspects of mobile software apps, actual outcomes of innovation are more somber. App markets in certain industries are hypercompetitive[4] and dominated by a handful of apps [4]. For instance, as of the first quarter of 2018, more than 80 percent of all Android apps had less than five thousand downloads, while only 0.1 percent of Android apps had more than five million downloads[5] . To cope with such hypercompetition, firms or developers are often compelled to constantly add new features or functionalities by releasing new versions of an app on a monthly or even bi-weekly basis (McIlroy et al. 2015). Yet, precisely because of the necessity of such high update frequency, firms or developers are often faced with a *strategic dilemma*[6] in terms of how to choose one type of app innovation against another. Here, app innovation is defined as adding new features or functionalities to an existing app [5].

On one hand, firms or developers are afforded various strategic choices in terms of what and how to innovate. New features or functionalities can be new business functions that provide new categories of product or service offerings or new supporting service functionalities (SSFs) that enhance the existing offerings of an app. The former expands the boundaries of an app, while the latter increases the functional depth of an app. For example, Meituan, an original group-buying services provider in China, constantly adds new business functions that provide categories of product or service offerings beyond its original offering, such as food delivery, hotel reservations, and ride-hailing

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[1] https://www.data61.csiro.au/en/Our-Work/Future-Cities/Planning-sustainable-infrastructure/Digital-Innovation
[2] https://go.appannie.com/report-app-economy-forecast-part-two
[3] https://www.statista.com/statistics/268251/number-of-apps-in-the-itunes-app-store-since-2008/
[4] Hypercompetition is a characteristic of markets where organizations use tactics to disrupt competitive advantage by industry leaders and the advantage is difficult to sustain [[3]].
[5] https://www.statista.com/statistics/269884/android-app-downloads/
[6] Note: All italics throughout the paper have been added by the authors to emphasize specific points.

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services, becoming an "everything app" that encompasses almost all aspects of local services[7] . Meanwhile, it also adds new SSFs that pertain to the group-buying service, such as the functionality of daily recommendations and filtering by a plaza. Besides, because of the modular and transparent nature of software platforms, firms or developers can act as either pioneers that innovate new app features or as followers that imitate successful app features.

On the other hand, the effectiveness of different types of app innovation is uncertain. Although it is plausible that app innovations that introduce new categories of product or service offerings or new SSFs can increase an app's capabilities and thus meet customers' heterogeneous demand, anecdotal and empirical evidence suggests that customer reactions to app innovations are mixed. There are numerous tutorials that teach users how to undo an update or go back to an older version of an app because of undesired new features[8] . Moreover, while it seems to be an effective strategy to follow a pioneering app and introduce similar successful features, the effort could also be counterproductive. For example, Alipay, a third-party mobile and online payment platform in China, added a social feature, "Circles," to its 9.9.7 app version on November 24, 2016. That feature resembled the popular friends circle feature of WeChat, the largest instant messaging app in China, and allowed users to join various interest circles and share messages or photos. However, due to the poor design of the posting and commenting rules, the function backfired and caused a significant negative impact on Alipay[9] . Given the easy substitutability among apps, if innovation of an app fails to achieve a favorable outcome, negative usage experience will reduce customer intentions to continue using the app and drive customers to rival apps, thereby undermining the original intention to obtain competitive advantages. Therefore, it is important to improve our understanding of how customers evaluate different types of app innovation.

Previous digital innovation literature mainly focuses on the antecedents of app innovation from the platform perspective. Much of the literature implicitly assumes that attracting a large number of app developers and facilitating their unprompted innovation results into positive outcomes [6,7]. Accordingly, empirical studies have examined how user characteristics [8], network effects [9], platform boundary resources [10–13], governance mechanisms [14,15], and platform entry [5,16] affect app innovation. However, these studies are mostly conducted from the platform perspective, while there are limited studies on the effects of app innovation from the perspective of app developers.

Although some recent studies in the app update literature directly investigate the effects of app innovation, the results have been far from conclusive and the underlying theoretical mechanisms have been unclear. Some studies have demonstrated that app innovation significantly improves the quality of an app and thus increases app performance, such as downloads, ranks, and ratings [4,15,17], whereas other studies argue that customers react negatively to app innovation, thus decreasing app performance [17,18]. The rationale behind such negative reactions is speculated to be economic, that is, the adoption costs (such as learning costs) outweigh the potential benefits [18]. However, after failing to find evidence of the economic impact [17], scholars theorize about behavioral reasons, such as a routine-seeking behavior by customers.

We posit that one of the reasons for the inconsistent findings in the extant literature could be due to a homogenous view of app innovation. Changes to app features or functionality are treated identically and customers are assumed to evaluate functionality changes independently among other competing apps. This coarse-grained view is insufficient to capture multiple facets of app innovation and thus may mask underlying tensions. This study attempts to open the black box and investigate how customers evaluate different types of app innovation. Accordingly, we are motivated to ask three research questions:

1 What are the different types of app innovation?
2 *How do different types of app innovation affect the valence of customer evaluations?*
3 *How does the availability of competing apps influence the valence of customer evaluations of app innovation?*

We draw on the technological innovation literature and the early-mover advantage literature to conceptualize app innovation as app core innovation and app support innovation. We incorporate the quality of early-mover apps as a contingent condition that influences customer evaluations of app core or support innovation introduced by followers, which we label as app core imitation and app support imitation. We then develop our hypotheses on customer evaluations of different types of app innovation. Our data include the release notes and app reviews of seven online Chinese travel apps available from Apple's App Store, competing in the hypercompetitive travel market. We further test our model using ordinary least squares with panel-corrected standard errors (OLS-PCSE) and conduct topic modeling of app reviews as supplementary analyses.

Our results indicate that app core innovation increases, while app support innovation decreases the valence of customer evaluations. In the latter case, the effect is because of a tradeoff between creating interaction value and disrupting customers' established routines. For followers that "imitate" innovations, the effect of app support imitation on the valence of customer evaluations is negatively contingent on the quality of early-mover apps. Such a negative contingent effect is not evident for app core imitation. These results are further discussed as to how they contribute to research and practice.

2. Theoretical background

2.1. App-related literature

An application (app) is a software designed to run on a particular developmental platform [14,19]. The developmental platform can be a web browser (e.g., Firefox) [15], a mobile app market (e.g., Apple's App Store or Google Play) [20], or a social media platform (e.g., Facebook) [21]. *An app update* is the release of a new version of an existing app [16,22]. A release can be one of five types – (1) a feature update or major update, which introduces new features or functionalities [5,17,23]; (2) a technical non-feature update, which corrects flaws [5,23]; (3) an incremental update, which improves and refines existing features or functionalities [16]; (4) a commercial update, which introduces price cuts or promotions or increases the scale of product or service offerings sold on an app; and (5) a package release, which consists of any two of the above four types. Compared with the other types of app updates that focus on the improvement or exploitation of existing features or functionalities, adding new features or functionalities can provide substantial advances in both the number and diversity of app functionalities and are primary sources of competitive advantage under hypercompetitive app markets [17]. Consistent with previous studies, we define *app innovation* as adding new features or functionalities to an existing app [5].

Studies on the effects of app innovation belong to a broad research stream of *factors that affect app success*. Table 1 summarizes the key findings of related literature and their implications for our study. Overall, research into factors that affect app success or demand discusses the impacts of *app characteristics* (such as age) [24], *developer actions* (including category or platform positioning [24–26], app portfolios [26], monetization strategies [20,27], app updates [4,15,17,18,22,28,29]), *copycats* [2], or *past performance* (such as

[7] https://www.ft.com/content/e8e37194-f41e-11e6 – 8758-6876151821a6

[8] An illustration of a tutorial can be found at https://www.dignited.com/42657/heres-how-to-undo-an-android-app-update-if-youre-not-ready-for-the-new-version/

[9] https://blogs.wsj.com/chinarealtime/2016/11/28/social-feature-turns-chinas-alipay-into-a-hook-up-app/

Table 1
Summary of findings and implications on the effects of app innovation.

Study	Key findings	Implications
[2]	High-quality, non-deceptive copycats decrease the demand for original apps, and low-quality, deceptive copycats increase the demand for originals.	Apps can be easily copied by rivals. Apart from app features, the demand for an app is contingent on the quality of rival apps.
[4]	Major updates increase app downloads.	App innovation adds new app functionalities that significantly improve app quality.
[17]	Feature updates increase app downloads but decrease app ratings.	While app innovation attracts new customers by increasing the perceived capability of an app, existing customers react negatively to app innovation for behavioral reasons.
[18]	Feature updates are supposed to have an inverse U-shaped relationship with app success (the authors have not tested this).	App innovation is not universally beneficial to customers – if the number of changes surpasses customers' absorptive capacity, app innovation can be counterproductive.
[24]	Quality (feature) updates positively impact app demand.	App innovation is an indicator of the quality of an app.
[26]	Quality (feature) updates contribute up to a threefold improvement in the survival rate of an app.	App innovation is an indicator of the quality of an app and developer effort.

Note: The terms of feature updates and major updates are interchangeable in app innovation.

rankings and user ratings) [25,30,31] on app demand or success.

In terms of developer actions, prior literature has found that it is extremely difficult to achieve and sustain superior performance (such as appearing and remaining in the top-ranking charts) in hypercompetitive app markets [32]. It is argued that firms or developers should deliberately position themselves in less-competitive categories and broaden their app offerings across categories and platforms to create positive spillover effects and realize scope economies [24–26]. For instance, to maximize revenue, firms or developers are encouraged to provide a free version of paid apps (i.e., freemium) [20,33] and in-app purchase options [24,26,27]. Although these studies acknowledge that app updates are important determinants of app success, they often marginalize app updates as peripheral or control variables.

For studies that focus on app updates, the relevant literature mainly investigates the effects of update frequency and update type. A large proportion of these studies deem that frequent updates improve the quality of an app, attract customer attention, and add value to customers, thus leading to superior market performance [4,15,18,22,28,34,35]. This stream of research views app updates as an ongoing process of incremental refinements of existing apps and holds the view that it is the frequency or rate of the update rather than the update itself that determines app performance [15]. However, some recent studies have found that the positive effect of update frequency does not hold for updates that only correct flaws [23], indicating the need to identify different types of app updates and their subsequent effects.

Despite the difficulty in identifying different types of app updates, some literature explicitly focuses on app innovation and using version numbers (e.g., 1.0.0 and 1.1.0) to distinguish app innovation from minor technical improvements like bug fixes [4,15], or feature-related keywords in release notes to identify app innovation [17]. Nevertheless, here too the effects of app innovation are unclear. While some studies found that app innovation significantly improves the quality of an app, and thus is beneficial to increasing app performance [4,17], other studies argue that app innovation can decrease app performance [17,18]. One reason for the decrease in performance is that the adoption costs (such as learning costs) of new features or functionalities outweigh the potential benefits [18]. However, when counting the number of new features as a proxy for gauging the degree of change customers experience as they adopt an app innovation, Feorderer and Heinzl (2017) [17] did not find evidence of the economic reasoning related to adoption costs and thus speculated that there may be a behavioral phenomenon, such as a routine-seeking behavior by customers, that induces the negative reactions to app innovation.

We posit that the reason for the inconsistent findings and the unclear underlying mechanisms is due to the assumption that customers view new features or functionalities as homogeneous and evaluate them independently with other competing apps. Indeed, features or functionalities may differ in ways that have asymmetric implications for performance. Such functionalities are not assessed by customers in isolation but in comparison to competing apps that better satisfy their needs in hypercompetitive app markets [2]. Precisely because of this, the valence of customer evaluations is a desirable performance indicator to capture how well app innovation satisfies customer needs and how such assessments are influenced by superior or inferior competitive apps [15,17]. Other app performance metrics, such as downloads and ranks, are sufficient to measure the extent of customer attention drawn by app innovation but do not provide any direct indication of whether the customer satisfies with the innovation. Instead, the valence of customer evaluations is a more direct assessment of how customer needs are satisfied after use or comparison with competing apps.

Below, we first draw from the technological innovation literature to identify typologies of app innovation. Then, based on the early-mover advantage literature, we include the quality of early-mover apps as a moderator in influencing customer evaluations of innovations.

2.2. Technological innovation literature

Differentiating types of innovation with different competitive effects has been an important theme in the technological innovation literature [36]. Researchers have developed numerous typologies of innovation, such as the radical versus incremental [37], disruptive versus routine [38,39], architectural versus modular [40], and core versus peripheral [41,42]. For product innovation, the literature suggests that products can be viewed as hierarchically ordered subsystems or components and it is important to specify innovations at the component level of analysis from innovations at the product level of analysis [36]. Similarly, by demarcating innovations that are core to the product from those that are in support of or are peripheral to the product, we can develop a fine-grained understanding of product evolution through different types of innovation as an ongoing innovation process [41,43].

Core components are those that are tightly connected to other components and are associated with strategic performance parameters. Because of high interdependence with other components, changes in core components will have a cascading effect on other components, which will also require accompanying changes, thereby driving system-level innovation. Thus, core innovations often lead to the introduction of new products and serve as strategic bottlenecks for product performance [41]. For example, an engine is the core component of cars. Making the change from gasoline-powered car engines to electric-powered motors triggers subsequent changes in peripheral components, such as lightening the car body and enhancing front shock absorbers, which in turn results in the introduction of a new car product – the electric car. In contrast, peripheral components are loosely connected to other components and tactically support core components. Changes in peripheral components will have minor effects on other components and the product as a whole. Therefore, peripheral innovations often pertain to improvements in existing products and are not associated with strategic performance parameters [36].

As adding new features or functionalities to an existing app is a continuous stream of innovation over time, app innovation does not fit neatly with radical, disruptive, or architectural innovation. Therefore, in line with the ongoing process of product innovation, we perceive an app as a purely digital product that is composed of a nested hierarchy of features or functionalities. Accordingly, we distinguish app innovations as app core innovation and app support innovation.

We define *app core innovation (ACInn)* as adding a new business function that provides a new category of product or service offering to an existing app [36,44–46]. The category of the product or service offering can be viewed as the industrial classification of products or services in a hierarchical category structure (such as the twenty-four app categories and a number of subcategories described by Apple's App Store[10]). The introduction of a new category of product or service offering to an app is represented by adding a new business function to the front end of the app and is accomplished by developing both new core subsystems that are instrumental to what the business is and accompanying changes to other supporting subsystems. Thus, app core innovations are strategic moves to enter new markets and broaden the business scope of an app. It is worth noting that contrary to the introduction of new stand-alone products due to changes in the core components in the technological innovation literature, the new category of product or service offerings is introduced to an existing product (i.e., an existing app). Such convergence is enabled by the homogenization and reprogrammability of digital technologies [6]. For example, started as an instant messaging app, WeChat has continuously morphed to add services like payments, content subscriptions, games, and financial services, and has become a one-stop portal that is beyond the single purpose of instant messaging[11] . Each of the new services is associated with the development of new core subsystems that are fundamental to the provision of a specific business function. Therefore, app core innovations will increase the variety of product or service offerings available from an existing app and thus can create multifunctional value for customers.

In contrast, *app support innovation (ASInn)* is defined as adding new supporting service functionalities that pertain to existing product or service offerings [36,44,45]. Supporting service functionalities (SSFs) are supplementary technological features that support customers as they interact with an app and derive value from products or services throughout the interaction process [44,47,48]. The addition of new SSFs requires developing new supporting subsystems that are peripheral to an existing business function and often have minor impacts on the app as a whole. Thus, app support innovations are tactical moves to refine existing markets and deepen the business offerings of an app. For instance, WeChat constantly adds new SSFs to improve its messaging services, such as the functionality of sharing and editing photos, video and voice calls, group talk, voice messaging, and real-time location sharing. Therefore, app support innovations help customers better derive value from an app's existing product or service offerings and thus can create interaction value for customers.

Importantly, in hypercompetitive environments, competitors closely monitor innovations in the market and customers are well aware of competitors' offerings. Therefore, customer evaluations of the value of new features depend on whether there are comparable apps that provide similar features as well as their relative quality in satisfying customer needs.

2.3. Early-mover advantages literature

The early-mover advantages literature has demonstrated that the quality of original innovation is an important contingent condition that determines the effectiveness of similar innovations introduced by followers [49]. Early movers can gain preemptive advantages over followers by achieving positive differentiation, building customer switching costs [50,51], shaping customers' perceptual structures and preferences toward the innovation [51] as well as establishing stronger ties between the innovation and unique complementary resources [52]. Followers are often at a disadvantage in making up the preemptive advantages. To effectively compete with early movers, followers need to "imitate" with a high-quality innovation that outperforms in comparison with the original innovation [49], thus appropriating value. Otherwise, the followers' imitative efforts can be counterproductive and can even foster positive impacts on the original innovation.

The quality of early-mover apps as a contingent condition in influencing customer evaluations of app imitation has also been studied in the recent app development literature [2]. Because of the transparent and open innovation nature of the developmental platforms on which apps reside, previous app development literature has demonstrated that successful pioneering innovations are often followed by imitators in an attempt to bypass the risks of pioneering and participate in the market [2,13,53]. Using the simulation approach, some studies found that imitation is an effective strategy for achieving superior app performance [53,54]. However, a recent empirical study found that the effects of app imitation are contingent on the quality of competing apps that already provide similar features (hereafter, labeled as *early-mover apps*) [2]. When confronting a set of competing apps, customers are more likely to compare and choose the one with higher quality. Thus, higher quality imitated apps become substitutes for the original app, while lower quality imitated apps promote the original app. When there are no alternatives, an app is not subject to such a comparison.

Accordingly, to capture the nuanced differences in terms of dependencies among competing apps in influencing customer evaluations, we conceptualize app core and app support innovation introduced by followers as *app core imitation (ACImi)* and *app support imitation (ASImi)*[12], and they are only new to the app but not new to the market [55,56]. Because ACInn and ASInn provide features that are new to the market and do not have a benchmark for comparison, quality comparisons that influence customer evaluations only pertain to ACImi and ASImi. Moreover, because previous app development literature has demonstrated the positive effect of app imitation and the moderating role of the quality of early-mover apps [2,53,54], this study directly considers the moderating effect of the quality of early-mover apps on the relationship between app core/support imitation and the valence of customer evaluations.

3. Research model and hypotheses

Based on the literature and theoretical logic above, we propose our model and specific hypotheses. The unit of analysis is an individual new feature introduced by app innovation. Fig. 1 provides an overview of the typologies of app innovation. Fig. 2 represents our research model and Table 2 summarizes the definitions of the constructs in our research model. In proposing our hypotheses, we first hypothesize the positive effects of ACInn and ASInn on customer evaluations by discussing the multifunctional value and interaction value created by the two types of app innovations. We then proceed to consider how the quality of early-mover apps serves as a comparison benchmark in influencing customer evaluations of ACImi and ASImi.

3.1. App core innovation and customer evaluations

As indicated, ACInn refers to adding a new business function that provides a novel category of product or service offering to an existing app [36,44–46]. By pioneering new product or service offerings, a focal app can create positive differentiation and increase its perceived

[10] https://developer.apple.com/app-store/categories/

[11] https://medium.com/@miaozhen.zhang/chinas-wechat-the-power-of-the-super-app-dc144657625e

[12] By imitation, we specifically refer to the new product or service offerings, or SSFs, that are not first introduced by an app and do not exclude situations when followers learn from the pioneer and introduce similar offerings or SSFs with superior quality.

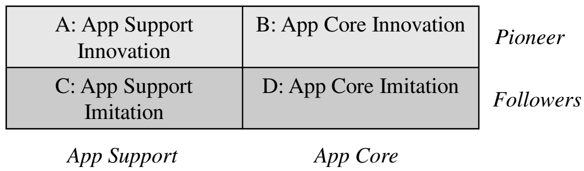

Fig. 1. Typology of app innovation.

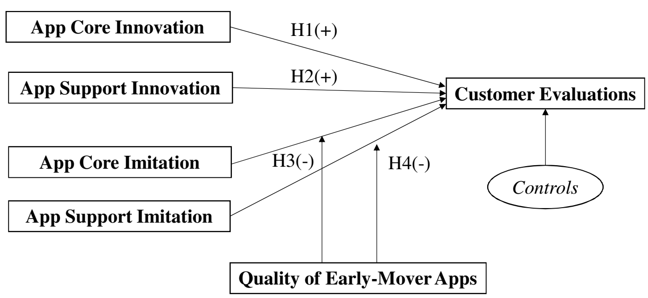

Fig. 2. Research model.

advantages over competing apps [57]. Previous literature has demonstrated that in the context of product evaluations, customers often judge a product more positively if it contrasts with, rather than be similar to, other products [46]. Thus, customers will positively assess an ACInn because it provides new product or service offerings that are currently not available elsewhere.

Moreover, ACInn increases the scope of product or service offerings in an app and thus adds multifunctional value to customers [45]. Rather than introducing a stand-alone app with new product or service offerings that require the additional downloading of another app, adding new offerings to an existing app eliminates the redundancy and increases the functional variety of the app. Relevant studies in the marketing literature have investigated the impacts of adding new features to a product on customer evaluations and have found that additional product features are beneficial to increasing product capability, customer utility, and valence of customer product evaluations [57–60]. Besides, the new product or service offerings can complement the existing offerings and thus offer customers one-stop shopping experience and a seamlessly integrated solution. Although we concur that the pioneer should invest in a large number of resources and undertake risks or uncertainties, these costs are internal facing rather than experienced by customers. Therefore, customers will perceive ACInn as beneficial and thus positively evaluate the innovation. Accordingly, we hypothesize

Hypothesis 1. *App core innovations are positively associated with the valence of customer evaluations*

3.2. App support innovation and customer evaluations

App support innovation adds new SSFs that pertain to existing product or service offerings [36,44,45]. The new SSFs can improve the customer usage experience of an app in ways that add interaction value to the customer [44,47,48]. Supporting service functionalities are technical features that support customers' interactions with an app and help derive value from the products or services the app offers, such as search, recommendation, product comparison, and order management functionalities provided by shopping apps. Previous online service literature has demonstrated that SSFs are useful in helping differentiate and facilitate the use of product or service offerings and increasing customer perceptions about the quality of a website and thus positively impact customer evaluations [44]. We posit that a positive relationship still holds in the app context. Because of the limited size of interaction interfaces, the SSFs of apps play a critical role in facilitating the usability of an app and customers' continued intentions to use it [61]. Through the addition of new SSFs, both the number and diversity of SSFs in an app increase, raising the likelihood of effectively addressing customers' changing needs and enhancing their usage experiences through a simplified interaction process. Therefore, we hypothesize that

Hypothesis 2. *App support innovations are positively associated with the valence of customer evaluations*

3.3. App core imitation and customer evaluations

App core and app support imitations refer to innovations that are not pioneering. They reflect following early movers to add the same category of product or service offering, as well as the same related SSFs, to an existing app. In a transparent digital environment, competitors have a good sense of each other's innovations as well as the performance achieved by those innovations [19]. They will attempt to duplicate an innovation when it generates above-average returns.

For ACImi, the high quality of early-mover apps indicates that the existing products or services are already of a high quality that meet customer needs. Moreover, due to the imperfectly imitable nature of a new category of product or service offering, early-mover apps can develop preemptive advantages over late-entrant apps and the followers are often at a disadvantage in quality comparisons with early-mover apps [50,51]. A developer's entry into a new or niche market is tied to what its app does strategically and often requires the developer to build IT and complementary resources as well as a system for its configuration [62]. Thus, the know-how for the novel products or services is unique and imperfectly imitable [62–65]. To outsiders, the process is opaque and they do not understand in sufficient detail how the innovation is implemented or decipher what particular elements generate superior performance. Thus, in the face of such causal ambiguity, it takes time for followers to duplicate the app core innovation. During this time, early-mover apps can achieve preemptive advantages by building their customer bases and shaping customer preferences and perceptual structures as well as developing stronger ties between the innovation and unique complementary resources [51,52]. As a result, customers can develop natural preferences toward early-mover apps [50,51] and the early-mover apps can also enhance the quality of the new product or service offerings through learning-by-using and the accumulation of critical resources [52].

Under such conditions, it is hard for followers to enter the market by offering similar product or service offerings of superior value. Comparable and additional resources are also needed for efficient

Table 2
Definition of constructs.

Construct	Definition	Supporting literature
App core Innovation	Adding a new business function that provides a new category of product or service offering to an existing app.	[2,36,44,45,46]
App core Imitation	Following a pioneer and adding the same business function that provides similar product or service offerings to an existing app.	
App support Innovation	Adding new supporting service functionalities that pertain to existing product or service offerings to an existing app.	[2,36,44,45]
App support Imitation	Following a pioneer and adding the same supporting service functionalities to an existing app.	
Quality of Early-Mover Apps	The quality of early-mover apps that have already provided imitated innovations.	[2]
Customer evaluations	The valence of customer evaluations in terms of how well an app innovation meets their needs.	[15,17]

competition with early-mover apps. Moreover, as customer preferences and perceptual structures are shaped by early-mover apps, the product or service already provided to them becomes the standard against which the app core imitation is judged. Therefore, because of the comparisons to superior quality early-mover apps and customer preferences toward them, the evaluation of an app core imitation is negatively influenced by the quality of early-mover apps. Thus, we hypothesize that

Hypothesis 3. *The effect of app core imitations on the valence of customer evaluations is negatively moderated by the quality of early-mover apps*

3.4. App support imitation and customer evaluations

App support imitation involves the addition of SSFs that are not first to market. By simply mimicking well-performing SSFs or enhancing functionalities with a better design, followers can achieve the benefits of adding interaction value to customers and improving the customer usage experience. Moreover, through reverse engineering, followers can readily and quickly imitate similar but improved SSFs [13,19]. However, a positive relationship can be attenuated by the quality of early-mover apps. High-quality early-mover apps indicate that customers highly value apps that have already provided the new supporting functionalities, facilitate the use of the app, and simplify the interaction process. According to early-mover advantages literature, customers' perceptive structures of new SSFs are shaped and informed by the efforts of early-mover apps [50,51] and influence their evaluations of ASImi accordingly. When followers subsequently add the new SSFs, which perform similar functions, customers implicitly expect the perceived usability to be the same or better as existing ones. Thus, instead of affording differentiating advantages, the similarity to and quality comparisons with early-mover apps that have already provided the new SSFs can affect the valence of customer evaluations [46]. Accordingly, we propose that

Hypothesis 4. *The effect of app support imitations on the valence of customer evaluations is negatively moderated by the quality of early-mover apps.*

4. Methodology

4.1. Research context

For a number of reasons, we chose seven leading online travel firms (OTFs) in China – Ctrip, Qunar, eLong, Tuniu, Fliggy, LY, and Lvmama – and the timeframe from January 2011 to April 2015 as our research context. Above all, core innovation and support innovation are discernable and comparable in the online travel industry, which sets clear boundary conditions for our constructs. As it is a service industry, core innovation focuses on reservation services for a fixed set of travel activity elements, such as hotels, flights, package tours, and car rentals, while support innovation involves generic support of service functionalities specific to travel-related services, such as mobile check-in and flight status. More importantly, this was a rare opportunity to study a fairly closed hypercompetitive environment. Ever since the 2008 Beijing Olympics, the demand for travel in China has increased by leaps and bounds. The large and dynamic consumer needs for travel have attracted many entrepreneurs to innovate and compete in the industry, among which the seven OTFs are major players and accounted for approximately 90 percent of the market share in China as of 2015[13] . The most intense rivalry occurred from January 2011 to April 2015. Shortly thereafter, Ctrip acquired eLong in May 2015 and Qunar in October 2015, which marked the end of the rivalry among them.

During this period of intense rivalry, apps were the major arena for OTFs to innovate and compete[14] . Because of heterogeneous and unaddressed customer needs in the travel market, OTFs were constantly looking for opportunities in product markets and innovated to supply novel traveling reservation services and supporting service functionalities. However, the competitive advantages were ephemeral because each app tracked app innovation by the others very closely and dynamically made changes to gain an edge. In addition, during this period and even today, switching costs among online travel apps are low and customers often use most of them to compare products, services, and prices, in an attempt to maximize utility. Thus, the unique hypercompetitive context enabled us to observe pervasive innovation and imitation in terms of app core and app support as well as differential customer evaluations.

[13] https://www.analysys.cn/analysis/trade/detail/1000800/

[14] https://www.analysys.cn/article/analysis/detail/1000268/

4.2. Data collection

We further restricted our data analysis to the seven OTFs' iOS apps from January 2011 to April 2015 period, i.e., 52 months in total. The seven OTFs each conducted their business through their own single app to give customers a one-stop shopping experience. Thus, we were able to observe the OTFs' app core and app support innovations by tracking updates in new versions of their apps. Moreover, because of the inaccessibility of Google Play and no standard distribution channels for Android apps in China, iOS apps are more feasible than Android apps. Extant studies have also found that the effects of app innovation are more evident in Apple's App Store than in Google Play [4].

Subsequently, we collected data on seven samples of the apps from January 2011 to April 2015 from Apple's App Store. Our data collection consists of app information and app reviews. App information includes app name, description, initial release date, and release notes for each version. Release notes include version release date, version number, and a description of key changes involved in an update. Release notes have been demonstrated as valid sources to extract updated features [5,17,22]. Also, using a Python crawling program, we obtained 138,276 unique reviews about our sample apps. Our app review data involves the reviewer's ID, review date, review title, review content, and rating. Ratings consist of one to five "stars." The unit of analysis is an individual new feature added to a new app version.

4.3. Variables and measurement

4.3.1. Measures of dependent variables

We aggregated the *average rating* and *positive review ratio* between two versions to measure the valence of customer evaluations of app innovation(s). Online product reviews are widely used as a proxy to reflect customer evaluations of a product after it has been used [66]. App reviews as a specific form of customer reviews of a digital product have been demonstrated to be effective in gauging how customers assess an app innovation after use [17] as well as how they make comparisons with competing apps that have similar offerings. Valence, volume, and variance are three well-established metrics in the online review literature, among which valence is often measured by average rating [67,68]. However, for reviews spanning a long period of time, as in our case, review ratings present a J-shape distribution, providing biased views if aggregated indiscriminately. As a result, researchers suggest to not solely rely on the average rating, but also to incorporate positive or negative reviews to eliminate potential bias [67,68]. Moreover, because an app innovation may induce different degrees of positive and negative reviews if we consider the two metrics simultaneously, we may not obtain consistent findings. A positive review ratio represents the percentage of positive reviews, covering the overall condition. We, therefore, used the average rating and the positive review ratio to comprehensively capture the valence of customer evaluations. They also serve to cross-validate our results. The positive review ratio was operationalized by the number of positive reviews (reviews with ratings higher than three stars) divided by the total number of reviews between two versions for app i and is labeled *Pos. Review Ratio by Version*. The average rating was average ratings between two versions of app i and is labeled *Ave. Rating by Version*.

4.3.2. Measures of independent variables

Innovation-related variables were extracted from textual release notes by applying structured content analysis [69]. Prior studies often use either the release numbers directly [15] or feature-related keywords in release notes [5,17] to identify app innovation. However, those ways of operationalization provide limited insights into the types of new features added to a new app version. To untangle differential customer evaluations of app innovations, it is necessary to analyze the textual release notes in detail. We applied structured content analysis to identify specific changes made in an update for our sampled apps. Structured content analysis is an effective approach to reduce qualitative text into a unit-by-variable matrix [69]. We referred to prior work that used the approach to identify and classify IT components (such as knowledge- and process-oriented IT apps) [70,71] and competitive actions [72,73] from news articles to conduct the common procedures of the approach.

Structured content analysis relies on a previously developed coding scheme to identify items of interest [71]. To develop the coding scheme contextualized in online travel apps, we consulted two industry experts and carefully investigated randomly selected release notes. Apart from mapping the theoretical definitions of app innovation to corresponding descriptions in release notes, we also identified other types of app updates that are technical nonfeature updates, incremental updates, and commercial updates. To further ensure the inclusiveness of our update categories and clear definitions, we conducted pilot coding to refine the initial coding scheme. We finally identified ten subcategories of updates and then grouped them into four broad categories: app innovation, technical nonfeature updates, incremental updates, and commercial updates. Definitions, keywords, and examples of those categories were provided for coding purposes (see details in Table A1 in Appendix A). In the formal coding process, to ensure reliability, two independent coders separately coded the release notes based on our defined typology. The inter-rater agreement was 0.88, exceeding the minimum acceptable value of 0.7 [70]. Disagreements were discussed with a third coder until a consensus was reached. After completing the above processes, we identified the category to which each change in an update belonged, setting up the data for further analysis.

After the formal coding process, we had a list of app core and app support updates by app *i* in chronological order. Online travel apps normally use similar sentences to describe their app innovations, enabling us to match comparable app innovations. Accordingly, we coded app core and app support updates as innovations if they were the first to be introduced to the market and coded similar but later updates as imitations. Accordingly, *app core innovation* (*ACInn*) was operationalized by the number of new categories of service offerings that were first introduced by app *i* in month *t*. The categories of services offered by online travel apps primarily include (1) accommodation, (2) transportation, (3) attractions, (4) dining, (5) shopping, (6) entertainment, (7) packaged tours, and (8) travel supplements [74]. *App core imitation (ACImi)* was operationalized by the number of new categories of service offerings that were not first introduced by app *i* in month *t*.

Similarly, *app support innovation (ASInn)* was operationalized by the number of new SSFs that were first introduced by app *i* in month *t*. *App support imitation (ASImi)* was operationalized by the number of new SSFs that were not first introduced by app *i* in month *t*. As the seven online travel apps offer SSFs around eight broad service categories, we relied on prior studies on online customer service. In particular, to identify SSFs, we focused on the five sequential activities customers follow when making product or service purchase decisions: (1) needs recognition (such as search filters), (2) alternatives identification (such as recommendation), (3) alternatives evaluation (such as price comparison), (4) product acquisition (such as order fulfillment and payment), and (5) postpurchase (such as order management and refunds). Based on the descriptions, we identified SSFs from release notes in chronological order. If a particular SSF was first introduced by app *i* in month *t*, we coded it as an app support innovation. A similar SSF that was subsequently introduced by other apps was coded as app support imitation. For example, Qunar was the first of the seven competing apps to introduce the functionality of adding travel orders to Passbook in September 2012 and thus it was coded as an ASInn initiated by Qunar. Following Qunar, the functionality was quickly introduced by Ctrip, eLong, and Lvmama and thus was coded as an ASImi by those apps.

4.3.3. Measures of the moderator

Consistent with extant studies that use online reviews as a proxy for product quality [2,20], we used the average ratings of early-mover apps in month *t* to operationalize the quality of early-mover apps (*EarlyMoverAppQuality*). We relied on the matched sample of app core/support innovation vs. app core/support imitation to identify early-mover apps for any app core/support imitation introduced by focal app *i*. Accordingly, we dynamically identified apps that had already offered the imitated core product or service offering or imitated SSFs and then used average ratings of those apps in month *t* to measure the quality of early-mover apps.

4.3.4. Measures of control variables

The other types of app updates, i.e., nonfeature updates, incremental updates, and commercial updates, identified from release notes are used as control variables. Technical nonfeature updates (*TechNonfeaUpdate*) refer to flaw corrections or technical changes that are not directly related to the core functionalities of an app [23] including (1) bug fixes; (2) changes of app interface; (3) improvements in stability, security, or technical performance; (4) compatibility to iOS systems; and (5) new content [4,23,75]. Technical nonfeature updates were measured by the number of changes in subcategories of technical nonfeature updates for app *i* in month *t*.

Incremental updates (*IncreUpdate*) refer to updates that improve existing supporting service functionalities, e.g., optimizing voice search functionalities and were measured by the number of incremental updates for app *i* in month *t*.

Commercial updates (*CommerUpdate*) refer to updates that (1) introduce price cuts or promotions or (2) increase the scale of product or service offerings sold on an app. Commercial updates were operationalized by the number of changes in the two subcategories for app *i* in month *t*.

In addition, because we aggregated all of our variables on a monthly basis, we controlled for the number of updates (*NumUpdate*) for app *i* in month *t*. Moreover, because of our empirical setting, we further added *Quarter* as a dummy to control for the seasonal effects of travel. Overall, Table 3 provides descriptive statistics.

4.4. Econometric model

We used OLS-PCSE to examine customer evaluations of different kinds of app innovation and the moderating effect of the quality of early-mover apps. However, app developers may self-select to supply innovation, creating a selection bias. Therefore, we adopted the Heckman two-stage model to address the issue [76]. In the first stage, we created a dichotomous "choice variable" to indicate the presence (1) or absence (0) of app innovation by app *i* in month *t*. We next ran a Probit model with the dichotomous variable to estimate the probability of app innovation. In reference to previous literature, the predictors of the Probit model include a variance of ratings, review volume, app age, days since the last update for app *i* in month *t-1*, and month dummies [17,22]. We then computed the inverse Mills ratio, which is the non-selection hazard for each observation, and incorporated it as a control variable in our second-stage models. Accordingly, we specify the following equation for our models:

$$\begin{aligned} Y_{i,t+1} = \ & \beta_0 + \beta_1 TechNonFeaUpdate_{i,t} + \beta_2 IncreUpdate_{i,t} \\ & + \beta_3 CommerUpdate_{i,t} + \beta_4 NumUpdate_{i,t} + \beta_5 InverseMillsRatio_{i,t} \\ & + \beta_{6-8} Quarter_{Dumi,t} + \beta_{9-15} App_{Dumi} \end{aligned} \tag{1}$$

$$+ \beta_{16} ACInn_{i,t} + \beta_{17} ASInn_{i,t} + \beta_{18} ACImi_{i,t} + \beta_{19} ASImi_{i,t} \tag{2}$$

$$+ \beta_{20}\, EarlyMoverAppQuality_{i,t} \tag{3}$$

$$\begin{aligned} & + \beta_{21} ACImi_{i,t} \times EarlyMoverAppQuality_{i,t} + \beta_{22} ACImi_{i,t} \\ & \times EarlyMoverAppQuality_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{4}$$

Table 3
Descriptive statistics.

Variable name	Label	Obs.	Mean	Std. Dev.	Min	Max
App Core Innovation	1	36	0.184	0.489	0	3
App Support Innovation	2	112	0.808	1.217	0	8
App Core Imitation	3	47	0.240	0.551	0	3
App Support Imitation	4	102	0.660	0.986	0	5
Quality of Early-Mover Apps	5	250	4.551	0.375	2.500	4.926
Technical Nonfeature Updates	6	188	1.444	1.245	0	7
Incremental Updates	7	37	0.196	0.535	0	4
Commercial Updates	8	125	0.876	1.153	0	7
Number of Updates	9	250	1.292	0.600	1	5
Pos. Review Ratio by Version	10	250	0.834	0.201	0	1
Ave. Rating by Version	11	250	4.347	0.719	1	5

Note: Obs. denotes the number of observations.

In the equation, $< i, t >$ represents app-month combination; $Y_{i,t+1}$ represents the two dependent variables[15], i.e., *Pos. Review Ratio by Version*, and *Ave. Rating by Version;* and App_{Dum_i} denotes the app dummies to control for the unobserved individual effects. To test our hypotheses, we present four sets of models in a stepwise manner: Eq. (1) with control variables was used as the baseline model for testing the main effects; Eq. (2) with control variables and four types of app innovation (i.e., *ACInn, ASInn, ACImi, and ASImi*) was used to test the main effects[16] ; Eq. (3) with control variables, four types of app innovation, and quality of early-mover apps was used as the baseline model for testing the moderating effects; and Eq. (4) with control variables, four categories of app innovations, quality of early-mover apps, and interaction terms was used to test the moderating effects.

As our data are cross-sectional, time-series data with a small set of entities (i.e., seven apps) and a large number of time periods (i.e., 52 months), the data may be subject to correlation and heteroscedasticity. We, therefore, performed a Wooldridge test to check whether there is an autocorrelation [77], Wald tests to check the existence of heteroscedasticity [78], and a Breusch-Pagan Lagrange multiplier test to examine the dependence between panel units on our models. Those tests indicate the existence of group-wise heteroscedasticity and contemporaneous correlation across panel units and the existence of autocorrelation for all models.

To address the above issues, researchers suggest the use of OLS-PCSE [79] and feasible generalized least squares (FGLS) [80,81]. However, FGLS is not feasible in our context because of the requirements of balanced data. If we did balance our dataset, we would lose many observations. If we only corrected heteroskedasticity and autocorrelation, we may get distorted results considering the prevalence of contemporaneous correlation in our models. We, therefore, adopted OLS-PCSE as our major estimation procedure. For autocorrelation, we adopted panel-specific auto-regression to better incorporate panel-specific heterogeneities.

Furthermore, the correlation matrix in Appendix B shows that our variables are not highly correlated. We also computed the variance inflation factors (VIF) to test for any possible multicollinearity. The VIFs for all variables in our models are less than the critical value of 10 (the highest is 2.45), eliminating potential concerns about multicollinearity issues.

[15] *Note:* The dependent variables are calculated by version, i.e., Pos. Review Ratio by Version and Ave. Rating by Version, which does not identically represent "next month" but the time between two versions.

[16] Considering that the potential correlation between different types of app innovations may raise the issue of multicollinearity, we estimated separate models for each type of app innovation and a full model that contains four types of app innovation. The results are almost identical. Therefore, for brevity, we only report the results of the full model in Section 5 and attach the results of the separate models in Appendix C. Moreover, we also changed the order in which controls and independent variables were entered; there is no change in the significance of coefficients.

5. Results

5.1. Main effects

Table 4 shows the regression results for the main effects. As predicted by H1, app core innovations are positively associated with the valence of customer evaluations. As shown in Table 4, the coefficients of *App Core Innovation* are positive and significant in models 2.1 and 2.2, suggesting that app core innovations will significantly increase positive review ratios and average ratings between two versions. The results indicate that ACInn has a significant positive effect on the valence of customer evaluation. Thus, hypothesis 1 is supported.

Hypothesis 2. predicted that app support innovations are positively associated with market performance. Table 4 shows that the coefficients of *App Support Innovation* are negative and significant in models 2.1 and 2.2, indicating that ASInn will significantly decrease positive review ratios and average ratings received between two versions. Therefore, hypothesis 2 is not supported. However, *App Core Imitation* and *App Support Imitation* show no significant impacts in models 2.1 and 2.2. We posit that the results confirm our suspicions about the negative moderating effect of the quality of early-mover apps. We report the results of moderating effects in the next section.

5.2. Moderating effects

Table 5 reports the results of moderating effects. Models 3.1 and 3.2 incorporate controls and predictors based on which models 4.1 and 4.2 add the first interaction term, models 4.3 and 4.4 add the second interaction term, and models 4.5 and 4.6 are full models that contain the two interaction terms. As predicted by H3, the effect of app core imitation on the valence of customer evaluations is negatively moderated by the quality of early-mover apps. However, although the coefficients for the interaction term, *ACImi X Quality of Early-Mover Apps*, in models 4.1, 4.2, 4.5, and 4.6 are positive, the coefficients are not significant. Thus, we did not find significant evidence that supports hypothesis 3.

In contrast, the coefficients for the interaction term, *ASImi X Quality of Early-Mover Apps*, across models 4.3, 4.4, 4.5, and 4.6 are all negative and significant, which suggests that the effect of ASImi on the valence of customer evaluations is negatively moderated by the quality of early-mover apps. Besides, it is worth noting that the coefficients of *App Support Imitation* are not significant. We posit that there are potential crossover interactions that lead to the insignificant main effects, meaning that when the direction of the main effects is contrary on the low-level versus the high-level of *Quality of Early-Mover Apps*, the overall effects of *App Support Imitation* on the valence of customer evaluations are averaged out. Moreover, previous studies have pointed out that “when the focus of the tests is on the interaction effects (as in our hypotheses), the significance of the main effects is not of substantive interest” [[82], p. 666]. Thus, hypothesis 4 is supported. We discuss the implications for those findings in detail in the discussion section.

5.3. Robustness check

We made the following efforts to ensure the robustness of our findings. First, we used fixed-effect (FE) models or random-effect (RE) models with cluster-robust standard errors as alternative estimation procedures to check the robustness of our findings. The FE or RE models are common methods for panel data and can be selected based on criteria generated by Hausman tests. However, although an FE model or RE model with cluster-robust standard errors allows the existence of heteroskedasticity and autocorrelation, they cannot address the issue of contemporaneous correlations across panel units that exists in all of the models. Thus, we used OLS-PCSE as our main estimation procedure and included app dummies in our models to control for unobserved time-invariant fixed factors associated with a specific app. Here, based on the

Table 4
Results of main effects.

VARIABLES	Model 1.1 Pos. Review Ratio by Version	Model 1.2 Ave. Rating by Version	Model 2.1 Pos. Review Ratio by Version	Model 2.2 Ave. Rating by Version
Controls				
Technical Nonfeature Update	0.010	0.023	0.012	0.027
	(0.008)	(0.026)	(0.008)	(0.026)
Incremental Update	0.014	0.015	0.022	0.038
	(0.017)	(0.049)	(0.018)	(0.051)
Commercial Update	0.003	0.004	0.004	0.010
	(0.009)	(0.026)	(0.009)	(0.026)
Number of Updates	−0.037**	−0.092*	−0.032*	−0.097*
	(0.017)	(0.054)	(0.017)	(0.054)
Inverse Mills Ratio	−0.243***	−0.880***	−0.253***	−0.908***
	(0.054)	(0.204)	(0.053)	(0.195)
Quarter dummies	YES	YES	YES	YES
App dummies	YES	YES	YES	YES
Predictors				
App Core Innovation *(H1)*			**0.032***	**0.106***
			(0.018)	(0.058)
App Support Innovation *(H2)*			**−0.019****	**−0.054****
			(0.008)	(0.026)
App Core Imitation			−0.009	0.029
			(0.019)	(0.058)
App Support Imitation			−0.001	0.008
			(0.010)	(0.030)
Constant	1.003***	4.971***	0.997***	4.964***
	(0.030)	(0.106)	(0.030)	(0.101)
Observations	240	240	240	240
R-squared	0.269	0.582	0.291	0.600
Number of apps	7	7	7	7

Note: Standard errors are in parentheses. All estimates are corrected for heteroskedasticity, contemporaneous correlation, and autocorrelation. The number of observations is reduced because of missing data when computing the inverse Mills ratio.

*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

criteria generated by the Hausman tests, we applied the FE model for the main effects and RE model for the moderating effects. We conducted the FE model or RE model through the robust option of xtreg in Stata as sensitive tests of our results. The results of the additional analyses are presented in Appendix D. The results remained unchanged, suggesting that our findings are not subject to one specific method. Second, considering the fact that customers may react to app innovations in lagged ways [15], we used positive review ratio and average rating aggregated by the following month as alternative measures for the valence of customer evaluations of app innovation to cross validate our results. As shown in Table D1 in Appendix D, the qualitative nature of the results does not change, raising confidence in our main findings.

5.4. Supplementary analyses

Given that our results show a robust negative impact of app support innovations on the valence of customer evaluations, which are contrary to our hypothesis, we conducted further analyses on negative reviews in an attempt to decipher the potential causes. In particular, we performed a Latent Dirichlet Allocation model [83] to extract topics from negative reviews customers posted on our sample apps after app support innovations. Negative reviews were selected based on the criteria that ratings were less than three stars. Among the topics that emerged from the topic modeling approach, there were two topics that were directly related to negative reactions to app support innovations. The keywords/phrases underlying the topics included "not as good as the previous version," "quit on," "no improvements," "disappointments," "not usable." Other topics were general complaints on price discrimination and service quality. We will reflect on those findings in the following section.

6. Discussion

The skewed outcome in app markets suggests that more research is needed on effective innovation strategies to cope with hypercompetition. This study sought to clarify the effects of different types of app innovation on the valence of customer evaluations. Our findings provide insights into how firms or developers innovate and compete in hypercompetitive app markets. Two of our four hypotheses are supported. Next, we reflect on the theoretical implications, surmise the reasons for unsupported hypotheses, and propose guidelines for practical use. Key findings and implications to theory and practice are summarized in Table 6.

6.1. Theoretical implications

Above all, we provide rich insights into the nature of app innovation by uncovering two types of app innovation from the feature level and demonstrate how app innovation impacts customer evaluations, thus contributing to the reconciliation of mixed findings and the clarification of the underlying theoretical mechanisms in the app innovation literature and the broad app updates literature. Prior studies view app innovation as homogenous and mainly investigate the impact of a dichotomy of app innovation [4,15,17,18,23], but those studies found mixed results and the underlying theoretical rationale remains unclear.

In contrast, we argue that one of the major reasons for the inconsistent findings is treating app innovation as a monolithic entity, which fails to capture underlying tensions. Grounded in the technological innovation literature [36,41], we take a structural perspective of an app as a digital product that is composed of a nested hierarchy of features or functionalities. We differentiate app innovation by classifying new features that relate to new business functions that provide new categories of product or service offerings (which we label as app core innovation) as opposed to new features that are new SSFs that pertain to existing product or service offerings (which we label as app support innovation). Our results suggest their differential impacts – ACInn increases the valence of customer evaluation, whereas ASInn decreases the valence of customer evaluations. The results indicate that by adding a new business function and providing a new category of product or service offering, ACInn can add multifunctional value to customers, who also perceive it as beneficial. Conversely, ASInn – adding new SSFs associated with existing product or service offerings – encounters a tradeoff between adding interaction value and interrupting customers' established routines. Because of changing customer needs and a competitive environment, new SSFs are expected to better assist customers in interacting with an app and deriving the value of existing product or service offerings provided by an app. However, because basic SSFs are provided at the initial provision of the product or service offering, the new SSFs build on, complement, or replace existing functionalities. As such, customers are often required to adjust their familiar routines based on existing SSFs and integrate new ways into their established habits. In other words, when executing the same task, familiar responses may no longer work, and customers need to give up their old habits and learn the new interaction rules [18]. The learning costs and adjustments in familiar routines make customers reluctant to accept the changes brought by ASInn [17,84,85].

Therefore, by surfacing the contradictory forces of two types of app innovation, we safeguard against situations where one particular type of app innovation is dominant. We also demonstrate the differences between ACInn and ASInn – the former adds multifunctional value to customers, while the latter encounters a tradeoff between adding interaction value and disrupting customers' established routines. Thus, we provide a holistic view of when and how app innovation will result in the superior or inferior valence of customer evaluations.

Second, we provide a more nuanced understanding of customer evaluations of app imitation in hypercompetitive app markets by differentiating two types of imitation from the feature level and demonstrating how the quality of early-mover apps influences the valence of customer evaluations.

Table 5
Results of moderating effects.

VARIABLES	Model 3.1 Pos. Review Ratio by Version	Model 3.2 Ave. Rating by Version	Model 4.1 Pos. Review Ratio by Version	Model 4.2 Ave. Rating by Version	Model 4.3 Pos. Review Ratio by Version	Model 4.4 Ave. Rating by Version	Model 4.5 Pos. Review Ratio by Version	Model 4.6 Ave. Rating by Version
Controls								
Technical Nonfeature Update	0.006	0.024	0.006	0.024	0.006	0.022	0.006	0.022
	(0.007)	(0.026)	(0.007)	(0.026)	(0.007)	(0.025)	(0.007)	(0.025)
Incremental Update	0.010	0.041	0.010	0.042	0.012	0.047	0.012	0.048
	(0.014)	(0.051)	(0.014)	(0.050)	(0.014)	(0.051)	(0.014)	(0.051)
Commercial Update	0.001	−0.001	0.001	−0.001	0.000	−0.004	0.000	−0.004
	(0.007)	(0.027)	(0.007)	(0.027)	(0.007)	(0.026)	(0.007)	(0.026)
Number of Updates	−0.021	−0.071	−0.021	−0.069	−0.026*	−0.091*	−0.025*	−0.090*
	(0.015)	(0.054)	(0.015)	(0.055)	(0.014)	(0.051)	(0.014)	(0.051)
Inverse Mills Ratio	−0.240***	−0.899***	−0.240***	−0.901***	−0.245***	−0.924***	0.061**	0.192**
	(0.056)	(0.209)	(0.056)	(0.209)	(0.054)	(0.201)	(0.024)	(0.087)
Quarter dummies	YES	YES	YES	YES	YES	YES	YES	YES
App dummies	YES	YES	YES	YES	YES	YES	YES	YES
Predictors								
App Core Innovation	0.022	0.016	0.022	0.014	0.022	0.014	0.017	0.012
	(0.016)	(0.059)	(0.016)	(0.059)	(0.015)	(0.057)	(0.015)	(0.057)
App Support Innovation	−0.015**	−0.056**	−0.015**	−0.056**	−0.012*	−0.045*	−0.012*	−0.044*
	(0.007)	(0.026)	(0.007)	(0.026)	(0.007)	(0.025)	(0.007)	(0.025)
App Core Imitation	0.001	0.025	0.000	0.011	−0.002	0.015	−0.008	−0.007
	(0.016)	(0.058)	(0.019)	(0.070)	(0.016)	(0.057)	(0.019)	(0.069)
App Support Imitation	0.001	0.010	0.001	0.010	0.007	0.033	0.008	0.034
	(0.008)	(0.030)	(0.008)	(0.030)	(0.009)	(0.031)	(0.009)	(0.031)
Quality of Early-Mover Apps	0.092	0.425	0.101	0.534	−0.078	−0.248	−0.056	−0.107
	(0.091)	(0.327)	(0.110)	(0.405)	(0.112)	(0.408)	(0.129)	(0.467)
Interactions								
ACImi X Quality of Early-Mover Apps *(H3)*			0.008	0.116			0.035	0.180
			(0.079)	(0.298)			(0.080)	(0.296)
ASImi X Quality of Early-Mover Apps *(H4)*					**−0.078****	**−0.303****	**−0.080****	**−0.310****
					(0.035)	(0.126)	(0.035)	(0.126)
Constant	0.875***	4.331***	0.862***	4.169***	1.135***	5.359***	1.100***	5.148***
	(0.140)	(0.505)	(0.169)	(0.620)	(0.176)	(0.641)	(0.202)	(0.728)
Observations	240	240	240	240	240	240	240	240
R-squared	0.440	0.577	0.453	0.607	0.528	0.611	0.545	0.635
Number of apps	7	7	7	7	7	7	7	7

Note: Standard errors are in parentheses. All estimates are corrected for heteroskedasticity, contemporaneous correlation, and autocorrelation. The number of observations is reduced because of missing data when computing the inverse Mills ratio.
*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Table 6
Summary of findings and implications to theory and practice.

Findings	Theoretical Implications	Practical Implications
App core innovations increase the valence of customer evaluations.App support innovations decrease the valence of customer evaluations.	Uncovering two types of app innovations from the feature level can reveal rich insights into the nature of app innovation and enhance our understanding of how app innovation impacts the valence of customer evaluations. Our study also helps reconcile the mixed findings and clarify the underlying theoretical mechanisms in terms of how customers evaluate app innovation.	Firms or developers should continuously innovate in products or services to add multifunctional value to customers and gain preemptive advantages.Firms or developers should be cautious innovating supporting service functionalities and make sure they integrate well into customers' established habits.
High-quality early-mover apps attenuate the effect of app support imitation on the valence of customer evaluations, whereas the negative contingent effect is not evident for app core imitation.	Differentiating two types of app imitation from the feature level and incorporating the quality of early-mover apps as a contingent condition in influencing customer evaluations can provide a more nuanced understanding of the performance impact of app imitation in hypercompetitive app markets.	Followers that "imitate" innovations should ensure that they provide superior or at least equivalent quality as early-mover apps.

Some recent studies in the app development literature have demonstrated the positive effects of app imitation [53,54] and have discussed how the quality and deceptive level of imitation apps (which they call copycats) affect the demand for original apps [2]. However, by imitation, previous studies focus on the app level and refer to copying an original app. In contrast, we focus on the feature level and perceive app imitation as introducing the similar product or service offerings or SSFs following early movers' efforts – which we label as app core imitation and ASImi correspondingly.

Our results provide compelling evidence that high-quality early-mover apps attenuate the effect of ASImi on the valence of customer evaluation due to similarity to and quality comparisons with early-mover apps. We did not find the negative contingent effect on app core imitation. One possible explanation is that supporting functionalities are easier to compare and thus are more susceptible to quality comparisons [86]. New SSFs are introduced to better help customers derive value from the existing core product or service offerings. Given a set of apps that provide similar SSFs, it is relatively easy for customers to assess how well the SSFs help them achieve their interaction goals with the app. In contrast, it is hard to distinguish among the core products or services offered by equivalent rivals in our samples, such as the ride-hailing services offered by Uber and Lyft. The assessment of core product or service offerings can also differ in contextual situations, such as time [57]. Therefore, compared with app core imitations, app support imitations are more susceptible to quality comparisons among early-mover apps in a hypercompetitive environment.

Third, we also contribute to the digital innovation literature by shifting the focus from the platform to app developers and directly investigating the impacts of app innovation and imitation, thus enriching our understanding of intra-platform competition and the performance implications to app developers. Guided by the theoretical lens of layered modular architecture, the digital innovation literature holds the view that the value of a software platform is realized by attracting a large number of heterogeneous app developers and fostering their unprompted innovations [6,7]. Accordingly, prior relevant studies mainly focus on how to facilitate app innovation from the platform perspective. That is, the antecedents of app innovation include user characteristics [8], network effects [9], platform boundary resources [10–13], governance mechanisms [14,15], and platform entry [5,16]. However, along with the facilitated innovation is the hypercompetition inside the platform. In such a hypercompetitive environment, the market is on a "knife's edge" where little things can tip the balance in favor of one app or another as they continue to compete dynamically by seeking opportunities to innovate or imitate to get ahead of one another. Therefore, although unprompted app innovations are beneficial to a platform in general, a better understanding of the effects of individual app innovations are critical for app developers to achieve long-term success. In this study, as illustrated earlier, we take an initial attempt to delve into typologies of app innovation by taking a structural perspective on new features and considering the pervasive innovation and imitation strategies in app development. We further unveil the different mechanisms that affect customer evaluations. As such, we complement the existing digital innovation literature by shifting the platform perspective of exploring antecedents of app innovation to the app developer's perspective of investigating the direct effects of app innovation and imitation.

Although the findings of our study are within the context of online travel apps, the basic concepts of app core vs. support innovation and quality of early-mover apps and their influence on customer evaluations can be extended to other contexts (e.g., the app category of Navigation, Shopping, and Social Networking[17] exhibit both innovations). Within this context, the imitation of features among competing apps are pervasive, while in other contexts (e.g., the category of Book, Music, Weather, and Photo and Video), most apps just provide one primary offering. Thus, the app innovation in these categories may not necessarily reflect the duality of innovation proposed in this study and may mainly focus on adding new SSFs to improve the primary offering.

6.2. Practical implications

Our results also have important implications for formulating effective innovation strategies to compete in hypercompetitive app markets. Above all, firms or developers should not hesitate to initiate app core innovations by adding new business functions to provide new categories of product or service offerings to an existing app. According to our results, customers highly value app core innovations and the effects of app core imitation are not contingent on the quality of early-mover apps. Therefore, firms or developers should continuously explore unmet customer needs and innovate in product or service offerings, thus gaining preemptive advantages. They should also be sensitive to rivals' innovative digital moves and act as a fast follower.

Contrary to the beneficial consequences of app core innovations, firms or developers should be cautious of innovating supporting service functionalities. As suggested by our findings, customers are more likely to react negatively to app support innovations and the evaluations of app support imitations are more likely to be influenced by the quality of early-mover apps. Considering that SSFs play a critical role in helping customers derive value from product or service offerings throughout the interaction process, firms, or developers should pay more attention to those functionalities and introduce well-designed functionalities that integrate well with customers' established usage habits. For followers that "imitate" innovations, they should ensure that they provide quality that is superior or at least equivalent to early movers. Otherwise, it is very hard for them to achieve the desired outcomes.

6.3. Limitations and future directions

Our study has some limitations that could serve as avenues for future research. First, we made an initial attempt to investigate the effect of adding a new business function to provide a category of product or service offering and new SSFs to an existing app. Future studies can extend the research and explore other contingent conditions, such as the complexity or nature of the base app. Second, we are particularly interested in how customers evaluate different types of app innovation and imitation. The valence of customer evaluations as measured by aggregated ratings received between two app versions by its nature is a short-term performance indicator. Future studies can relate the identified typologies of app innovation and imitation to other outcome variables, such as the active user base or revenues, and explore long-term or temporal effects that can generate interesting findings. Third, although we have applied alternative measures and alternative estimating procedures to ensure the robustness of our findings, we acknowledge that the use of OLS-PCSE as our main estimation procedure does not allow isolating bias-free estimates. Future research may address this issue in more robust research designs that combine OLS-PCSE with FGLS or establish control groups by using matching methods.

Declaration of Competing Interest

None.

CRediT authorship contribution statement

Hengqi Tian: Conceptualization, Formal analysis, Methodology, Writing - original draft, Writing - review & editing. **Varun Grover:** Conceptualization, Validation, Writing - review & editing. **Jing Zhao:** Conceptualization, Validation, Supervision. **Yi Jiang:** Formal analysis, Investigation.

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Appendix A Coding scheme

[17] For a complete list of iOS app categories and their descriptions in Apple's App Store, please visit: https://developer.apple.com/app-store/categories/.

Table A1
Coding scheme.

Categories	Definitions	Subcategories	Descriptions/Examples	Keywords
App Innovation	Add new features or functionalities to an existing app.	App core updates	Add new business functions that provide new categories of product or service offerings to an existing app. The categories of reservation services offered by online travel apps broadly include (1) accommodation, (2) transportation, (3) attractions, (4) dining, (5) shopping, (6) entertainment, (7) packaged tours, and (8) travel supplements. Example keywords for each category are listed in the right column, with the corresponding number.	Add reservation services for (1)Accommodation, such as domestic hotels, international hotels, and inns (2)Transportation, such as flights, car rentals, trains, and buses (3)Tourist attractions, such as tickets for places of interest or scenic spots (4)Food, such as local restaurant reservations (5)Tourist shopping, such as global shopping and receiving refunds on duties (6)Entertainment, such as themed events and local activities (7)Packaged tours, such as road trips and cruise lines (8)Travel supplements, such as visa, tour financing and Wi-Fi device rentals
		App support updates	Add new supporting functionalities (SSFs) to an existing app. Supporting service functionalities are supplementary technological features that help a customer navigate the app and support the entire transaction process. The categories of SSFs for online travel apps broadly include (1) needs recognition, (2) alternatives identification, (3) alternatives evaluation, (4) product acquisition, and (5) postpurchase. Example keywords for each category are listed in the right column, with the corresponding number.	Add functionalities that help customers (1) Make sense of their needs or preferences, such as search filters (2) Search for alternate and related products/services, such as related product recommendations (3) Conduct in-depth comparisons among generated alternatives, such as detailed product comparisons (4) Facilitate the completion of online transactions, such as order fulfillment, payment, and one-click ordering. (5) Follow the purchase of products or services, such as writing reviews, order management, and ticket refunds.
Technical Nonfeature Updates	Flaw corrections or technical changes that are not directly related to an app's core functionalities.	Bug fixes	Updates that involve bug fixes.	Bug fixes, fix, resolve, tackle, bug, problem, and crash
		Interfaces	Updates that involve changes in app interfaces, such as user interface redesign.	Interfaces, user interface, UI, icons, and new look
		Improvements in stability, security, or technical performance	Updates that improve the stability, security, or technical performance of an app.	Stability, security, and performance improvements
		Compatibility to iOS systems	Updates that fix compatibility with newly upgraded iOS systems.	Compatible with iOS systems
		New content	Updates that add synthesized information, such as adding an offline database for tour guides.	Information and data
Incremental Updates	Updates that improve existing SSFs.		For example, updates that optimize voice search functionality.	Optimize, refine, improve, and enhance
Commercial Updates	Updates that relate to commercial activities.	Promotion	Updates that cut prices or introduce promotions of product or service offerings sold on an app.	Promotion, sales, discounts, and price cuts
		Increases in offering scale	Updates that increase the scale of product or service offerings sold on an app, such as an increase of 1000 hotels in the domestic market on the Ctrip app.	Increase, add, expand, and quantity

Appendix B. Correlation matrix

Table B1

Table B1
Correlation matrix.

	1	2	3	4	5	6	7	8	9	10	11
1	1										
2	0.09	1									
3	0.30*	0.16*	1								
4	0.05	0.14*	0.05	1							
5	0.03	−0.01	0.13*	0.14*	1						
6	0.13*	0.26*	0.23*	0.09	0.38*	1					
7	0.05	0.13*	−0.02	0.01	−0.01	−0.08	1				
8	0.02	0.29*	0.07	0.01	0.07	0.33*	0.04	1			
9	0.09	0.23*	0.15*	0.10	0.19*	0.42*	0.04	0.29*	1		
10	−0.06	−0.15*	0.004	0.05	0.22*	0.20*	−0.03	0.04	0.07	1	
11	−0.04	−0.13*	0.02	0.05	0.23*	0.21*	−0.04	0.04	0.08	0.99*	1

Note: *$p < 0.05$.

Appendix C. Results of separate models for main effects

Table C1

Table C1
Results of separate models for main effects.

	Pos. Review Ratio by Version	Ave. Rating by Version	Pos. Review Ratio by Version	Ave. Rating by Version	Pos. Review Ratio by Version	Ave. Rating by Version	Pos. Review Ratio by Version	Ave. Rating by Version	Pos. Review Ratio by Version	Ave. Rating by Version	Pos. Review Ratio by Version	Ave. Rating by Version
Controls												
Technical Nonfeature Update	0.010	0.023	0.009	0.021	0.012	0.026	0.010	0.024	0.009	0.023	0.012	0.027
	(0.008)	(0.026)	(0.008)	(0.026)	(0.008)	(0.026)	(0.008)	(0.026)	(0.008)	(0.027)	(0.008)	(0.026)
Incremental Update	0.014	0.015	0.015	0.016	0.021	0.034	0.014	0.014	0.013	0.016	0.022	0.038
	(0.017)	(0.049)	(0.018)	(0.050)	(0.018)	(0.051)	(0.017)	(0.049)	(0.017)	(0.049)	(0.018)	(0.051)
Commercial Update	0.003	0.004	0.002	0.005	0.005	0.010	0.003	0.004	0.003	0.005	0.004	0.010
	(0.009)	(0.026)	(0.009)	(0.026)	(0.009)	(0.026)	(0.008)	(0.025)	(0.009)	(0.026)	(0.009)	(0.026)
Number of Updates	−0.037**	−0.092*	−0.038**	−0.100*	−0.032*	−0.085	−0.036**	−0.096*	−0.0358**	−0.0911*	−0.032*	−0.097*
	(0.017)	(0.054)	(0.017)	(0.053)	(0.017)	(0.054)	(0.017)	(0.055)	(0.017)	(0.054)	(0.017)	(0.054)
Inverse Mills Ratio	−0.243***	−0.880***	−0.238***	−0.900***	−0.249***	−0.899***	−0.245***	−0.873***	−0.245***	−0.877***	−0.253***	−0.908***
	(0.054)	(0.204)	(0.054)	(0.198)	(0.053)	(0.199)	(0.055)	(0.207)	(0.053)	(0.202)	(0.053)	(0.195)
Quarter dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
App dummies	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
App Core Innovation *(H1)*			**0.033***	**0.104***							**0.032***	**0.106***
			(0.018)	(0.059)							(0.018)	(0.058)
App Support Innovation *(H2)*					**−0.020****	**−0.046***					**−0.019****	**−0.054****
					(0.008)	(-0.025)					(0.008)	(0.026)
App Core Imitation							−0.004	0.029			0.009	0.029
							(0.019)	(0.058)			(0.019)	(0.058)
App Support Imitation									−0.004	−0.005	−0.001	0.008
									(0.010)	(0.030)	(0.010)	(0.030)
Constant	1.003***	4.971***	1.003***	4.980***	0.996***	4.965***	1.004***	4.969***	1.005***	4.970***	0.997***	4.964***
	(0.030)	(0.106)	(0.030)	(0.103)	(0.030)	(0.104)	(0.030)	(0.105)	(0.030)	(0.105)	(0.030)	(0.101)
Observations	240	240	240	240	240	240	240	240	240	240	240	240
R-squared	0.269	0.582	0.276	0.598	0.282	0.606	0.269	0.594	0.269	0.600	0.291	0.600
Number of apps	7	7	7	7	7	7	7	7	7	7	7	7

Note: Standard errors are in parentheses. All estimates are corrected for heteroskedasticity, contemporaneous correlation and autocorrelation.
*** $p < 0.01$, ** $p < 0.05$, and * $p < 0.1$.

Appendix D. Robustness tests

Table D1
Robustness tests.

	Pos. Review Ratio by Version		Ave. Rating by Version		Pos. Review Ratio by Month		Ave. Rating by Month	
	FE	RE	FE	RE	PCSE	PCSE	PCSE	PCSE
Controls								
Technical Nonfeature Update	0.012	0.005	0.0406	0.016	0.022**	0.020**	0.074**	0.066**
	(0.008)	(0.008)	(0.0287)	(0.031)	(0.009)	(0.009)	(0.031)	(0.030)
Incremental Update	0.022	0.019	0.0758	0.069	0.026	0.024	0.087	0.081
	(0.022)	(0.017)	(0.0781)	(0.061)	(0.017)	(0.017)	(0.059)	(0.054)
Commercial Update	0.004	0.003	0.0171	0.0003	0.011	0.009	0.034	0.025
	(0.009)	(0.005)	(0.0288)	(0.016)	(0.009)	(0.009)	(0.032)	(0.030)
Number of Updates	−0.032	−0.029	−0.125	−0.090	−0.015	−0.019	−0.067	−0.078
	(0.039)	(0.030)	(0.133)	(0.107)	(0.018)	(0.017)	(0.061)	(0.059)
Inverse Mills Ratio	−0.253	−0.224*	−0.876	−0.821*	−0.266***	−0.258***	−0.578***	−0.537***
	(0.170)	(0.127)	(0.595)	(0.450)	(0.055)	(0.0587)	(0.188)	(0.200)
Quarter dummies	YES	YES	YES	YES	YES	YES	YES	YES
App dummies	YES	YES	YES	YES	YES	YES	YES	YES
App Core Innovation	**0.032*** **	−0.001	**0.148** **	−0.053	**0.032* **	**0.030* **	**0.147** **	**0.142** **
	(0.008)	(0.013)	(0.055)	(0.0664)	(0.019)	(0.018)	(0.069)	(0.068)
App Support Innovation	**−0.019** **	**−0.024** **	**−0.065** **	**−0.0800* **	**−0.015* **	−0.009	**−0.058** **	−0.040
	(0.006)	(0.012)	(0.020)	(0.0434)	(0.008)	(0.008)	(0.029)	(0.027)
App Core Imitation	−0.009	−0.007	−0.007	−0.00885	−0.012	−0.016	−0.039	−0.046
	(0.013)	(0.024)	(0.056)	(0.0877)	(0.020)	(0.024)	(0.072)	(0.086)
App Support Imitation	−0.001	0.013	−0.005	0.0459	−0.007	0.001	−0.037	−0.011
	(0.010)	(0.012)	(0.039)	(0.0465)	(0.010)	(0.010)	(0.035)	(0.033)
Quality of Early-Mover Apps		−0.189		−0.665		−0.029		−0.041
		(0.147)		(0.472)		(0.136)		(0.479)
App Core Imitation X Quality of Early-Mover Apps		−0.042		−0.138		−0.0004		−0.043
		(0.086)		(0.284)		(0.092)		(0.339)
App Support Imitation X Quality of Early-Mover Apps		**−0.123* **		**−0.450** **		**−0.113*** **		**−0.371*** **
		(0.063)		(0.221)		(0.041)		(0.140)
Constant	0.914***	1.203***	4.641***	5.649***	0.995***	1.052***	4.882***	4.985***
	(0.060)	(0.256)	(0.212)	(0.825)	(0.029)	(0.214)	(0.099)	(0.753)
Obs.	240	240	240	240	240	240	239	239
R-squared	0.124	0.123	0.125	0.121	0.279	0.298	0.256	0.276
Number of apps	7	7	7	7	7	7	7	7

Note: For FE or RE models, robust standard errors are in parentheses. For PCSE models, standard errors are in parentheses and the estimates are corrected for heteroskedasticity, contemporaneous correlation, and autocorrelation.
*** p < 0.01, ** p < 0.05, and * p < 0.1.

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